

Design and Analysis of Green and Sustainable IoT Technologies for Future Wireless Communications

EDITED BY

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Introduction to Green IoT devices

1

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1.1 Introduction to IoT and its environmental impact

1.1.1 What is IoT?

The Internet of Things (IoT) is a system of linked devices that exchange data across the Internet [1]. These sensors, actuators, and communication modules-equipped devices provide real-time monitoring, control, and automation in a variety of uses including smart homes, healthcare, agriculture, transportation, and industrial automation [2].

1.1.2 Arising environmental challenges

IoT devices' broad acceptance has transformed daily life and businesses, allowing formerly unheard-of degrees of data-driven decision-making, connectivity, and automation. Still, this fast spread of IoT technologies has brought major environmental problems. The lifetime of IoT devices—including their manufacture, running, and disposal—defines these obstacles. We explore the main environmental issues connected with IoT devices below.

1.1.2.1 Energy consumption

Often in remote or difficult-to-reach areas, IoT devices are meant to run continuously to offer real-time monitoring and control. Although this ability is quite useful, significant energy consumption results from it. Important problems include data centers, battery reliance, ongoing operation, and cloud computing [3]. Many IoT devices, such as surveillance cameras and smart sensors, run around-the-clock, which drives great energy demand. For instance, a single smart home gadget—such as a thermostat or security camera—may use just a tiny bit of energy, but when multiplied by millions of devices worldwide, the total energy usage becomes somewhat noteworthy. Moreover, a lot of IoT gadgets run on batteries. Regular battery changes not only raise running expenses but also help to damage the environment by battery manufacture and disposal. IoT devices create enormous volumes of data that are often handled and kept in energy-intensive data centers. Large amounts of electricity consumed by these data centers help to explain world energy usage and carbon emissions. Recent

estimates indicate that data centers account for about 1% of world electricity use; this figure is anticipated to increase significantly as the IoT develops.

Electronic waste

The short lifetime of many IoT devices aggravates the worldwide e-waste issue. Discarded electronic equipment, sometimes known as e-waste, often have toxic components that might endanger human health or the environment. Important concerns are limited device lifetime, toxic materials, and recycling difficulties [4]. More precisely, many Internet of Things devices are made with planned obsolescence—that is, they are meant to have a limited lifetime. Frequent replacements encouraged by this cause e-waste to rise. For instance, as newer versions are unveiled, smart home appliances like wearable fitness trackers or voice assistants are sometimes changed every few years. Apart from that, IoT gadgets sometimes have harmful elements such as cadmium, mercury, and lead, which, if improperly disposed of, can seep into the ground and water. Much of the world's e-waste is sent to underdeveloped nations, so inappropriate management of e-waste there poses major environmental and health hazards. Moreover, the intricate architecture of IoT devices—which frequently combine several materials and components—makes recycling challenging. Many technologies are not meant to be disassembled, and the absence of uniform recycling policies aggravates the problem. Furthermore, the extensive application of lithium-ion batteries in Internet of Things devices begs issues with resource depletion and battery waste pollution. Consequently, a good amount of e-waste either burns or finds their way in landfills, spewing dangerous toxins into the surroundings.

Carbon footprint

IoT devices have a carbon footprint that includes greenhouse gas emissions produced all during their lifetime, from manufacture to disposal. Important contributors are end-of-life emissions, operating emissions, and manufacturing emissions [5]. Energy-intensive operations including the procurement and processing of raw materials, component manufacture, and device assembly comprise the production of IoT devices. For instance, semiconductor manufacture—which is necessary for Internet of Things devices—requires a lot of energy and produces large emissions. IoT devices' running energy consumption adds to their carbon footprint. For gadgets that depend on non-renewable energy sources especially, this is quite alarming. IoT devices running coal-based electricity, for example, have a far larger carbon impact than those running renewable energy. Particularly by landfilling or incineration, the disposal of IoT devices generates methane and carbon dioxide. Further adding to emissions is the movement of e-waste to disposal sites or recycling centers.

Resource depletion

Rare earth metals, copper, and gold are among the few natural resources needed for IoT devices' manufacture. Among important issues are resource shortages and rare earth metals. Most IoT devices, including sensors and communication modules, depend on rare earth metals such dysprosium and neodymium [6]. Deforestation, soil

erosion, and water contamination follow from the environmentally disastrous extraction of these resources. Consequently, the growing demand for IoT devices is stressing world supply of important resources. For instance, the manufacturing of lithium-ion batteries, which are extensively utilized in Internet of Things devices, depends on lithium, a resource that is growingly limited.

Impact on biodiversity

Furthermore affecting the environment are IoT devices' effects on biodiversity. Important problems include pollution and damage of habitat. Raw material extraction for Internet of Things devices sometimes entails mining operations that disturb ecosystems and harm natural habitats. For rare earth metals, for instance, mining has been connected to the degradation of wetlands and forests. IoT device and component disposal might cause harmful chemicals to leak into the environment, therefore damaging ecosystems and wildlife. For example, heavy metals found in e-waste can poll water supplies, therefore compromising aquatic life.

1.1.3 The need for Green IoT

The fast expansion of the IoT has resulted in major technological developments allowing smarter homes, businesses, hospitals, and communities. But the environmental effect of conventional IoT devices has caused major issues that call for Green IoT development. Green IoT is centered on designing IoT devices and systems that reduce environmental damage while preserving or perhaps improving performance and functionality. We investigate the main drivers and approaches behind Green IoT below.

Reducing energy consumption

Energy consumption is one of the most critical environmental challenges posed by IoT devices. Green IoT aims to address this issue through several strategies such as energy-efficient hardware, energy harvesting, and optimized data transmission. Designing IoT devices with low-power processors, sensors, and communication modules can significantly reduce energy consumption [7]. For example, microcontrollers with advanced sleep modes and energy-efficient wireless protocols like Zigbee or LoRaWAN are increasingly being used in Green IoT applications. Green IoT devices can leverage renewable energy sources such as solar, thermal, or kinetic energy to power themselves. For instance, solar-powered sensors in agricultural fields can operate indefinitely without the need for battery replacements, reducing both energy consumption and waste. Transmitting data over long distances consumes substantial energy. Green IoT systems often use edge computing to process data locally, reducing the need for frequent data transmission to centralized cloud servers. This not only saves energy, but also reduces latency.

Using sustainable materials

The production of IoT devices often relies on non-renewable resources and hazardous materials. Green IoT promotes the use of sustainable materials to mitigate the issues of biodegradable and recyclable materials, non-toxic substances, and lightweight and durable designs [8]. Green IoT devices can be designed using biodegradable plastics or recyclable metals, reducing the environmental impact of their production and disposal. For example, some companies are experimenting with biodegradable circuit boards made from organic materials. Traditional IoT devices often contain toxic substances like lead, mercury, and cadmium. Green IoT devices avoid these materials, using safer alternatives that are less harmful to the environment and human health. Using lightweight and durable materials reduces the amount of raw materials needed for production and extends the lifespan of devices. For instance, aluminum and magnesium alloys are increasingly being used in IoT device casings due to their strength and recyclability.

Extending device lifespan

Many IoT devices have a limited lifetime that greatly adds to electronic garbage (e-waste). By stressing longevity and durability through modular design, firmware upgrades, and strong construction [9], Green IoT tackles this problem. Easy repairs and updates made possible by modular IoT devices help to extend their useful lives. For instance, one can change the sensors or communication components of a modular smart thermostat without throwing away the complete gadget. Frequent firmware updates help IoT devices to remain relevant for longer times and improve their security and performance. This cuts e-waste and lessens the need for regular replacements. IoT devices should be built to survive in hostile environmental circumstances, including high temperatures or dampness, therefore guaranteeing their prolonged operation. For industrial IoT applications, for example, tough sensors are designed to survive in demanding surroundings.

Promoting recycling and reuse

IoT devices' disposal presents major environmental problems. Green IoT advocates a circular economy approach whereby devices are made to be recycled and used again. Easy disassembly of IoT devices will help to enable the component recycling [10]. For instance, modular designs of smart homes and cellphones let customers replace certain components instead of throwing away the whole gadget. Take-back initiatives let manufacturers gather end-of-life IoT devices for refurbishing or recycling. Companies like Apple and Dell have already established successful take-back programs for their electronic products. Used IoT devices can be repurposed for secondary applications. For instance, retired smartphones can be used as security cameras or home automation controllers, extending their useful life and reducing e-waste.

Reducing carbon footprint

The carbon footprint of IoT devices encompasses emissions from their production, operation, and disposal. Green IoT aims to minimize this footprint through various measures. Using renewable energy sources in the production of IoT devices can significantly reduce their carbon footprint [11]. For example, factories powered by solar or wind energy produce fewer emissions compared to those relying on fossil fuels. Green IoT devices are designed to operate with minimal energy consumption, reducing their carbon emissions during use. For instance, smart lighting systems that use energy-efficient LEDs and motion sensors can drastically cut energy use in buildings. Proper disposal and recycling of IoT devices prevent the release of greenhouse gases from landfills and incineration. Green IoT promotes the use of certified e-waste recycling facilities to ensure environmentally friendly disposal.

Enhancing resource efficiency

The production of IoT devices relies on finite natural resources, such as rare earth metals and lithium. Green IoT makes use of alternative materials and resource-efficient production to support environmental sustainability. Advanced manufacturing methods, including additive manufacturing (3D printing), can lower material waste and raise resource efficiency. 3D-printed IoT device casings, for instance, save waste by using just the required quantity of material. Green IoT investigates using less ecologically harmful and more plentiful alternative materials. For IoT components, researchers are looking at substituting graphene and other nanomaterials for rare earth metals, for example.

1.2 Enabling technologies for Green IoT

Green IoT aims to reduce environmental effect and energy usage while nevertheless preserving flawless connectivity and operation. Several main enabling technologies help IoT networks to reach sustainability and energy economy.

1.2.1 Energy-efficient wireless communication

Adaptive power control, energy-aware Medium Access Control (MAC) protocols, and duty-cycling algorithms assist lower power usage in IoT networks [12]. Cognitive radio and dynamic spectrum access technologies maximize spectrum use and reduce energy waste.

1.2.2 Reconfigurable Intelligent Surfaces (RIS)

With clever reflection and manipulation of wireless signals, RIS is a new technology improving spectrum and energy efficiency [13]. RIS lowers power needs in Green IoT systems by maximizing phase shifts and focusing signals toward designated receivers.

1.2.3 Energy harvesting

IoT devices can gather thermal, mechanical, RF, solar, and mechanical vibrations [14] from ambient sources. This promotes self-sustaining functioning, hence lowering reliance on conventional battery-powered systems and prolonging IoT device lifetime.

1.2.4 Artificial Intelligence (AI) and Machine Learning (ML)

In Internet of Things networks, artificial intelligence and machine learning methods maximize intelligent energy management, predictive maintenance, and resource allocation [15]. Effective data routing, congestion control, and anomaly detection made possible by artificial intelligence-driven algorithms help to lower unneeded energy consumption.

1.2.5 Low-power communication protocols

Designed to guarantee consistent connectivity while consuming little power, lightweight communication protocols including Bluetooth little Energy (BLE), Zigbee, LoRaWAN, and Narrowband IoT (NB-IoT). Large-scale deployed battery-operated IoT devices depend on these protocols.

1.2.6 Edge and fog computing

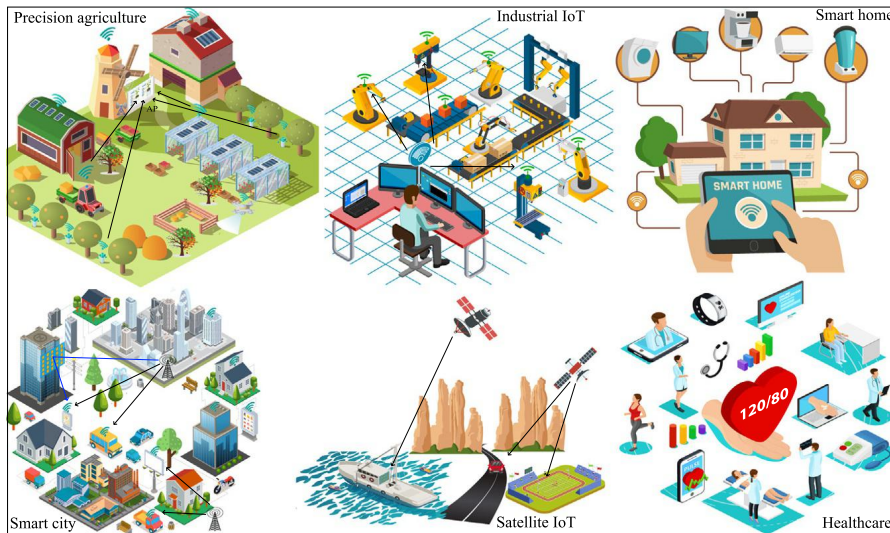
Edge and fog computing process data near to the source instead of depending just on cloud computing, therefore lowering the demand for energy-intensive cloud transfers [16]. Using localized processing helps these technologies improve response times and lower general network energy usage.

1.2.7 Software-Defined Networking (SDN) and Network Function Virtualization (NFV)

SDN and NFV enable dynamic network configuration, virtualized resource allocation, and traffic optimization, leading to more energy-efficient IoT networks [17]. These technologies help minimize redundant network operations and enhance adaptive energy management.

1.2.8 Green data centers and cloud computing

Energy-efficient data centers powered by renewable energy sources help mitigate the carbon footprint of IoT applications [18]. Cloud computing platforms with optimized resource allocation and cooling mechanisms further support sustainable IoT ecosystems.

**FIGURE 1.1**

Use cases of Green IoT.

1.2.9 Backscatter communication and tags

Backscatter communication is a promising technique for ultra-low-power IoT devices, enabling data transmission by reflecting existing RF signals rather than generating new ones [19]. Backscatter tags operate without batteries, harvesting energy from ambient sources such as Wi-Fi, cellular, and TV signals. This technology is particularly useful for applications like RFID-based tracking, smart agriculture, and passive environmental sensing, where minimizing power consumption is critical.

1.3 Applications of Green IoT devices

Green IoT devices are transforming various sectors by enabling smarter, more efficient, and environmentally friendly solutions. These applications leverage energy-efficient technologies, sustainable materials, and advanced data analytics to minimize environmental impact while enhancing functionality. Below, we explore the key applications of Green IoT across different domains, shown in Fig. 1.1.

1.3.1 Smart homes

Green IoT devices are revolutionizing smart homes by reducing energy consumption and promoting sustainable living. Key applications include energy-efficient lighting, smart thermostats, Water-Saving Systems, and energy monitoring [20]. Smart lighting systems use energy-efficient LED bulbs and motion sensors to automatically

adjust lighting based on occupancy and natural light levels. For example, Philips Hue and LIFX offer smart lighting solutions that can be controlled via smartphones, reducing unnecessary energy use. Devices like the Nest Thermostat learn user preferences and optimize heating and cooling schedules to minimize energy consumption. These thermostats can reduce household energy use by up to 20%, significantly lowering carbon emissions. Smart irrigation systems, such as those offered by Rachio, use weather data and soil moisture sensors to optimize watering schedules, reducing water waste. Smart faucets and showerheads similarly track water use and offer real-time feedback to promote conservation. Like those from Sense or Emporia, smart plugs and energy monitors measure the energy use of particular appliances, therefore enabling homeowners to find and cut energy-intensive gadgets.

1.3.2 Smart cities

By besting resource utilization and lowering environmental effect, green IoT is absolutely essential in creating sustainable smart cities. Important uses are waste management, energy distribution, intelligent traffic control, and environmental monitoring [21]. Real-time traffic flow, monitored by IoT-enabled sensors and traffic lights, adjusts signal timings to lower idle and congestion. Cities such as Barcelona and Singapore, for instance, deploy IoT technologies to increase traffic efficiency, therefore reducing fuel usage and emissions. Sensible waste bins with sensors track fill levels and maximize waste collecting paths, therefore lowering fuel consumption and running costs. IoT solutions for effective garbage management come from companies like Bigbelly and Enevo. Integrating renewable energy sources like solar and wind, smart grids monitor and control energy distribution using IoT devices. For example, Copenhagen employs IoT-enabled smart grids to help it to reach its target of carbon-neutrality by 2025. Real-time monitoring of air quality, noise levels, and water quality using IoT sensors helps cities to respond early in order to mitigate pollution. For instance, IoT sensors in the Breathe London project track air quality to guide policy decisions.

1.3.3 Precision agriculture

Precision farming methods enabled by green IoT are revolutionizing agriculture by besting resource use and waste reduction. Important uses include cattle monitoring, crop health monitoring, soil and weather monitoring, and [22]. IoT sensors track nutrient levels, temperature, and soil moisture to give farmers real-time data that maximizes fertilization and irrigation. The CropX system, for instance, reduces water use by up to 25% by delivering exact irrigation recommendations based on soil sensors. Hyper-local weather forecasts made possible by IoT-enabled weather sensors enable farmers to schedule their planting and harvesting operations. IoT solutions for agricultural weather monitoring come from companies like Davis Instruments and Metos. IoT-equipped drones track crop condition and identify pests and illnesses early on. Targeted treatments made possible by this help to lower the demand for chemical fertilizers and pesticides. For precise crop spraying, for example, the DJI Agras drone is

rather popular. IoT devices track cattle's health and whereabouts, therefore allowing farmers to maximize feeding and identify diseases early on. IoT solutions for cattle management are offered by businesses including Allflex and HerdDogg.

1.3.4 Healthcare

Green IoT devices are improving healthcare outcomes while reducing energy consumption and carbon emissions. Key applications include wearable devices, remote patient monitoring, smart hospitals, and telemedicine. Wearables like Fitbit and Apple Watch monitor vital signs such as heart rate, blood pressure, and activity levels, enabling remote health monitoring [23]. These devices reduce the need for frequent hospital visits, lowering energy consumption and carbon emissions. IoT-enabled medical devices, such as glucose monitors and ECG monitors, allow patients to manage chronic conditions from home. For example, the Dexcom G6 continuous glucose monitoring system provides real-time data to patients and healthcare providers, reducing the need for in-person consultations. IoT devices optimize energy use in hospitals by monitoring and controlling lighting, heating, and cooling systems. For instance, the Cleveland Clinic uses IoT systems to reduce energy consumption and improve patient comfort. IoT-enabled telemedicine platforms allow patients to consult with healthcare providers remotely, reducing travel-related emissions. Platforms like Teladoc and Amwell have seen significant adoption, especially during the COVID-19 pandemic.

1.3.5 Industrial IoT (IIoT)

Green IoT is driving sustainability in industrial settings by enabling predictive maintenance, energy monitoring, and process optimization. Key applications include predictive maintenance, energy monitoring, process optimization, and sustainable supply chains. IoT sensors monitor the condition of machinery and predict failures before they occur, reducing downtime and energy waste [24]. For example, Siemens uses IoT-enabled predictive maintenance to optimize the performance of industrial equipment. IoT devices track energy consumption in factories, identifying inefficiencies and opportunities for savings. Companies like Schneider Electric and Siemens offer IoT solutions for industrial energy management. IoT systems optimize manufacturing processes by monitoring and adjusting parameters in real-time. For instance, General Electric uses IoT to optimize the performance of its wind turbines, increasing energy output and reducing maintenance costs. IoT devices track the environmental impact of supply chains, enabling companies to make more sustainable decisions. For example, IBM's Food Trust platform uses IoT to track the carbon footprint of food products from farm to table.

1.3.6 Satellite IoT

Satellite IoT extends the reach of Green IoT to remote and underserved areas, enabling global connectivity and environmental monitoring. Key applications include

environmental monitoring, disaster management, precision agriculture in remote areas, and maritime and aviation monitoring [25]. Real-time monitoring of deforestation, glacier melting, and ocean health using satellite IoT devices supplies vital information for climate study and policy development. Sentinel satellites of the European Space Agency, for instance, track environmental changes using IoT sensors. Real-time monitoring of natural disasters such as hurricanes, earthquakes, and wildfires, which is made possible via satellite IoT, improves reaction times and lowers damage by means of better control. To watch and forecast natural disasters, for example, the NASA Earth Observing System employs IoT-enabled satellites. For areas lacking consistent internet access, satellite IoT offers connectivity for precision agriculture. By tracking soil conditions, meteorology, and crop health using satellite data, farmers can maximize resource utilization and lower waste. By tracking ship and aircraft locations and environmental impact, satellite IoT helps to enable more effective routing and lowers emissions. For maritime and aircraft IoT uses, for instance, the Iridium satellite network offers worldwide access.

1.4 Challenges in Green IoT

While Green IoT holds immense potential for creating a sustainable and environmentally friendly IoT ecosystem, its widespread adoption faces several challenges. These challenges span technical, economic, and regulatory domains, and addressing them is crucial for realizing the full potential of Green IoT. Below, we explore these challenges in detail.

1.4.1 Technical challenges

The development and deployment of Green IoT devices involve overcoming several technical hurdles. These challenges stem from the need to balance performance, energy efficiency, and reliability.

Balancing performance and energy efficiency

Green IoT devices have to minimize energy use while also delivering great performance. Striking this balance is difficult, since energy-efficient designs can compromise processing power, communication range, or functionality. Low-power microcontrollers, for instance, can cut energy use, but restrict the device's capacity to run sophisticated calculations or support fast-moving communication protocols.

Ensuring reliable operation with energy harvesting

Green IoT devices in far-off or difficult-to-reach areas must be powered by energy collecting systems include solar or kinetic energy. These methods, however, often offer erratic and changeable energy, which makes dependability of operation difficult. Solar-powered sensors, for example, could find it difficult to operate consistently in low-light or cloud cover, so sophisticated energy management systems are needed to store and control acquired energy.

Managing the complexity of edge computing and AI algorithms

Optimizing the performance of Green IoT devices depends critically on edge computing and artificial intelligence techniques. Their computational and memory needs make deploying these technologies on resource-limited devices difficult, though. Running machine learning algorithms on low-power IoT devices, for instance, could call for specialized hardware or optimized software frameworks, hence escalating development complexity and cost.

1.4.2 Economic challenges

The adoption of Green IoT practices often involves higher upfront costs and economic barriers, which can hinder widespread implementation.

Higher upfront costs for sustainable materials and technologies

Often requiring sustainable materials and cutting-edge technologies, green IoT devices might be more costly than conventional substitutes. For instance, rare earth-free components or biodegradable plastics could raise manufacturing costs, therefore reducing the competitiveness of Green IoT devices on the market. Higher initial investments involved in energy-efficient hardware and energy harvesting systems also discourage producers and consumers.

Lack of incentives for manufacturers to adopt Green IoT practices

Particularly in very competitive industries, many manufacturers give cost control and profitability top priority over environmental issues. Companies can be reluctant to spend in Green IoT technologies without financial incentives or legislative rules. For sustainable manufacturing techniques, for example, the absence of tax benefits or subsidies can deter businesses from implementing environmentally friendly designs and methods.

1.4.3 Regulatory and policy challenges

The lack of consistent regulations and standardized guidelines poses significant challenges for the development and deployment of Green IoT devices.

Inconsistent regulations across regions

Regarding energy efficiency, e-waste management, and the usage of hazardous materials, different nations and areas have different rules. Manufacturers producing Green IoT devices for worldwide markets find difficulties resulting from this inconsistency. A gadget compliance with European Union rules, for instance, might not satisfy criteria in the United States or Asia and calls for expensive changes or alternative product lines.

Lack of standardized guidelines for Green IoT design and deployment

Lack of consistent policies for Green IoT design and implementation complicates development process and reduces interoperability. Manufacturers find it challenging to guarantee compliance and compatibility across devices since, for example, there are no global criteria for sustainable material certifications or energy-efficient communication protocols. For consumers, who could find it difficult to spot really sustainable IoT items, this lack of standardizing also generates ambiguity.

1.5 Future directions

With lots of chances for invention and teamwork, Green IoT has bright future. Growing demand for sustainable technology will depend much on developments in energy-efficient technologies, standardization, and cooperative efforts to shape Green IoT going forward. We go into great detail below on these future paths.

1.5.1 Advances in energy-efficient technologies

The development of energy-efficient technologies is essential for reducing the environmental impact of IoT devices. Future advancements in this area will focus on improving performance while minimizing energy consumption.

Development of ultra-low-power processors and sensors

Researchers and manufacturers are working on designing processors and sensors that consume minimal power without compromising performance. For example, ultra-low-power microcontrollers like the ARM Cortex-M series and energy-efficient sensors such as those from Bosch Sensortec are already making strides in this direction. Future innovations may include processors that leverage quantum computing or neuromorphic engineering to achieve unprecedented energy efficiency.

Integration of advanced energy harvesting techniques

Energy harvesting technologies, such as solar, thermal, and kinetic energy, will continue to evolve, enabling IoT devices to operate autonomously without relying on traditional batteries. For instance, advancements in flexible solar panels and piezoelectric materials will allow energy harvesting to be integrated into a wider range of IoT devices, from wearable gadgets to industrial sensors. Additionally, hybrid energy harvesting systems that combine multiple energy sources (e.g., solar and thermal) will enhance reliability and efficiency.

1.5.2 Standardization and certification

Standardization and certification are critical for ensuring the consistency, interoperability, and credibility of Green IoT devices. Future efforts in this area will focus on establishing global standards and promoting eco-friendly products.

Establishing global standards for Green IoT devices

The development of global standards for energy efficiency, sustainable materials, and e-waste management will provide a unified framework for manufacturers and consumers. Organizations like the International Telecommunication Union (ITU) and the Institute of Electrical and Electronics Engineers (IEEE) are already working on standards for IoT sustainability. Future standards may include guidelines for energy-efficient communication protocols, such as LoRaWAN and NB-IoT, as well as requirements for the use of recyclable and non-toxic materials.

Introducing certification programs to promote eco-friendly products

Certification programs, such as Energy Star and EPEAT, will play a key role in promoting Green IoT devices. These programs provide consumers with a reliable way to identify eco-friendly products, encouraging manufacturers to adopt sustainable practices. Future certification programs may include criteria for carbon footprint, energy harvesting capabilities, and end-of-life recyclability, ensuring a holistic approach to sustainability.

1.5.3 Collaborative efforts

Collaboration between governments, industries, and researchers is essential for driving innovation and accelerating the adoption of Green IoT. Future efforts will focus on fostering partnerships and raising public awareness.

Encouraging collaboration between governments, industries, and researchers

Governments, industries, and academic institutions must work together to address the technical, economic, and regulatory challenges of Green IoT. For example, public-private partnerships can fund research and development projects, while government incentives can encourage companies to adopt sustainable practices. Collaborative initiatives like the European Union's Horizon 2020 program and the U.S. Department of Energy's Advanced Research Projects Agency-Energy (ARPA-E) are already driving innovation in Green IoT.

Promoting public awareness and consumer demand for sustainable IoT solutions

Raising public awareness about the environmental impact of IoT devices and the benefits of Green IoT is crucial for driving consumer demand. Educational campaigns, eco-labeling, and incentives for purchasing sustainable products can encourage consumers to make environmentally conscious choices. For instance, companies like Apple and Google are already promoting their eco-friendly initiatives, such as using recycled materials and reducing carbon emissions, to attract environmentally conscious consumers.

1.6 Conclusion

A revolutionary way to solve the environmental problems caused by the explosive spread of conventional IoT technologies is provided by green IoT devices. Green IoT presents a road to a more sustainable and environmentally friendly IoT ecosystem by including circular economy concepts, sustainable materials, and energy-efficient designs. The relevance of Green IoT, its main ideas, enabling technologies, applications, difficulties, and future paths has been investigated in this chapter.

Adoption of Green IoT presents many difficulties. Technical challenges including handling the complexity of edge computing and artificial intelligence algorithms, balancing performance and energy efficiency, guaranteeing dependable operation using energy harvesting technologies, and so addressing technical obstacles. Significant challenges also come from economic hurdles, including more upfront costs for sustainable materials and technologies as well as from manufacturers' lack of incentives to embrace Green IoT techniques. Moreover, unequal rules among different areas and the lack of common standards for Green IoT design and implementation hamper the evolution and acceptance of sustainable IoT solutions.

Notwithstanding these obstacles, Green IoT has bright potential. More sustainable IoT devices are making possible by developments in energy-efficient technology such ultra-low-power CPUs and sophisticated energy harvesting methods. While cooperative projects between governments, businesses, and researchers are driving innovation and fast adoption of Green IoT, standardizing and certification activities are helping to set worldwide rules and promote environmentally friendly goods. Growing public knowledge of and consumer demand for sustainable IoT solutions also motivates producers to give environmental sustainability top priority.

Green IoT is ultimately a need for creating a sustainable future as much as a technology advancement. We may fully actualize Green IoT by tackling technical, financial, and regulatory obstacles and using the chances given by developments in technology, standardization, and teamwork. This will help to further more general objectives of sustainability and climate action in addition to lessening the environmental effect of IoT devices. A greener IoT environment has yet to be reached, hence constant research, creativity, and teamwork are crucial to realize this vision.

References

- [1] F. Xia, L.T. Yang, L. Wang, A. Vinel, et al., Internet of things, *International Journal of Communication Systems* 25 (9) (2012) 1101.
- [2] S. Li, L.D. Xu, S. Zhao, The Internet of Things: a survey, *Information Systems Frontiers* 17 (2015) 243–259.
- [3] K. Georgiou, S. Xavier-de Souza, K. Eder, The IoT energy challenge: a software perspective, *IEEE Embedded Systems Letters* 10 (3) (2017) 53–56.
- [4] B. Modarress Fathi, A. Ansari, A. Ansari, Threats of Internet-of-Thing on environmental sustainability by e-waste, *Sustainability* 14 (16) (2022) 10161.

- [5] F.-J. Alvarado-Alcon, R. Asorey-Cacheda, A.-J. Garcia-Sanchez, J. Garcia-Haro, Carbon footprint vs energy optimization in IoT network deployments, *IEEE Access* 10 (2022) 111297–111309.
- [6] G.S. Kuaban, E. Gelenbe, T. Czachórski, P. Czekalski, J.K. Tangka, Modelling of the energy depletion process and battery depletion attacks for battery-powered Internet of Things (IoT) devices, *Sensors* 23 (13) (2023) 6183.
- [7] R. Arshad, S. Zahoor, M.A. Shah, A. Wahid, H. Yu, Green IoT: an investigation on energy saving practices for 2020 and beyond, *IEEE Access* 5 (2017) 15667–15681.
- [8] V. Pecunia, L.G. Occhipinti, R.L. Hoyer, Emerging indoor photovoltaic technologies for sustainable Internet of Things, *Advanced Energy Materials* 11 (29) (2021) 2100698.
- [9] M. Asiri, T. Sheltami, L. Al-Awami, A. Yasar, A novel approach for efficient management of data lifespan of IoT devices, *IEEE Internet of Things Journal* 7 (5) (2019) 4566–4574.
- [10] R. Holanda Filho, W.A. de Brito, M.G. Paiva, P.A.C. Klemensov, L.S. de Oliveira, A sustainable recycling ecosystem scheme based on IoT to promote social benefits, *Procedia Computer Science* 238 (2024) 344–351.
- [11] P. Asopa, P. Purohit, R.R. Nadikattu, P. Whig, Reducing carbon footprint for sustainable development of smart cities using IoT, in: *2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)*, IEEE, 2021, pp. 361–367.
- [12] W. Mao, Z. Zhao, Z. Chang, G. Min, W. Gao, Energy-efficient industrial Internet of Things: overview and open issues, *IEEE Transactions on Industrial Informatics* 17 (11) (2021) 7225–7237.
- [13] M. Ahmed, S. Raza, A.A. Soofi, F. Khan, W.U. Khan, S.Z.U. Abideen, F. Xu, Z. Han, Active reconfigurable intelligent surfaces: expanding the frontiers of wireless communication-a survey, *IEEE Communications Surveys and Tutorials* (2024).
- [14] S. Zeadally, F.K. Shaikh, A. Talpur, Q.Z. Sheng, Design architectures for energy harvesting in the Internet of Things, *Renewable and Sustainable Energy Reviews* 128 (2020) 109901.
- [15] F. Samie, L. Bauer, J. Henkel, From cloud down to things: an overview of machine learning in Internet of Things, *IEEE Internet of Things Journal* 6 (3) (2019) 4921–4934.
- [16] J. Ni, K. Zhang, X. Lin, X. Shen, Securing fog computing for Internet of Things applications: challenges and solutions, *IEEE Communications Surveys and Tutorials* 20 (1) (2017) 601–628.
- [17] S. Bera, S. Misra, A.V. Vasilakos, Software-defined networking for Internet of Things: a survey, *IEEE Internet of Things Journal* 4 (6) (2017) 1994–2008.
- [18] O. Oloruntoba, Green cloud computing: AI for sustainable database management, *World Journal of Advanced Research and Reviews* 23 (03) (2024) 3242–3257.
- [19] F. Jameel, S. Zeb, W.U. Khan, S.A. Hassan, Z. Chang, J. Liu, Noma-enabled backscatter communications: toward battery-free IoT networks, *IEEE Internet of Things Magazine* 3 (4) (2020) 95–101.
- [20] B.L.R. Stojkoska, K.V. Trivodaliev, A review of Internet of Things for smart home: challenges and solutions, *Journal of Cleaner Production* 140 (2017) 1454–1464.
- [21] Y. Qian, D. Wu, W. Bao, P. Lorenz, The Internet of Things for smart cities: technologies and applications, *IEEE Network* 33 (2) (2019) 4–5.
- [22] N. Ahmed, D. De, I. Hussain, Internet of things (IoT) for smart precision agriculture and farming in rural areas, *IEEE Internet of Things Journal* 5 (6) (2018) 4890–4899.
- [23] S.B. Baker, W. Xiang, I. Atkinson, Internet of Things for smart healthcare: technologies, challenges, and opportunities, *IEEE Access* 5 (26) (2017) 521–26544.

- [24] I. Butun, M. Almgren, V. Gulisano, M. Papatriantafilou, *Industrial IoT*, Springer, 2020.
- [25] X. Chen, Z. Xu, L. Shang, Satellite Internet of Things: challenges, solutions, and development trends, *Frontiers of Information Technology & Electronic Engineering* 24 (7) (2023) 935–944.

Designing an end-to-end sustainable IoT network: a comprehensive guideline

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2.1 Introduction

Traditional wireless systems have focused on rate-hungry, human-centric applications, including extended reality, virtual reality, and conference calling. These systems were designed to prioritize high data rates and optimized to improve quality-of-experience (QoE) and support seamless human-to-human communication. In contrast, the vision of the Internet of Things (IoT) has transformed the demands and architectures of wireless systems by introducing new constraints and objectives. IoT networks require support for massive machine-to-machine communication, with billions of interconnected devices operating under strict constraints of energy efficiency, network sustainability, scalability, and long-range connectivity. The scale and diversity of IoT deployments, ranging from smart cities and industrial automation to environmental and agricultural monitoring, demand technologies that minimize energy consumption, extend network lifetime, and ensure reliable communication across wide geographical areas. Addressing these constraints has reshaped wireless system design by prioritizing sustainability and scalability in architectures. This chapter details the principles and methodologies for designing an end-to-end sustainable IoT network, emphasizing energy efficiency, scalability, and long-term operational feasibility across diverse applications.

2.1.1 Historical perspective

In this section, we briefly discuss the emergence of the IoT paradigm of communication. The conceptual foundation of the IoT dates back to 1999, when Kevin Ashton introduced the term in the context of supply chain optimization at Procter & Gamble [1,2]. He envisioned a system of interconnected physical objects capable of

autonomous and efficient communication, laying the groundwork for the global IoT ecosystem. While the concept of IoT emerged in the late 1990s, it was not until the early 2000s that wireless communication technologies began to integrate machine-centric communication into standard infrastructures.

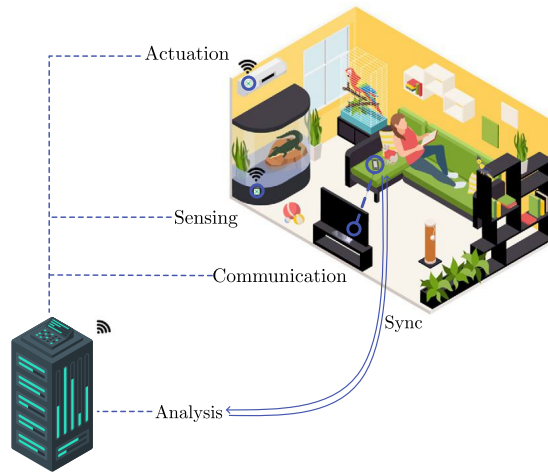
From 1G to 3G, wireless networks were primarily designed for voice communication and basic data services, lacking the technologies necessary for supporting large-scale, interconnected IoT ecosystems [2]. The evolution of IoT was catalyzed by advancements in sensor technology, enhanced computing capabilities, and the development of optimized communication protocols, which enabled seamless data collection, processing, and exchange, forming the backbone of modern IoT applications. The introduction of 4G networks marked a turning point for IoT systems and enabled higher data rates, lower latency, and higher system capacity. The increased bandwidth and lower latency facilitated real-time data exchange between devices and supported the development of low-power wide-area networks (LPWAN), specifically designed for long-range, low-power IoT use cases [2–4].

The emergence of 5G networks has further revolutionized the IoT landscape by supporting a massive number of connected devices with capabilities such as ultra-reliable low-latency communication (URLLC) and enhanced mobile broadband (eMBB [5]. These advancements enable seamless integration of IoT devices across sectors, including smart cities, healthcare, and industrial automation. However, despite these advancements, 5G is limited by the lack of scalability, which is imperative to support mass-scale next-generation networks [6]. Future applications, which include holographic communication [7], immersive reality [8], real-time autonomous systems, etc., demand higher data rates, seamless coverage, and ultra-low latency. Furthermore, the expansion of MTC and the integration of billions of IoT devices into intelligent ecosystems further strain 5G's scalability and energy efficiency.

6G networks aim to address these shortcomings by prioritizing diverse metrics that are critical for next-generation applications, e.g., reliability for mission-critical systems, spectral efficiency for denser networks, and energy efficiency for reduced operational costs. 6G systems will have sustainable designs, ensuring networks can support massive connectivity while minimizing environmental and operational impacts through optimized energy consumption. This will enable network scalability by supporting large-scale IoT ecosystems, facilitating global connectivity in remote regions, and maintaining consistent performance as network density and device diversity increase.

2.2 Fundamentals of IoT

IoT networks extend beyond the human-centric traditional wireless systems to create an interconnected ecosystem of data, devices, processes, and persons. This paradigm has created diverse opportunities across different sectors and presents new challenges that demand sustainable, scalable, and secure solutions. The IoT vision aims to create

**FIGURE 2.1**

IoT functions.

a seamlessly interconnected network where devices operate autonomously with minimal human intervention. IoT devices encompass a vast variety of physical objects, ranging from wearable devices and household appliances to industrial machinery and autonomous vehicles. These objects or things are connected to the internet and equipped to realize one or more of the following functions, also illustrated in Fig. 2.1.

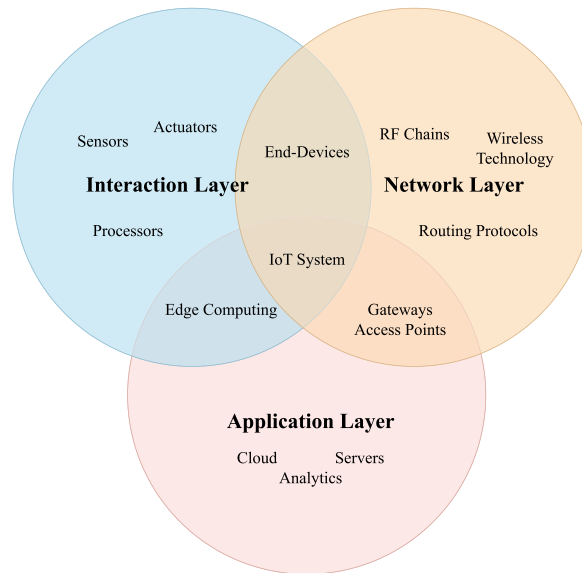
1. **Sense:** Sensing is the ability to gather data about and from the environment.
2. **Analyze:** Devices can also have the ability to process and interpret the collected data to derive actionable insights.
3. **Communicate:** IoT devices have the ability to receive and transmit processed or raw information to neighboring nodes and central access points.
4. **Actuate:** Actuation involves executing specific actions or commands to control physical systems based on the analyzed data or received instructions.

2.2.1 Architecture of IoT

The architecture of IoT systems is segregated into different layers which perform specific functions to ensure seamless communication, data processing, and device management. We briefly describe IoT architecture in Fig. 2.2, and describe it as follows [9,10]:

Application layer

The application layer provides an interface between the network and the end user and enables use-case specific services and functionalities through IoT devices and platforms [11–14]. Here, raw data is converted into insights, and the actionable directives are propagated toward the network devices. The functions of the application layer are described as follows:

**FIGURE 2.2**

Architecture of IoT systems.

- **Data processing:** Aggregating and interpreting the collected data is a core function of IoT systems. This is realized in the application layer by using advanced analytics frameworks to extract actionable insights.
- **Service provisioning:** The application layer delivers use-case specific services such as remote monitoring, and automation. These services are tailored to meet user requirements and application demands.
- **User interaction:** The application layer also has interfaces for user interactions, which can be implemented as web portals, mobile applications, or application programming interfaces (APIs). These interfaces provide seamless control and monitoring of IoT devices.
- **Device management:** The application layer facilitates device registration, firmware updates, and node maintenance to ensure optimal performance.

Network layer

The network layer enables data transmission between IoT devices, gateways, and central servers [11–14]. Routing, connectivity, and protocols are implemented in this layer. The key functionalities are as follows:

- **Data routing:** The network layer ensures efficient delivery of data packets across the IoT system. This is achieved through energy-aware routing protocols designed to optimize resource usage while maintaining reliable communication paths.

- **Connectivity management:** Establishing and maintaining communication links is a key function of the network layer. It employs technologies such as low-power wide-area networks (LPWANs) for long-range connectivity or short-range standards like Zigbee or Bluetooth for high-density deployments.
- **Interoperability:** The network layer combines heterogeneous technologies such as LPWANs, Bluetooth low energy (BLE), and WiFi to enable seamless communication between devices operating on different protocols or standards.
- **Network optimization:** Reducing power consumption and improving spectral efficiency are critical for IoT systems. Techniques such as duty cycling, adaptive modulation, energy harvesting, backscattering, etc. are realized in this layer.

Interaction layer

The interactions of the end-devices with the environment are managed at this layer, e.g., sensing, data collection, and actuation. This layer facilitates real-time interaction between the physical world and the IoT ecosystem.

- **Data aggregation:** The interaction layer gathers data from the environment using end-devices. This data is then preprocessed to ensure it is ready for further analysis in higher layers of the IoT architecture.
- **Operation management:** This layer also enables seamless operation among diverse sensors and actuators. The formats and protocols to enable efficient communication with the network layer are implemented here.
- **Control:** The interaction layer executes control commands received from higher layers. These commands are realized as physical actions, e.g., turning on a device, adjusting a parameter or initiating a process, etc.
- **Environmental interaction:** This layer realizes direct interaction with the physical world through sensing and actuation. Sensors measure parameters, e.g., temperature, humidity, motion, etc., while actuators influence the environment by controlling devices or systems.

2.2.2 Network entities in IoT

In the context of IoT systems, network entities are classified according to their specific roles and operational functions within the architectural framework, as shown in Fig. 2.2. These entities are distributed across multiple layers and facilitate key processes such as data acquisition, transmission, processing, and decision-making. The fundamental components that constitute an IoT network include:

End-devices

End-devices serve as the foundational nodes within an IoT network, integrating sensors and actuators to facilitate direct interaction with the physical environment. These devices are tasked with capturing real-time data from their surroundings, executing localized computations, and transmitting relevant information to intermediary gateways or centralized processing servers. The embedded sensors within these nodes

continuously monitor key environmental parameters, including temperature, humidity, motion, and light intensity, converting these variations into electrical signals for further processing. To optimize network performance and minimize communication overhead, IoT end-devices often employ preprocessing techniques such as data filtering, aggregation, or compression before transmission. This localized data refinement not only conserves bandwidth, but also enhances the overall efficiency and responsiveness of the IoT system. End-devices in IoT networks are inherently resource-constrained with limited energy availability, computational capacity, and storage. To operate efficiently within these constraints, they leverage lightweight communication protocols such as the constrained application protocol (CoAP) [15] and message queuing telemetry transport (MQTT) [16], which minimize data overhead and optimize transmission efficiency. Additionally, energy conservation techniques, including duty cycling, where devices alternate between active and sleep states [17], and energy harvesting from ambient sources are employed to extend operational time [18]. End-devices operate in the interaction layer where they serve as the critical interface between the physical environment and the broader IoT ecosystem, facilitating real-time sensing, data acquisition, and actuation while ensuring minimal resource utilization.

Gateways

Gateways function as critical intermediaries within IoT architectures and bridge the communication gap between resource-constrained end-devices and high-capacity processing servers. Their primary roles are to enable seamless connectivity, aggregate data from multiple IoT nodes, and perform protocol translation to ensure interoperability across heterogeneous networks. Additionally, they serve as access points for diverse communication technologies, including Zigbee, LoRaWAN, Wi-Fi, and Bluetooth Low Energy (BLE). Through these capabilities, gateways enhance network reliability, support device heterogeneity, and enable seamless integration within the broader IoT ecosystem. A fundamental role of gateways in IoT networks is to facilitate interoperability by bridging heterogeneous communication protocols. They perform protocol translation between device-level standards and network-layer protocols enabling necessary data exchange across diverse network infrastructures. Unlike resource-constrained end-devices, gateways possess greater computational power and energy reserves, allowing them to support advanced functionalities such as encryption for secure communication, error correction to enhance data integrity, and interference management to maintain signal quality in congested environments.

Processing servers

Processing servers serve as the computational houses of IoT networks, encompassing both cloud platforms and edge computing workstations to handle data-intensive tasks such as storage, analysis, and decision-making. Cloud servers provide scalable and centralized resources and enable large-scale data aggregation, and advanced analytics which extract actionable insights from IoT-generated data. These platforms support high-volume processing and long-term storage. In contrast, edge and fog

computing workstations bring computational capabilities closer to data sources, performing localized preprocessing to reduce latency, conserve bandwidth, and enable real-time decision-making for latency-sensitive applications. By distributing computational tasks across cloud and edge infrastructures, IoT networks achieve a balance between efficiency, responsiveness, and scalability, optimizing performance for a diverse range of use cases. Processing servers are integral to IoT architectures and execute complex tasks such as data fusion, anomaly detection, predictive analytics, and long-term storage. These systems are distinguished by their high computational power, extensive storage capacity, and capability to seamlessly integrate with APIs. Beyond data processing, they enforce stringent security measures, including encryption, access control, and compliance frameworks to safeguard data integrity and uphold privacy regulations. Functioning primarily at the application layer, processing servers transform raw sensor data into actionable insights and enable advanced decision-making in IoT applications across domains such as smart cities, industrial automation, and healthcare.

2.2.3 Types of IoT

IoT systems have versatile application domains, as shown in Fig. 2.3, which address specific sector needs, operational challenges, and QoS requirements. This section describes the major IoT application types, highlighting their technical requirements, network characteristics, and use cases.

Consumer applications

Consumer IoT (CIoT) applications enable and assist personal experiences by integrating automation, real-time data processing, and seamless connectivity into everyday life. Key use-cases of CIoT are wearable devices [19], tracking devices [20], and smart homes [21]. Some of these use-cases are illustrated in Fig. 2.4. In smart homes, IoT systems automate and control home devices and manage lighting, thermostats, and security cameras using technologies like Zigbee, Wi-Fi, and Bluetooth low energy (BLE). These devices monitor and actuate different environmental parameters and adapt to user preferences. Wearable devices, e.g., fitness trackers, smartwatches, and health monitors, collect real-time data on physical activities and health metrics. This data is processed locally or transmitted to gateways or mobile phones to provide insights and alerts. Tracking devices leverage GPS and LPWAN technologies like LoRaWAN and Sigfox to provide accurate, long-range tracking for personal items, pets, or individuals [22]. Consumer IoT devices prioritize low power consumption to extend battery life in portable and wearable devices. They must be designed to provide reliable performance during movement and have moderate data rate requirements which efficiently handle periodic updates and event-driven communication. Security and privacy protocols are also integrated into consumer IoT to protect sensitive user data, including health and location information. For example, smart assistants centralize the control of IoT devices, BLE-enabled fitness trackers offer real-time health insights, and LPWANs ensure reliable connectivity over extended ranges, making CIoT an indispensable component of modern lifestyle.

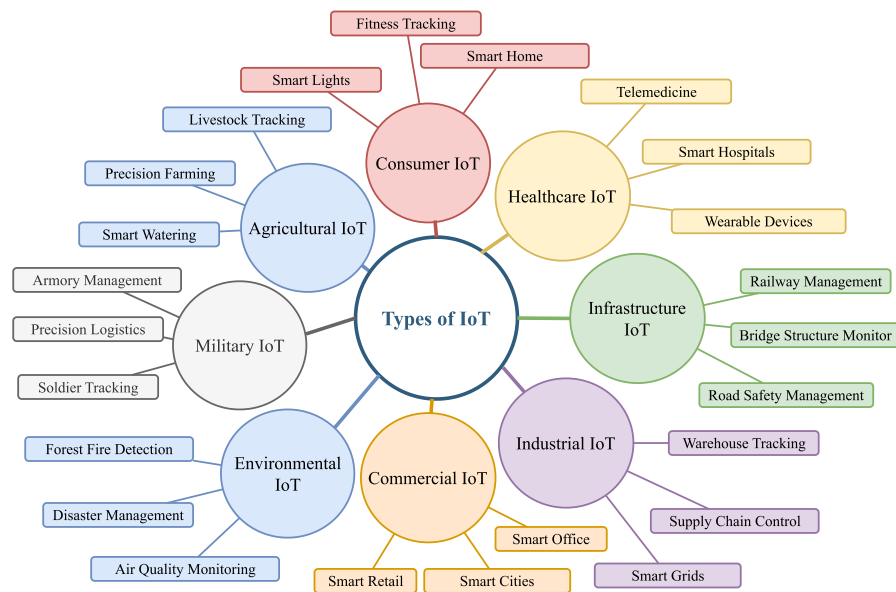


FIGURE 2.3

Types of IoT.

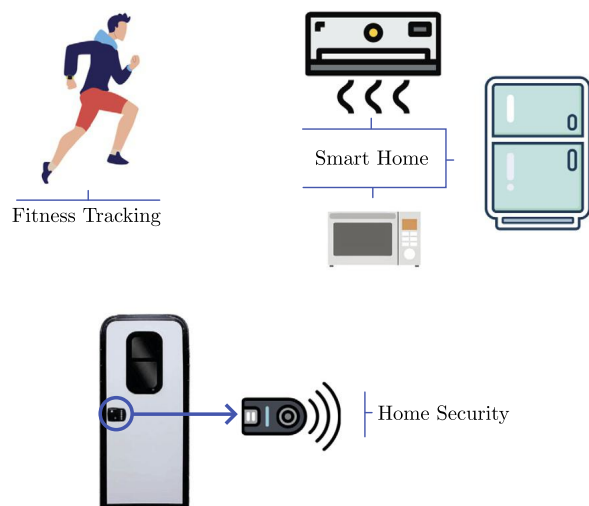


FIGURE 2.4

Consumer applications.

Commercial applications

IoT of commercial things (IoCT) optimizes enterprise operations by integrating IoT technologies into urban cities [23], office systems [24], and retail processes [25]. Smart city applications are included in IoCT and include use-cases such as urban infrastructure monitoring, traffic control, smart parking, and waste management. These systems use real-time data, collected by sensors, to identify traffic congestion, monitor resource usage, and optimize municipal services. Smart offices implement IoT solutions to improve workspace processes by monitoring energy consumption, tracking employee activities, and automating environmental controls. Retail stores utilize IoT for smart shopping experiences by enabling personalized recommendations, in-store navigation, and automated checkouts powered by IoT beacons and sensors. Commercial IoT systems require scalable design to support large deployments across cities and enterprises. They must ensure the reliability of critical services, e.g., traffic management and waste monitoring, etc. [26,27], while minimizing energy consumption for continuous operation. Interoperability is essential for enabling IoCT as it includes a diverse set of requirements and devices. For example, smart parking systems use LoRaWAN to detect and communicate available parking spaces, while traffic monitoring systems enable real-time traffic flow optimization. IoT-enabled waste bins provide immediate updates on fill levels, allowing for more efficient waste collection.

Industrial applications

Industrial IoT (IIoT) systems utilize IoT devices to monitor, automate, and optimize industrial processes such as warehouse tracking [28], supply chain control [29], and smart grids [30]. Warehouse tracking systems use RFID, BLE, and LPWAN technologies to monitor inventories, and provide efficient supply management. Control applications such as predictive maintenance and fault detection automate production lines by leveraging IoT sensors and machine learning. Smart grids collect and process data about power generation, transmission, and consumption. This enables efficient energy distribution and significantly reduces operational costs. Industrial IoT systems require high reliability and low latency to support critical operations. Low latency ensures real-time responsiveness for automation and control tasks. Predictive maintenance using IoT sensors can prevent costly equipment failures in industrial plants. Furthermore, manufacturing can be streamlined using IoT-integrated robotics, creating efficient, precise, and manageable processes.

Infrastructure applications

IoT of infrastructure things (IoIT) improves the safety and reliability of critical infrastructures by integrating real-time monitoring and automated maintenance using IoT sensors. IoIT use cases span transportation systems [31], railway management [32], and public safety systems [33]. In transportation systems, sensors can be embedded in bridges and roads to measure structural integrity, traffic loads, and environmental conditions. The sensors can detect anomalies such as stress cracks or overloads and alert maintenance teams to avoid disasters. Railway management systems can

track train locations, schedules, and conditions using IoT-enabled sensors, improving safety and operational efficiency. Public safety systems can also utilize IoT sensors to monitor environmental hazards and enable real-time emergency response. IIoT prioritizes long-term reliability for decade-long deployments and ensures continuous operation with minimal maintenance. Scalable and high-precision designs are required to cover extensive geographical areas and enable safety-critical applications. Energy efficiency is critical for devices deployed in remote locations. For example, smart bridges equipped with load and vibration sensors provide real-time monitoring of structural health.

Healthcare applications

Healthcare IoT (HIIoT) improves medical services and processes by enabling real-time monitoring and remote diagnostics using wearable devices, telemedicine [34], and smart hospitals [35]. Wearable devices track vital signs such as heart rate, glucose levels, and blood pressure, which provides information critical to healthcare providers [36]. These devices transmit data to cloud platforms or mobile applications and enable continuous monitoring for early detection of health issues. Telemedicine platforms also use IIoT systems to facilitate remote consultations, diagnostics, and patient monitoring [37]. This improves the efficiency of hospitals and enables immediate consultations. Smart hospitals integrate IIoT systems to optimize patient flows, and equipment management. HIIoT demands ultra-reliable communication for accurate data transmission. Low latency is also essential for real-time monitoring and alerts, as healthcare processes are extremely critical and can have disastrous consequences. Strong data security measures are also required in HIIoT systems to protect sensitive patient information. Examples include IIoT-enabled glucose monitors for diabetic patients and smart hospital beds equipped with pressure sensors to prevent bedsores.

Agricultural applications

Agricultural IoT (AIIoT) leverages advanced sensors, wireless communication, and data analytics to optimize farming practices. It enables use-cases such as precision farming [38], livestock management [39], and smart irrigation systems [40]. Precision farming systems use IIoT sensors to measure soil moisture, nutrient levels, and weather conditions, which provide real-time data for informed decision-making regarding farming schedules. Livestock management systems track animal health, behavior, and location using IIoT-enabled collars and tags, which improves the efficiency of farming processes. Smart irrigation systems automate water delivery by analyzing soil and weather data and provide optimal resource utilization and waste reduction. AIIoT systems require low power consumption for remote sensors as the farms have expansive areas. These systems must also be seamlessly integrated with data analytics platforms to provide actionable insights. For example, IIoT-based soil moisture sensors help farmers optimize irrigation schedules. GPS-enabled livestock trackers monitor herd movement and enhance productivity. Smart greenhouses equipped with IIoT systems control temperature, humidity, and lighting, hence improving crop yield and reducing labor costs.

Military applications

Military IoT (MIoT) leverages advanced sensing, communication, and analytics to improve situational awareness, operational efficiency, and decision-making in defense environments. MIoT systems provide real-time intelligence and support mission-critical operations [41]. They enable surveillance and reconnaissance of enemy activities and battlefield conditions using unmanned aerial vehicles (UAVs), ground-based sensors, and autonomous vehicles. These systems transmit secure, real-time data to command centers and improve tactical decision making. MIoT also transforms logistics using IoT-enabled tracking devices, e.g., RFID tags and GPS units, etc., to monitor military assets, streamline inventory, and optimize resource distribution. Wearable IoT devices further enhance troop safety by monitoring soldier vitals. They can alert command centers to potential health risks or emergencies in real time.

Environmental applications

Environmental IoT (EIoT) systems monitor and manage ecosystems to provide pollution control [42], resource management, and disaster mitigation [43]. IoT-enabled sensors measure environmental parameters such as air quality, water quality, soil conditions, etc. [44], to transmit data in real-time to centralized systems for analysis and actionable insights. For example, air quality monitoring networks deployed in urban areas continuously track pollutant levels, enabling city administrators to implement timely measures, such as traffic rerouting, emission reduction policies, etc. Similarly, IoT-based water quality monitoring systems detect contamination, ensuring regulatory compliance and safe resource utilization. These systems require energy-efficient and scalable designs to operate reliably in remote and harsh environments. Energy harvesting techniques are vital to EIoT systems as they extend the operational lifespan of sensors. They also have low-rate requirements and have reduced bandwidth usage for seamless transmission across vast geographical areas.

2.3 Fundamentals of sustainability

Sustainability refers to the design and operation of IoT systems with minimal environmental impact, optimized resource utilization, and network scalability. With the proliferation of IoT devices — from smart homes to industrial automation — achieving sustainable designs has become a multidimensional challenge. It requires addressing and minimizing different expense verticals, including energy consumption, deployment complexity, hardware design, spectrum allocation, processing efficiency, and maintenance. Each expense vertical presents distinct challenges and opportunities for sustainable IoT, as shown in Table 2.1.

Table 2.1 Fundamentals of sustainability in IoT.

Factor	Impact	Challenges	Solutions
Energy Consumption	Defines power efficiency and network lifetime; affects sensing, data processing, communication, and actuation.	High power demand for RF transmission; real-time processing in constrained environments; limited battery life in remote deployments.	Low-power communication protocols; energy harvesting (solar, kinetic, thermal); adaptive power management techniques.
Deployment Challenges	Determines ease of installation, integration, and scalability of IoT networks.	Remote and inaccessible deployments require specialized equipment; interoperability between heterogeneous devices; high initial costs.	Modular and scalable network architectures; standardized protocols; automated configuration and provisioning tools.
Hardware Design	Encompasses RF chains, antenna modules, sensors, and processors for data collection, communication, and computation.	High energy consumption in real-time applications; environmental impact of non-recyclable materials; difficulty in repairing miniaturized components.	Use of energy-efficient components; recyclable materials; modular designs for easy maintenance and upgrades.
Spectrum Allocation	Governs wireless communication reliability, efficiency, and congestion management.	Spectrum congestion in densely populated areas; interference in unlicensed bands (Wi-Fi, Zigbee); limited bandwidth in LPWAN systems.	Dynamic spectrum access; cognitive radio techniques; spectrum sensing and adaptive frequency management.
Processing Ability	Defines how IoT devices analyze and manage data locally or centrally to extract insights.	High computational burden for real-time applications; limited processing power in edge devices; increased energy consumption.	Lightweight AI algorithms; edge computing; federated learning for distributed model updates; over-the-air (OTA) computations.
Network Maintenance	Involves hardware repairs, software updates, and battery replacements in large-scale deployments.	Frequent maintenance is costly and resource-intensive; firmware updates introduce security vulnerabilities; remote device access is challenging.	Predictive maintenance using IoT sensors; OTA firmware updates with secure authentication; modular hardware replacement strategies.

2.3.1 Energy consumption

Energy consumption is critical in IoT systems as it directly impacts network lifetime and operational efficiency. IoT devices perform energy-intensive tasks, e.g., sensing, data processing, communication, actuation, etc. Furthermore, most devices operate in energy-constrained environments and rely on batteries, which are impractical to replace in remote deployments. For example, an environmental IoT system or infrastructure monitoring system must operate for years without human intervention. It is also directly influenced by the network architecture. Wireless data transmission consumes substantial energy due to the demands of radio frequency (RF) chain functions, e.g., source coding, channel coding, modulation, amplification, etc. Devices using cellular technologies, e.g., 3G, 4G, or 5G, etc., have higher energy footprints compared to low-powered, IoT-specific technologies, e.g., LoRa, Bluetooth, Zigbee, etc. Additionally, continuous data transmission to cloud servers or access points/gateways exacerbates energy consumption in real-time applications such as monitoring and supply chain management. Energy-hungry tasks such as anomaly detection, data preprocessing, and predictive analytics, further add to the burden. Devices deployed in isolated environments face even greater challenges. Addressing these issues requires sustainable designs such as energy harvesting, low-power communication protocols, and efficient processing techniques.

2.3.2 Deployment challenges

Deployment challenges are associated with installing, integrating, and scaling IoT devices across diverse environments. IoT systems usually consist of a diverse set of devices with unique communication protocols, processing capabilities, and power requirements. In large-scale deployments such as smart cities, forest fire detection systems, industrial plants, etc., thousands of devices coordinate to operate as a unified system. Devices may need to be installed in remote or inaccessible areas, which require specialized equipment and significant human effort, driving up costs and time. IoT systems must accommodate additional devices and increased data traffic without degrading performance. To manage this, sustainable deployments must be realized using modular designs, standardized protocols, and automation tools.

2.3.3 Hardware design

Hardware design in IoT systems encompasses the RF chains, antenna modules and processors responsible for sensing, communication, analysis, and actuation. The diversification of IoT applications has resulted in a wide range of hardware designs, from compact, lightweight wearable devices to robust industrial sensors capable of withstanding extreme environmental conditions. Each of these devices must balance performance, durability, and energy efficiency respective to their corresponding use-cases. Sensors can be of different types, such as optical, acoustic, and chemical sensors. Each sensor is tailored to a specific application. For example, air quality monitoring systems use chemical sensors to detect pollutants, while autonomous vehicles rely on LiDARs (light detection and ranging) and radars for real-time object

detection. These functions consume significant power, particularly during continuous operation for real-time applications. Furthermore, many components used in IoT systems rely on non-recyclable materials, leading to environmental concerns. Additionally, the miniaturization of IoT devices exacerbates environmental concerns, as smaller components are harder to repair or recycle. Addressing these challenges requires sustainable designs such as modular hardware, recyclable materials, and low-powered components.

2.3.4 Spectrum allocation

Spectrum allocation is the process of designating specific frequency ranges within the electromagnetic spectrum to various services and technologies. This ensures efficient and interference-free operation of wireless systems. IoT devices do not have high processing capabilities, therefore, efficient spectrum usage is critical to ensure reliable communication. Spectrum congestion has become a pressing issue in densely populated areas owing to the scale of IoT networks, which is ever-increasing. Furthermore, the utilization of unlicensed frequency bands such as 2.4 GHz for Wi-Fi and Zigbee, etc., exacerbates interference and reduces data throughput. Similarly, LPWAN technologies rely on sub-GHz frequency bands, which provide efficient long-range communication at the cost of limited bandwidth. Spectrum congestion also increases energy consumption as devices expend more power to retransmit lost or corrupted data. Dynamic and cognitive spectrum management techniques can empower the devices to sense and adapt to underutilized frequencies. However, implementing them complicates the design of IoT devices, which hinders sustainability.

2.3.5 Processing ability

IoT systems generate vast amounts of data from sensors, which must be processed to extract actionable insights. Therefore, IoT devices need processors to direct the collection and management of data locally or centrally. The computational demands of applications such as anomaly detection, predictive analysis, and real-time analytics strain the limited processing power of IoT devices. Local processing in the gateways or end-devices reduces the need for continuous data transmission to the cloud. However, these devices face constraints in terms of processing power, memory, and energy availability. The use of lightweight algorithms and energy-efficient processors can partially address these challenges. Over-the-air (OTA) computations can also mitigate these constraints. However, sustainable designs are required to balance the processing demands and energy constraints, especially in high-density IoT networks.

2.3.6 Network maintenance

Network maintenance processes are the activities required to ensure devices remain operational, e.g., hardware repairs, software updates, and battery replacements. Frequent battery replacements or firmware updates in large-scale deployments are

impractical, unsustainable, and resource-intensive. Additionally, IoT deployments in remote localities further complicate network maintenance. Predictive maintenance techniques can be employed to reduce maintenance costs. They use IoT sensors to identify potential failures before they occur and reduce network downtime. OTA updates can streamline the software maintenance process, but require secure and reliable communication channels to prevent failures or cyberattacks. Modular hardware designs can further simplify the replacement of faulty components and reduce waste.

2.4 Challenges of sustainable IoT

IoT ecosystems possess a unique set of characteristics which enables specific use-cases and distinguishes IoT from conventional wireless systems. These characteristics are critical to the proper functionality of IoT systems, but introduce significant sustainability challenges. These challenges demand a balance between the requirements that enable the functionality of IoT-enabled architectures, and resource consumption. In most cases, IoT devices are often deployed in locations where frequent battery replacement or maintenance is impractical, necessitating energy-efficient designs. These designs can take advantage of solar or ambient energy harvesting technologies to extend their operational lifecycle. Even though the data generated from a single IoT device is minuscule, the exchange of control information and data traffic from hundreds or thousands of nodes can become significant. Efficient data handling, storage, and processing solutions adopted on an individual and architectural level have the potential to minimize the environmental impact of IoT-enhanced ecosystems. Durable and low-cost hardware can support diverse applications across different deployment scenarios eliminating the complexity of device manufacturing and management. The key characteristics are shown with their corresponding sustainability challenges in Table 2.2, and are described as follows:

Table 2.2 Challenges of sustainable IoT.

Challenge	Impact	Problems	Solutions
Massive Scale	Billions of IoT devices require seamless management, data handling, and reliable communication.	High congestion, increased interference, bandwidth limitations, authentication complexity.	Edge computing, adaptive frequency management, hierarchical clustering, congestion control.
Scalability	IoT networks must support continuous growth in device count, data generation, and application demands.	Performance degradation, increased latency, inefficient routing, resource exhaustion.	Distributed processing, self-organizing networks, optimized congestion control, adaptive routing.

continued on next page

Table 2.2 (*continued*)

Challenge	Impact	Problems	Solutions
Heterogeneity	IoT systems integrate diverse devices with different protocols, energy needs, and data formats.	Compatibility issues, inefficient data standardization, increased processing overhead.	Middleware for interoperability, standardization of protocols, cross-layer optimization.
Autonomy	IoT devices require minimal human intervention for sensing, decision-making, and actuation.	Continuous sensing increases energy consumption, synchronization overhead in real-time systems.	Integrated sensing and communication (ISAC), power-efficient localization, event-driven processing.
Energy Efficiency	Long-term operation in constrained environments requires minimal power consumption.	High energy demand for sensing and communication, rapid battery depletion.	Ultra-low-power architectures, energy harvesting, efficient sleep-wake scheduling.
Low Transmission Rates	IoT traffic consists of small, burst transmissions rather than continuous data streams.	Inefficient bandwidth utilization, increased queuing delays, high protocol overhead.	Adaptive data compression, event-triggered transmission, traffic-aware scheduling.
Real-Time Communication	Applications like autonomous vehicles and industrial automation require low latency.	High power consumption for continuous connectivity, network congestion in time-sensitive applications.	Edge computing, time-sensitive networking, low-latency routing protocols.
Long-Range Connectivity	IoT must maintain communication across vast geographical areas.	High transmission power requirements, signal degradation, spectrum scarcity.	LPWAN protocols (LoRa, NB-IoT), satellite IoT, advanced error correction techniques.
Security & Privacy	IoT systems process large volumes of sensitive data and require robust protection.	Increased computational burden, vulnerability to attacks (e.g., jamming, spoofing).	Lightweight encryption, blockchain authentication, AI-driven anomaly detection.

Massive scale

Approximately 40 billion IoT devices are estimated to be operational by the year 2025 [45]. The versatility of IoT systems has accelerated their integration in a number of industries, including but not limited to smart home, healthcare, manufacturing, etc. The smart home sector is projected to constitute approximately 60% of all IoT applications, this statistic translates to more than 5 billion IoT devices [46]. The large scale of connections within this type of connectivity paradigm introduces problems related

to device management, data handling, storage and processing, and network scalability. Billions of devices generating real-time data can lead to data handling issues requiring novel methods for storage, processing, management, and analysis. Centralized architectures can lead to problems like latency, bandwidth limitations, channel access issues, data drops, corruption, energy efficiency, etc., especially in real-time applications like self-driving cars or mission-critical applications like manufacturing plants. These challenges are effectively mitigated using fog and edge computing architectures that bring the processing nodes closer to the IoT devices.

IoT devices are envisioned to be connected to each other and other nodes through wireless communication networks. The number of devices communicating over a wireless medium with limited capacity is a major concern especially in terms of congestion of the wireless medium and interference. Advanced resource allocation schemes are required that work to address these limitations, especially in dense network configurations. Adaptive frequency management and congestion control are also areas where significant improvement can be made to maintain reliable communication. Technologies like LoRaWAN, Sigfox, and NB-IoT focus on techniques that enable scalability in massive IoT networks. These protocols and technologies, however, require careful optimization for a good balance between range, bandwidth, and energy efficiency. The scale of the network formed by a massive number of IoT devices, also poses sustainability concerns. The energy consumption, hardware manufacturing waste, and wireless channel resource consumption for billions of devices have highlighted legitimate environmental concerns. Processes have to be put in place that not only allow for very low energy operation, but also produce recyclable waste and enable effective wireless resource consumption with robust hardware that allows for long-lasting operation. Proper device life-cycle tracking can also be implemented to evaluate the impact of devices from their point of manufacturing to their operation and final decommissioning. The life-cycle of devices provides insights about the environmental impact of devices, allowing for better analysis of devices for their environmental footprint. This footprint can then later be reduced by recognizing opportunities for improvement.

Scalability

Scalability refers to the ability of a network to support a growing number of connected devices, increase in data traffic, and explosion in application demands without performance degradation. A systematic structure capable of supporting repeating hierarchies, distributed processing, and dynamic control protocols can ensure the seamless scalability of extremely large and growing networks [47]. IoT networks are expected to form large and dense networks that can only be sustained using adaptive architectures and protocols. All the devices being added the IoT networks increase the data processing and management load, which has to provide resources to keep the network operational and meet QoS demands. Increased device interference and network congestion needs to be managed by appropriate protocols that can dynamically make optimal decisions for appropriate device resource management. These steps can ensure the scalability of IoT networks.

Heterogeneity

Heterogeneity refers to the integration of nodes in the network that have varying requirements, functions, and/or performance metrics. IoT nodes can vary in their nature and can be devices, sensors, and/or actuators. An IoT system can therefore be expected to form a heterogeneous network. In this network, a number of devices with varying power consumption, computational power, functions, and communication protocols exist. The optimization and management of such a system with varying requirements and configurations becomes increasingly complex. The management of a network with heterogeneous entities becomes complex and incurs additional resources to enable appropriate hardware compatibility, energy optimization, and data standardization. The different functions of devices operating within an ecosystem can cause them to have a different life cycle. Less resilient devices have to be frequently changed, contributing to waste production. The processing overhead involved in the interoperability of the devices in the network also decreases efficiency. Sustainable IoT designs account for this decrease in efficiency and work to reduce the overhead involved between devices while also minimizing waste by using devices with longer life cycles. Accounting for compatibility between devices can also lead to a decrease in energy consumption.

Autonomy

One of the key features of IoT systems is their ability to operate autonomously with minimal human intervention [48]. This is done by collecting data, processing it and taking appropriate actions in order to achieve an outcome. Systems that are designed to operate autonomously often have a sensing aspect underlining their operation. They achieve this by integrating technologies such as global positioning system (GPS) and radar for real-time positioning, motion detection, and spatial awareness. Due to the nature of the systems formed by autonomous IoT devices, they require continuous and reliable operation. This leads to significant energy demands, especially in the case of sensing and localization, where a constantly changing environment necessitates frequent updates and high computation. Integrated sensing and communication (ISAC) frameworks are efficient in their operation, but still require resources for synchronization and reliability [49]. In order to make autonomous systems more sustainable, power requirements, computational complexity and communication overhead must be balanced.

Energy efficiency

Energy-efficient operation in constrained environments is one of the most common operating conditions in the case of IoT systems. Monitoring of remote environments, wearable devices, underwater sensors, etc., are expected to be operational for a long period of time without the need to be maintained [50]. This need for long-term operation conflicts with the high power demands of continuous sensing, processing, and communication. In order to achieve low power consumption, devices often have to have lower processing power, lower update frequency, and a smaller feature set. As the IoT devices use and wear down their batteries, these batteries have to be replaced and thus contribute to environmental pollution. Ultra-low power designs or energy harvesting devices have to be made more robust for their widespread adoption.

Low transmission rates

IoT devices have a different transmission behavior, as compared to human-generated traffic, and are mostly focused on small transmissions in regular or semi-regular bursts. Applications such as environmental monitoring and asset tracking often require similar transmission behaviors. These types of behaviors can be configured for optimal power consumption for devices operating in constrained environments albeit at the cost of lower performance such as a lower number of updates, etc. Real-time communication requires frequent updates and degradation in performance may be observed with a decrease in the amount of updates. This can also become dangerous in situations where a slow update can lead to an increased risk of accidents, as in the case of autonomous vehicles. Some mechanisms might be able to handle the sporadic flows of IoT networks, including queueing, but these mechanisms also lead to processing overhead. Low transmission rate protocols may be developed that accommodate the sporadic nature of machine communication in IoT networks. However, due to the recent interest in the field, further testing and evaluation may be needed.

Real-time communication

Real-time communication allows IoT devices to adapt to dynamic conditions and respond to user interactions without significant delays. This capability is particularly critical in applications that demand immediate decision-making and action [51]. For instance, in autonomous vehicles, real-time communication ensures safety by enabling rapid responses to changing road conditions and potential hazards. Similarly, healthcare monitoring systems rely on real-time data to promptly detect and address critical patient health changes. Industrial automation also benefits from this characteristic, where time-sensitive processes require seamless communication to maintain operational efficiency and prevent costly disruptions. Real-time systems are characterized by their need for continuous connectivity, low latency, and high reliability, but these requirements often come at the cost of increased energy consumption and computational complexity. Ensuring real-time capabilities in large-scale IoT networks introduces additional challenges, such as managing network congestion, mitigating power drainage, and addressing hardware degradation over time. The sustainability of such systems relies on carefully optimized network architectures and the implementation of low-power, high-efficiency communication protocols. These measures must balance the trade-offs between maintaining real-time responsiveness and minimizing resource utilization to achieve practical and scalable IoT solutions.

Long-range connectivity

Long-range connectivity enables IoT devices to maintain communication across extensive geographical areas, making it suitable for diverse applications such as precision agriculture in rural farms, infrastructure management in smart cities, and monitoring in large industrial sites [52]. Technologies such as LoRaWAN and NB-IoT provide energy-efficient solutions for low-data-rate communication over long distances. Additionally, cellular networks, such as long-term evolution (LTE) and 5G offer higher data rates and reliability. These technologies collectively facilitate robust

communication in scenarios where extended coverage and dependable connectivity are paramount. Long-range communication systems often require higher transmission power to maintain reliable connectivity, particularly in environments characterized by significant signal attenuation or high levels of interference. This increased transmission power directly impacts energy consumption, posing a challenge for energy-constrained IoT devices. Moreover, ensuring dependable connectivity over extended distances can demand greater spectrum usage, potentially contributing to network congestion in densely deployed regions. The deployment and maintenance of long-range communication infrastructure, such as gateways and base stations, further amplify these challenges, contributing to the system's overall environmental footprint. Addressing these concerns necessitates a careful balance between achieving extended coverage and minimizing energy and resource consumption.

Security and privacy

IoT systems are responsible for processing and transmitting large volumes of sensitive data, including personal information, healthcare records, and critical industrial metrics. Protecting this data from unauthorized access and breaches requires robust security measures, such as encryption to safeguard data during transmission, authentication mechanisms to verify user and device identities, and stringent access control policies to restrict unauthorized interactions. These measures are essential for maintaining the integrity, confidentiality, and privacy of IoT networks, particularly in applications where data sensitivity and regulatory compliance are critical. The implementation of security protocols in IoT systems often introduces additional computational and communication overhead, which can lead to increased energy consumption and higher latency. Addressing emerging vulnerabilities requires frequent software updates, further consuming system resources, and necessitating constant monitoring to ensure robust security. Moreover, privacy concerns demand comprehensive and reliable data handling policies, adding complexity to system design and management. Developing sustainable IoT systems requires carefully balancing these security and privacy requirements with the need to minimize resource usage and reduce environmental impact. This calls for innovative approaches that optimize security measures while maintaining efficiency and scalability.

2.5 Design elements of sustainable IoT

The design of sustainable IoT systems is governed by various technical elements that influence network performance, energy efficiency, and scalability. These elements define how data is processed, transmitted, and managed within an IoT ecosystem. Optimizing these elements is essential for ensuring long-term operational efficiency while minimizing energy consumption and resource utilization. This section details the critical design elements that impact sustainable IoT networks.

2.5.1 Modulation schemes

Modulation schemes play a fundamental role in wireless communication by defining how digital information is encoded onto an analog carrier wave for efficient transmission. The choice of modulation technique directly impacts key performance metrics such as spectral efficiency, power consumption, and signal robustness in the presence of noise and interference. Low-order modulation schemes, such as binary phase shift keying (BPSK), offer superior noise immunity and lower energy requirements. These characteristics make them well-suited for long-range, low-power IoT applications where reliability and energy efficiency take precedence over data rate. Conversely, higher-order schemes like quadrature amplitude modulation (16-QAM, 64-QAM) enable significantly higher data throughput by encoding more bits per symbol, but necessitate a stronger signal-to-noise ratio (SNR) and higher transmission power. This trade-off makes high-order modulation preferable for bandwidth-intensive applications, but less suitable for power-constrained devices. Sustainable IoT networks leverage adaptive modulation that dynamically adjusts the modulation order in response to varying channel conditions, optimizing both throughput and energy efficiency. Advanced techniques such as orthogonal frequency-division multiplexing (OFDM), widely implemented in LTE and Wi-Fi, improve spectral efficiency by enabling parallel data transmission across multiple subcarriers while mitigating the effects of multipath fading. Low-power IoT technologies such as LoRa and Sigfox favor low-order modulation schemes to maximize energy efficiency and coverage.

2.5.2 Coding techniques

Coding techniques improve the reliability of IoT communication by detecting and correcting transmission errors. These techniques enhance data integrity at the cost of additional computational complexity and power consumption that might not be suitable for power-constrained IoT network infrastructures. Forward error correction (FEC) techniques, including low-density parity-check (LDPC) and Turbo codes, enable reliable communication between the sender and receiver by allowing the receiver to reconstruct the corrupted bits using the embedded redundancy [53–55]. Automatic repeat request (ARQ) mechanisms like hybrid ARQ (HARQ) used in LTE and 5G [56], optimize retransmissions based on error feedback. Sustainable coding techniques minimize overhead while ensuring sufficient error protection to reduce retransmissions, as retransmissions not only result in increased latency but also consume additional power. Polar codes are one example of highly efficient error correction codes with minimal computational cost [54]. Energy-efficient IoT networks aim for lightweight error correction mechanisms that adapt dynamically to channel conditions, preventing unnecessary power expenditure.

2.5.3 Antenna design

Antenna design directly affects signal propagation, interference mitigation, and energy efficiency of IoT systems. Antennas convert electrical signals into electromagnetic waves for transmission and reception. Directional antennas focus transmission

power in a specific direction, thereby improving range and reducing interference [57]. Omnidirectional antennas provide uniform radiation patterns, making them suitable for mesh networks and short-range IoT applications [58]. Multi-antenna technologies increase spectral efficiency by taking advantage of the spatial multiplexing provided by multiple antennas. These technologies enhance throughput and reliability without increasing bandwidth or power consumption. Sustainable IoT networks leverage energy-aware antenna designs, including passive backscatter antennas and reconfigurable intelligent surfaces (RIS), to enhance efficiency while maintaining robust connectivity.

2.5.4 Interference management techniques

Interference management ensures reliable communication in dense IoT networks by minimizing signal degradation caused by overlapping frequencies. Frequency planning and dynamic spectrum allocation can enhance spectrum utilization. The interference in this case is reduced by allocating orthogonal frequency bands to adjacent transmitters. Adaptive power control minimizes interference by adjusting transmission power based on network conditions. Modern IoT systems can employ advanced interference cancellation techniques including interference alignment and successive interference cancellation (SIC) in non-orthogonal multiple access (NOMA) systems [59]. These approaches aid in spectral reuse, enabling multiple devices to share the same frequency bands efficiently. Sustainable IoT networks implement low-power interference mitigation strategies to enhance spectrum management.

2.5.5 Spectrum allocation schemes

Spectrum allocation directs how frequency bands are assigned to IoT devices and affects network capacity, reliability, and efficiency. Dynamic spectrum access (DSA) enables IoT devices to opportunistically use underutilized frequencies, which improves spectrum efficiency [60]. Cognitive radio techniques, such as spectrum sensing and spectrum sharing, allow IoT networks to identify and utilize vacant frequency bands, which reduce network congestion [61]. Hybrid models, e.g., licensed shared access (LSA), combine fixed and dynamic spectrum strategies to ensure fair and sustainable spectrum allocation [62]. Efficient spectrum distribution maximizes throughput while minimizing interference and energy consumption.

2.5.6 Processor designs

IoT processor design impacts computational efficiency, power consumption, and real-time responsiveness. Low-power microcontrollers are optimized for energy-efficient processing in constrained environments. Edge AI processors enable on-device machine learning inference, which reduces dependence on cloud processing and minimizes data transmission overhead. Dynamic voltage and frequency scaling (DVFS) adjust processor power consumption based on workload demands, which optimizes energy efficiency while maintaining performance [63]. Sustainable processor designs

incorporate hardware accelerators, such as field-programmable gate arrays (FPGAs) and application-specific integrated circuits (ASICs), to execute specialized tasks with minimal energy usage.

2.5.7 Power allocation strategies

Efficient power allocation balances energy consumption and network performance in IoT deployments. Fixed power allocation maintains consistent transmission power levels and ensures stable connectivity. However, it can potentially waste energy in favorable channel and network conditions. Adaptive power control dynamically adjusts transmission power based on link quality, interference levels, and energy constraints. Energy-aware routing protocols further enhance power efficiency by selecting paths that minimize overall energy consumption. Sustainable IoT networks employ green power allocation frameworks and integrate renewable energy sources with intelligent power management technologies.

2.5.8 Multiple access techniques

Multiple access schemes regulate how various IoT devices share communication resources. Time-division multiple access (TDMA) assigns time slots to devices and reduces channel contention and energy consumption in low-power applications. Frequency-division multiple access (FDMA) separates communication channels into different, non-overlapping frequency bands, thus mitigating interference in dense networks. Orthogonal frequency-division multiple access (OFDMA) improves spectral efficiency by dynamically allocating subcarriers to users, whereas NOMA enhances network capacity by superimposing signals at different power levels, which enables simultaneous transmissions without increasing bandwidth requirements. Selecting appropriate multiple access techniques ensures functional communication while conserving energy.

2.5.9 Edge and fog computing

Edge and fog computing reduce latency and bandwidth usage by processing data closer to the source rather than relying on cloud infrastructure. Edge computing enables real-time analytics on IoT devices or gateways, which minimizes transmission overhead and improves response times. Fog computing distributes processing across intermediate nodes and balances computational loads while enhancing system scalability. These paradigms optimize resource utilization and contribute to sustainable IoT ecosystems by reducing network congestion and energy consumption.

2.6 Design considerations for sustainable IoT

IoT networks have a diverse set of critical metrics that evaluate their performance, efficiency, and applicability across versatile use cases. These metrics not only define the

technical capabilities of the IoT systems, but also affect sustainability as they govern resource utilization, energy consumption, and environmental impact. Optimization of network designs to meet these metrics efficiently ensures that IoT networks are enabling application-specific functions while adhering to sustainable design principles. This section provides a detailed analysis of the IoT design metrics and their effects on sustainability.

2.6.1 Data rate

The data rate is the speed at which information is transmitted and received between IoT devices, gateways, or access points. It is directly affected by the modulation schemes, power allocations, frequency-of-operation, antenna designs, network architectures, and coding techniques. The effects are briefly described as follows:

- **Modulation schemes:** Higher-order modulation schemes increase the number of bits transmitted per symbol. This improves the effective data rate of the wireless communication link. However, higher orders require higher signal-to-noise ratios (SNRs), and are more susceptible to noise. Hence, higher-order modulations may demand higher power to function feasibly.
- **Power allocation:** Transmission power dictates the strength of received signal over long distances. It also reduces bit errors, thus enabling higher data rates. However, high power utilization hinders sustainability and scalability. Power allocation must be optimized to provide sustainability and realize a balance between coverage, link throughput, and green functioning.
- **Frequency-of-operation:** Higher frequencies provide increased bandwidth and support higher data rates. For example, 5G millimeter-wave (mmWave) bands provide Gbps throughputs, but are limited in range compared to sub-GHz frequencies. Higher frequencies experience greater signal attenuation and reduced penetration through obstacles, making them less suitable for long-distance or non-line-of-sight applications.
- **Antenna design:** High-gain and directional antennas improve signal strength and minimize interference, hence, providing higher data rates. Multi-antenna technologies such as multiple-input multiple-output (MIMO) arrays enhance spectral efficiency using spatial diversity and enable higher throughput.
- **Network architectures:** Decentralized architectures such as mesh networks reduce congestion and improve data rates by optimizing routing paths. In contrast, centralized systems rely on efficient gateway management and maintain high throughput. In general, centralized systems can provide higher throughput owing to the higher processing ability and transmission powers available at the central gateways or access points.
- **Coding techniques:** Advanced error correction codes, such as LDPC (low-density parity check) and Turbo codes, improve the reliability of data transmission by correcting errors caused by noise or interference, indirectly supporting higher data rates.

- **Channel bandwidth:** Wider bandwidths improve link capacity and directly increase data rates. For example, Wi-Fi 6 (802.11ax) utilizes wider channels to achieve higher throughput.
- **Interference management:** Properly managing co-channel and adjacent-channel interference improves signal-to-interference-plus-noise ratio (SINR), which directly improves effective channel capacity. It also reduces retransmissions and indirectly enables higher data throughput.
- **IoT protocol design:** Efficient protocols with low overhead maximize the payload-to-header ratio, and indirectly enhance the effective data rates.
- **Processor design:** IoT devices with advanced hardware, e.g., high-speed processors and optimized transceivers, etc., support faster data processing and transmission, resulting in higher data rates.
- **Routing protocols:** Routing protocols dictate how data is localized through the network. Energy-efficient routing protocols are critical for ensuring optimal data paths, reducing delays, and maintaining throughput.

LPWANs such as LoRa and SigFox, support data rates of tens of kilobits per second (kbps), which is sufficient for low-rate and low-bandwidth applications, e.g., smart metering, smart lightening, and environmental monitoring. These technologies are designed for energy-efficient long-range communication, making them ideal for large-scale IoT deployments in remote or resource-constrained environments. Zigbee and BLE support data rates in the range of hundreds of kbps to a few megabits per second (Mbps). Zigbee provides data rates up to 250 Kbps and is well suited for industrial IoT, home automation, and smart city applications that demand medium-range connectivity. BLE offers a balance between energy efficiency and performance and enables data rates up to 2 Mbps for applications such as wearable devices, proximity-based interactions, and indoor navigation. In contrast, high-data-rate technologies such as Wi-Fi, long-term evolution (LTE), and 5G enable data rates ranging from Mbps to gigabits per second (Gbps). These technologies enable data-intensive applications, e.g., real-time video streaming, augmented reality (AR), telemedicine, industrial robotics, etc.

Higher data rates consume more energy due to the increased transmit power and computational demands. This trade-off between performance and energy efficiency hinders sustainability, particularly in resource-constrained environments. Sustainable designs can mitigate these challenges by employing adaptive modulation schemes, advanced routing algorithms, and complex interference management techniques. These designs provide an effective balance between power consumption and communication reliability, ensuring long-term operational efficiency in IoT networks.

2.6.2 Coverage

Coverage of a network is defined as the maximum geographical distance over which a signal can be transmitted and reliably received between communication devices. It is a critical design consideration for ensuring connectivity in large-scale IoT deployments, particularly in remote areas and harsh environments with physical obstructions. Applications such as smart agriculture and environmental monitoring heavily

depend on reliable, large-coverage networks to maintain system functionality. Coverage is influenced by the following factors:

- **Modulation schemes:** Lower-order modulation schemes provide higher noise tolerance and enable larger coverage. In contrast, higher-order modulation schemes improve spectral efficiency and provide higher data rates at the cost of reduced effective coverage and lower noise tolerance.
- **Transmission power:** An increase in the transmission power improves the effective strengths of the signal at the receivers and enables large propagation distances. However, this increased energy consumption can hinder sustainability of battery-powered devices.
- **Frequency-of-operation:** Lower frequencies (e.g., sub-GHz bands) have higher obstacle penetration abilities and support longer ranges of coverage. However, they provide lower data rates and shorter bandwidths. Higher frequencies (e.g., mmWave) suffer from greater attenuation and are less effective for long-range and non-line-of-sight applications. However, higher frequencies can provide higher bandwidths and higher effective throughputs.
- **Antenna design:** High-gain directional antennas focus energy in specific directions and extend the range of the communication system. Omnidirectional antennas provide uniform coverage but have reduced range. MIMO systems can provide a balance and improve coverage by leveraging spatial diversity and dynamically directing signals toward the desired devices.
- **Interference management:** Effective mitigation of co-channel and adjacent-channel interference can significantly improve the network's effective coverage.
- **Network architecture:** Multi-hop and mesh architectures expand coverage areas by relaying data through intermediate nodes. This reduces the need for high transmission power, but requires energy-efficient routing protocols.

LPWAN protocols provide long-range coverage (up to a few kilometers), which makes them ideal for applications like environmental monitoring in rural or remote areas. Zigbee and BLE have shorter ranges of operation and are well-suited for indoor IoT applications, such as home automation, smart offices, etc. Cellular networks (e.g., LTE and 5G) offer scalable coverage across diverse deployment scenarios and can enable high-rate and low-energy applications using different technical standards. Extending coverage necessitates higher transmission power, which increases energy consumption and impacts sustainability. Sustainable IoT designs utilize adaptive power allocation, energy-efficient routing protocols, and advanced antenna configurations to maintain reliable connectivity over large coverage areas while minimizing resource utilization.

2.6.3 Transmission frequency

Transmission frequency defines how often data transmission is initiated in an IoT network between end-devices, gateways, or central servers. It impacts system responsiveness and the age of information (AoI), which is a critical metric for real-time

applications, e.g., industrial automation and healthcare monitoring, etc. Applications with periodic or event-triggered data transmissions, such as environmental monitoring, benefit from lower transmission frequencies to conserve energy. However, real-time applications, such as autonomous vehicles and telemedicine, require frequent data transmissions to maintain low latency and provide updated information. The transmission frequency is influenced by the following factors:

- **Energy availability:** Battery-operated IoT devices often reduce the effective transmission frequency to conserve energy and do not enable real-time applications. Devices with continuous power sources can realize real-time and high transmission rate applications.
- **IoT protocols:** Efficient, low-overhead protocols enable more frequent data transmission without exhausting network resources. In contrast, high-overhead protocols offer enhanced functionality and robustness at the cost of increased energy and bandwidth consumption, which is inefficient in real-time applications.
- **Multiple access techniques:** Multiple access techniques reduce contention in high-transmission-frequency scenarios, and ensure reliable communication even in dense networks.
- **Processor design:** Devices with advanced processors and transceivers enable frequent transmissions more efficiently by reducing processing delays and power consumption.

BLE supports moderate transmission frequencies for event-driven communication in wearable devices, ensuring frequent updates with minimal latency. In contrast, LoRaWAN prioritizes scheduled transmissions for energy conservation in periodic applications, e.g., environmental sensing, infrastructure monitoring, etc. High-throughput technologies, e.g., 5G and LTE, etc., enable ultra-frequent transmissions in applications such as augmented reality (AR), telemedicine, and industrial robotics. Frequent transmissions increase energy demands and network congestion in dense IoT networks, which hinders network sustainability. To mitigate these challenges, adaptive scheduling, data aggregation, and event-triggered communication are employed in large-scale IoT systems.

2.6.4 Network densities

Network density quantifies the number of IoT devices operating within a defined spatial area and affects interference, bandwidth allocation, and network scalability. High-density networks, such as smart cities and industrial IoT systems, have high levels of interference, congestion, and resource contention. In contrast, low-density networks prioritize coverage and long-range communication, particularly in rural or sparsely populated areas. Network density is influenced by the following factors:

- **Interference management:** Dense networks increase co-channel and adjacent-channel interference, which degrades the signal quality. Advanced interference mitigation techniques are required to maintain reliable communication.

- **Multiple access techniques:** Efficient access schemes can allocate resources dynamically, which provides increased network traffic support while minimizing packet collisions.
- **Routing protocols:** Hierarchical and clustered routing protocols optimize communication paths, reducing congestion and improving energy efficiency in dense deployments.
- **Antenna design:** High directionality antennas and MIMO technology provide spatial diversity and enable advanced interference mitigation, which enable feasible and functional high-density deployments.
- **Bandwidth:** Wider allocated bandwidths can enable service to a higher number of devices, which improves network capacity and reduces delays in high-density environments.

Zigbee mesh networks are highly efficient for medium-density deployments in smart homes and industrial automation systems. In contrast, 5G networks leverage massive MIMO to support ultra-dense IoT applications in urban environments. LP-WAN technologies are designed for low-density and long-range deployments, and have high performance in long-range, low-rate applications. Sustainable designs in dense networks focus on reducing interference, minimizing energy consumption, and managing congestion. Device clustering, dynamic spectrum allocation, non-orthogonal multiple access, and adaptive scheduling techniques can enable efficient resource utilization and minimal environmental impact.

2.6.5 Network architecture

Network architecture is the structure and organization of devices in an IoT network. It can be centralized, decentralized, or hybrid in nature. Centralized architectures have a central hub or gateway for data aggregation and processing, while decentralized architectures, such as mesh networks, distribute communication and processing tasks across multiple nodes. Each of these architectures is optimized for specific performance metrics like scalability, fault tolerance, and energy efficiency. Network architecture is affected by the following factors:

- **Routing protocols:** Centralized systems rely on efficient routing to aggregate data at the hub, while decentralized systems use distributed routing to balance traffic loads and minimize congestion.
- **Processing distribution:** Centralized architectures realize data processing at the gateways, which reduces IoT device complexity. In contrast, decentralized systems leverage edge computing and perform localized processing, which reduces latency and bandwidth usage at the cost of higher device complexity and energy consumption.
- **Failure tolerance:** Decentralized systems provide higher resilience by rerouting traffic around failed nodes. This enables enhanced fault tolerance. In contrast, centralized architectures can experience single-point failures.

- **Energy efficiency:** Centralized systems typically consume less energy at end devices, as most processing is offloaded to the gateway. Decentralized systems distribute energy consumption more evenly across the network, but have higher energy footprints per end-device.

Centralized architectures are commonly employed in LPWAN technologies like Sigfox and LoRaWAN, where data from devices is routed to a central gateway. In contrast, Zigbee mesh networks implement decentralized architectures to improve scalability and fault tolerance in smart home and industrial IoT applications. Hybrid architectures (e.g., LTE and 5G, etc.) combine centralized and decentralized systems to optimize performance across versatile usage scenarios. Sustainability in network architectures requires a balance of energy efficiency, scalability, and fault tolerance. Techniques such as adaptive routing, hierarchical clustering, and edge computing improve the sustainability of both centralized and decentralized architectures.

2.6.6 Security

IoT security protocols protect data confidentiality, integrity, and availability during transmission between devices, gateways, and servers. These protocols use encryption, authentication, access control, and intrusion detection to prevent unauthorized access, breaches, and attacks. Owing to the densely connected nature of IoT systems, security breaches can compromise entire networks and result in data theft, unauthorized access, false alarms, or system disruptions. Critical applications such as telemedicine, industrial automation, and infrastructure monitoring require robust security measures to safeguard sensitive information. IoT network security is directed by the following factors:

- **Encryption techniques:** End-to-end encryption techniques, e.g., AES-128 and RSA, etc., ensure data confidentiality during transmission. These techniques require key exchange to realize functional communication.
- **Authentication mechanisms:** Robust authentication protocols, e.g., public key infrastructure (PKI) and biometrics, etc., verify device and user identities. They enable confidentiality and prevent eavesdroppers.
- **Access control:** Role-based access control restricts access to authorized users and devices, minimizing security risks.
- **Intrusion detection:** Real-time monitoring and anomaly detection systems can be deployed to identify and mitigate potential threats to the network.

Zigbee and BLE incorporate AES-128 encryption for secure communication and provide adequate security in local area IoT applications. Cellular networks use mutual authentication and SIM-based security procedures for enhanced protection. Blockchain is emerging as a promising candidate for secure IoT and can enable decentralized use-cases, particularly in supply chain management and critical infrastructure. Sustainable systems require lightweight cryptographic protocols and efficient authentication mechanisms to reduce energy consumption without compromising protection.

2.6.7 Privacy

Privacy in IoT systems protects personal and sensitive data collected by devices and provides user anonymity and controlled access to information. Unlike security measures, which safeguard data from unauthorized access and attacks, privacy protocols enable compliance with user consent and regulatory requirements. Privacy is a critical design metric for healthcare, smart homes, and wearable technology applications. Privacy can be enabled using the following:

- **Data anonymization:** Anonymity prevents the identification or tracking of individuals or devices within a communication system by dissociating transmitted data from identifiable information. Pseudonymization, encryption, and data obfuscation preserve privacy and mitigate the risk of surveillance.
- **Access control:** Access control mechanisms restrict data access to authorized users and applications based on predefined policies. Techniques such as role-based access control (RBAC) and attribute-based access control (ABAC) can enforce precise access policies to minimize privacy risks.
- **Data minimization:** Data minimization reduces privacy risks by collecting and processing the data necessary for a specific application or service.
- **Secure storage:** Secure storage protects stored data using encryption methods such as AES-128 or AES-256 and ensures that the information remains inaccessible to unauthorized entities.
- **Data transmission:** Data transmission protocols protect information during propagation by implementing encryption schemes such as TLS/SSL which provide confidentiality and integrity.

Healthcare IoT systems rely on data anonymization and secure transmission to protect patient information. Smart home platforms implement role-based access control to manage data privacy among devices and users. Decentralized systems use blockchains to enhance privacy by providing tamper-proof transaction records. Sustainable privacy practices must balance security measures with energy efficiency. Lightweight encryption and authorization algorithms can reduce the resource burden while protecting sensitive and identifiable information.

2.6.8 Reliability

Reliability is the network's capability to consistently ensure accurate data delivery and maintaining seamless operational functionality. It is characterized by performance metrics such as packet delivery ratio and bit error rate (BER) and is governed by mechanisms like error correction, interference mitigation, and the implementation of network redundancy. High reliability is essential for mission-critical applications, such as industrial automation, healthcare monitoring, and autonomous vehicles, where delays or data loss can result in catastrophic consequences. Reliability is influenced by the following factors:

- **Packet loss:** Reducing packet loss ensures consistent data delivery and minimizes retransmissions.

- **Error correction:** Techniques such as forward error correction and ARQ improve data reliability in noisy channels.
- **Network redundancy:** Redundant communication paths prevent data loss due to node or link failures.
- **Hardware design:** Devices designed for harsh environments can withstand extreme conditions and ensure uninterrupted operation.

LPWAN technologies implement error correction to improve network reliability in long-range, low-power networks. Cellular systems (e.g., LTE, 5G, etc.) provide ultra-reliable low-latency communication (URLLC) for critical applications. Zigbee mesh networks enhance reliability through redundant paths and ensure continuous data delivery by mitigating node failures. Sustainable designs focus on minimizing energy consumption associated with retransmissions and redundancy. Efficient error correction codes can achieve high reliability while conserving resources.

2.6.9 Latency

Latency is the time delay between the generation of data by an IoT device and its successful delivery to the intended destination. It includes any processing or transmission delays. Low latency is critical for real-time applications, e.g., autonomous driving, industrial automation, telemedicine, etc., where even minor delays can impact functionality. Latency is defined by the following factors:

- **Network congestion:** High traffic volumes increase queuing delays and worsen the end-to-end delay of successful data transmission.
- **Routing protocols:** Efficient routing protocols minimize path delays and ensure faster data delivery. They also minimize network congestion.
- **Processing time:** Faster processing at devices and gateways reduces the delay introduced by data handling.
- **Multiple access techniques:** Efficient access mechanisms reduce contention and packet collisions which cause delays in end-to-end successful transmission.

5G networks provide ultra-low latency communication and enable advanced applications such as augmented reality and autonomous vehicles. LPWAN systems prioritize energy efficiency but have higher latencies due to lower data rates and scheduled transmissions. Sustainable designs can be realized by using edge computing and adaptive routing to reduce latency while maintaining energy efficiency.

2.6.10 Network lifetime

Network lifetime is the operational duration of an IoT network before its components require significant maintenance, such as device replacements or battery recharging. It is a critical metric for sustainability and is the core focus of large-scale and remote deployments where frequent maintenance is impractical. Network lifetime is influenced by the following factors:

- **Energy efficiency:** Minimizing power consumption extends device lifetimes and reduces network downtime. Hence, modulation schemes, coding techniques, and routing protocols must be tailored to provide high energy efficiency.
- **Energy harvesting:** Energy harvesting technologies enable IoT device operation without frequent battery replacements by utilizing solar, thermal, and vibrational energy. For example, piezoelectric sensors in industrial IoT applications can convert mechanical vibrations into usable electrical energy and provide continuous operation in remote environments.
- **Duty cycling:** Duty cycling alternates between active and sleep states of the devices to conserve energy during periods of inactivity and extend network lifetimes in energy-constrained environments.
- **Hardware durability:** Robust and durable hardware designs reduce the need for frequent replacements, ensuring reliable operation over extended periods.
- **Battery capacity:** Devices with higher-capacity batteries provide longer operational durations, but may increase deployment costs and environmental impact.
- **Communication overhead:** Reducing the frequency of information transmission conserves energy and extends device lifetimes.

LoRa and Sigfox networks optimize network lifetime through low-power operation and infrequent transmissions. Energy harvesting technologies in industrial IoT enable continuous operation in power-constrained environments, reducing reliance on battery replacements. Sustainable designs focus on energy-efficient protocols, durable hardware, and energy harvesting solutions to extend operational durations without increasing environmental impact.

2.7 Conclusion

This chapter explores the architectural foundations, sustainability challenges, and design considerations of IoT networks. We define the layered IoT architecture of IoT systems and detail the roles of interaction, network, and application layers alongside key network entities such as end-devices, gateways, and processing servers. IoT applications are categorized into consumer, commercial, industrial, healthcare, agricultural, infrastructure, military, and environmental domains. These domains are analyzed based on technical constraints and operational demands. We identify sustainability challenges driven by large-scale deployments, heterogeneity, autonomy, real-time constraints, and security concerns. Core design elements, e.g., modulation schemes, coding techniques, antenna configurations, spectrum allocation, multiple access strategies, and power control mechanisms, etc., are discussed in the context of energy efficiency and network scalability. Finally, we define essential design considerations such as data rates, coverage, transmission frequency, network densities, security, privacy, reliability, and latency. These factors guide the development of sustainable, low-power, and high-performance IoT networks, ensuring long-term operational feasibility.

References

- [1] Khaled Salah Mohamed, An Introduction to IoT, in: Khaled Salah Mohamed (Ed.), *Bluetooth 5.0 Modem Design for IoT Devices*, Springer International Publishing, Cham, 2022, pp. 33–43, https://doi.org/10.1007/978-3-030-88626-4_2, ISBN: 9783030886264 (visited on 01/27/2025).
- [2] Mahnoor Anjum, et al., Theoretical Landscape of LPWANs, in: *Low-Power Wide-Area Networks: Opportunities, Challenges, Risks and Threats*, Springer International Publishing, Cham, ISBN 978-3-031-32935-7, 2023, pp. 3–37, https://doi.org/10.1007/978-3-031-32935-7_1.
- [3] Naga Srinivasarao Chilamkurthy, et al., Low-Power Wide-Area Networks: A Broad Overview of Its Different Aspects, *IEEE Access* 10 (2022) 81926–81959, <https://doi.org/10.1109/ACCESS.2022.3196182>.
- [4] Muhammad Abdullah Khan, et al., Applications of LPWANs, in: Ismail Butun, Ian F. Akyildiz (Eds.), *Low-Power Wide-Area Networks: Opportunities, Challenges, Risks and Threats*, Springer International Publishing, Cham, 2023, pp. 171–209, https://doi.org/10.1007/978-3-031-32935-7_6, ISBN: 9783031329357 (visited on 01/27/2025).
- [5] Benish Sharfeen Khan, et al., URLLC and eMBB in 5G Industrial IoT: A Survey, *IEEE Open Journal of the Communications Society* 3 (2022) 1134–1163, <https://doi.org/10.1109/OJCOMS.2022.3189013>.
- [6] Muhammad Abdullah Khan, et al., Machine Learning-Based Resource Allocation for IRS-Aided UAV Networks, in: *GLOBECOM 2023–2023 IEEE Global Communications Conference*, 2023, pp. 3051–3057, <https://doi.org/10.1109/GLOBECOM54140.2023.10437224>.
- [7] Chongwen Huang, et al., Holographic MIMO Surfaces for 6G Wireless Networks: Opportunities, Challenges, and Trends, *IEEE Wireless Communications* 27 (5) (2020) 118–125, <https://doi.org/10.1109/MWC.001.1900534>.
- [8] Olga Chukhno, et al., Interplay of User Behavior, Communication, and Computing in Immersive Reality 6G Applications, *IEEE Communications Magazine* 60 (12) (2022) 28–34, <https://doi.org/10.1109/MCOM.009.2200238>.
- [9] Zhihong Yang, et al., Study and application on the architecture and key technologies for IOT, in: *2011 International Conference on Multimedia Technology*, 2011, pp. 747–751, <https://doi.org/10.1109/ICMT.2011.6002149>.
- [10] Chang-Le Zhong, Zhen Zhu, Ren-Gen Huang, Study on the IOT Architecture and Gateway Technology, in: *2015 14th International Symposium on Distributed Computing and Applications for Business Engineering and Science (DCABES)*, 2015, pp. 196–199, <https://doi.org/10.1109/DCABES.2015.56>.
- [11] Nallapaneni Manoj Kumar, Pradeep Kumar Mallick, The Internet of Things: Insights into the building blocks, component interactions, and architecture layers, in: *Procedia Computer Science*, in: *International Conference on Computational Intelligence and Data Science*, ISSN 1877-0509, vol. 132, 2018, pp. 109–117, <https://doi.org/10.1016/j.procs.2018.05.170>, <https://www.sciencedirect.com/science/article/pii/S1877050918309049>.
- [12] Amir Abdullah, Harleen Kaur, Ranjeet Biswas, Universal layers of IoT architecture and its security analysis, in: *New Paradigm in Decision Science and Management: Proceedings of ICDSM 2018*, Springer, 2020, pp. 293–302.
- [13] Nallapaneni Manoj Kumar, Pradeep Kumar Mallick, The Internet of Things: Insights into the building blocks, component interactions, and architecture layers, *Procedia Computer Science* 132 (2018) 109–117.

- [14] Chang-Le Zhong, Zhen Zhu, Ren-Gen Huang, Study on the IOT architecture and gateway technology, in: 2015 14th International Symposium on Distributed Computing and Applications for Business Engineering and Science (DCABES), IEEE, 2015, pp. 196–199.
- [15] Z. Shelby, K. Hartke, C. Bormann, RFC 7252: The Constrained Application Protocol (CoAP), 2014, USA.
- [16] Eduardo Buetas Sanjuan, et al., Message Queuing Telemetry Transport (MQTT) Security: A Cryptographic Smart Card Approach, IEEE Access 8 (2020) 115051–115062, <https://doi.org/10.1109/ACCESS.2020.3003998>.
- [17] Arafat AA Shabaneh, et al., Review of energy conservation using duty cycling schemes for IEEE 802.15. 4 wireless sensor network (WSN), Wireless Personal Communications 77 (2014) 589–604.
- [18] Teodora Sanislav, et al., Energy harvesting techniques for internet of things (IoT), IEEE Access 9 (2021) 39530–39549.
- [19] T. Poongodi, et al., Wearable devices and IoT, in: A handbook of Internet of Things in biomedical and cyber physical system, 2020, pp. 245–273.
- [20] Swathi Ramnath, et al., IoT based localization and tracking, in: 2017 International Conference on IoT and Application (ICIOT), IEEE, 2017, pp. 1–4.
- [21] Mussab Alaa, et al., A review of smart home applications based on Internet of Things, Journal of Network and Computer Applications 97 (2017) 48–65.
- [22] Mahnoor Anjum, et al., Analysis of time-weighted LoRa-based positioning using machine learning, Computer Communications 193 (2022) 266–278, <https://doi.org/10.1016/j.comcom.2022.07.010>, <https://www.sciencedirect.com/science/article/pii/S0140366422002572>, ISSN: 0140-3664.
- [23] Jorge E. Gómez, et al., IoT for environmental variables in urban areas, Procedia Computer Science 109 (2017) 67–74.
- [24] T.F. Prasetyo, D. Zaliluddin, M. Iqbal, Prototype of smart office system using based security system, Journal of Physics. Conference Series 1013 (1) (2018) 012189, IOP Publishing.
- [25] Felipe Caro, Ramin Sadr, The Internet of Things (IoT) in retail: Bridging supply and demand, Business Horizons 62 (1) (2019) 47–54.
- [26] Omid Avatefipour, Froogh Sadry, Traffic management system using IoT technology-A comparative review, in: 2018 IEEE International Conference on Electro/Information Technology (EIT), IEEE, 2018, pp. 1041–1047.
- [27] Krishna Nirde, Prashant S. Mulay, Uttam M. Chaskar, IoT based solid waste management system for smart city, in: 2017 International Conference on Intelligent Computing and Control Systems (ICICCS), IEEE, 2017, pp. 666–669.
- [28] Carman Ka Man Lee, et al., A bluetooth location-based indoor positioning system for asset tracking in warehouse, in: 2019 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), IEEE, 2019, pp. 1408–1412.
- [29] Moayad Al-Talib, et al., Achieving resilience in the supply chain by applying IoT technology, Procedia CIRP 91 (2020) 752–757.
- [30] Alireza Ghasempour, Internet of things in smart grid: Architecture, applications, services, key technologies, and challenges, Inventions 4 (1) (2019) 22.
- [31] S. Muthuramalingam, et al., IoT based intelligent transportation system (IoT-ITS) for global perspective: A case study, in: Internet of things and big data analytics for smart generation, 2019, pp. 279–300.
- [32] Prashant Singh, et al., Internet of Things for sustainable railway transportation: Past, present, and future, Cleaner Logistics and Supply Chain 4 (2022) 100065.

- [33] Paula Fraga-Lamas, et al., A review on internet of things for defense and public safety, *Sensors* 16 (10) (2016) 1644.
- [34] Ahmed Shihab Albahri, et al., IoT-based telemedicine for disease prevention and health promotion: State-of-the-Art, *Journal of Network and Computer Applications* 173 (2021) 102873.
- [35] Lei Yu, Yang Lu, XiaoJuan Zhu, Smart hospital based on internet of things, *Journal of Networks* 7 (10) (2012) 1654.
- [36] Tuan Nguyen Gia, et al., IoT-based continuous glucose monitoring system: A feasibility study, *Procedia Computer Science* 109 (2017) 327–334.
- [37] Alexandru Archip, et al., An IoT based system for remote patient monitoring, in: 2016 17th international carpathian control conference (ICCC), IEEE, 2016, pp. 1–6.
- [38] Nurzaman Ahmed, Debashis De, Iftekhar Hussain, Internet of Things (IoT) for smart precision agriculture and farming in rural areas, *IEEE Internet of Things Journal* 5 (6) (2018) 4890–4899.
- [39] Wataru Iwasaki, Nobutomo Morita, Maria Portia Briones Nagata, IoT sensors for smart livestock management, in: *Chemical, gas, and biosensors for internet of things and related applications*, Elsevier, 2019, pp. 207–221.
- [40] Khaled Obaideen, et al., An overview of smart irrigation systems using IoT, *Energy Nexus* 7 (2022) 100124.
- [41] P. Raja, Swapnil Bagwari, IoT based military assistance and surveillance, in: 2018 International Conference on Intelligent Circuits and Systems (ICICS), IEEE, 2018, pp. 340–344.
- [42] Himadri Nath Saha, et al., Pollution control using internet of things (IoT), in: 2017 8th Annual Industrial Automation and Electromechanical Engineering Conference (IEME-CON), IEEE, 2017, pp. 65–68.
- [43] J. Ananthi, et al., Forest fire prediction using IoT and deep learning, *International Journal of Advanced Technology and Engineering Exploration* 9 (87) (2022) 246–256.
- [44] Dipika Roy Prapti, et al., Internet of Things (IoT)-based aquaculture: An overview of IoT application on water quality monitoring, *Reviews in Aquaculture* 14 (2) (2022) 979–992.
- [45] Aakash Acharjee, et al., Exploring the evolving landscape of security threats in IoT: Challenges and Countermeasures, *American Journal of Advanced Computing* 2 (2) (2023).
- [46] Shalini Chopra, et al., Factors Significantly Impacting Consumer Acceptance of Entertainment, Domestic, and Housekeeping Smart Home IoT Devices, <https://doi.org/10.21203/rs.3.rs-2068436/v1>, <https://www.researchsquare.com/article/rs-2068436/v1>, Sept. 2022 (visited on 01/27/2025).
- [47] Anisha Gupta, Rivana Christie, R. Manjula, Scalability in internet of things: features, techniques and research challenges, *International Journal of Computational Intelligence Research* 13 (7) (2017) 1617–1627.
- [48] Mohammed Ali Al-Garadi, et al., A survey of machine and deep learning methods for internet of things (IoT) security, *IEEE Communications Surveys and Tutorials* 22 (3) (2020) 1646–1685.
- [49] Mahnoor Anjum, Deepak Mishra, Aruna Seneviratne, Power-Efficient Transceiver Design for Full-Duplex Dual-Function Radar Communication Systems, in: 2024 IEEE 25th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), 2024, pp. 11–15, <https://doi.org/10.1109/SPAWC60668.2024.10694318>.
- [50] Kyriakos Georgiou, Samuel Xavier-de-Souza, Kerstin Eder, The IoT energy challenge: A software perspective, *IEEE Embedded Systems Letters* 10 (3) (2017) 53–56.

- [51] Davide Calvaresi, et al., The challenge of real-time multi-agent systems for enabling IoT and CPS, in: *Proceedings of the international conference on web intelligence*, 2017, pp. 356–364.
- [52] Mahmood A. Al-Shareeda, et al., Long range technology for internet of things: review, challenges, and future directions, *Bulletin of Electrical Engineering and Informatics* 12 (6) (2023) 3758–3767.
- [53] Bashar Tahir, Stefan Schwarz, Markus Rupp, BER comparison between Convolutional, Turbo, LDPC, and Polar codes, in: *2017 24th international conference on telecommunications (ICT)*, IEEE, 2017, pp. 1–7.
- [54] Shuai Shao, et al., Survey of turbo, LDPC, and polar decoder ASIC implementations, *IEEE Communications Surveys and Tutorials* 21 (3) (2019) 2309–2333.
- [55] Kenneth S. Andrews, et al., The development of turbo and LDPC codes for deep-space applications, *Proceedings of the IEEE* 95 (11) (2007) 2142–2156.
- [56] Christopher Lott, Olgica Milenkovic, Emina Soljanin, Hybrid ARQ: Theory, state of the art and future directions, in: *2007 IEEE information theory workshop on information theory for wireless networks*, IEEE, 2007, pp. 1–5.
- [57] Hong-Ning Dai, et al., An overview of using directional antennas in wireless networks, *International Journal of Communication Systems* 26 (4) (2013) 413–448.
- [58] Lan Jen Chu, *Physical limitations of omnidirectional antennas*, 1948.
- [59] Behrooz Makki, et al., A survey of NOMA: Current status and open research challenges, *IEEE Open Journal of the Communications Society* 1 (2020) 179–189.
- [60] Qing Zhao, Brian M. Sadler, A survey of dynamic spectrum access, *IEEE Signal Processing Magazine* 24 (3) (2007) 79–89.
- [61] Beibei Wang, K.J. Ray Liu, Advances in cognitive radio networks: A survey, *IEEE Journal of Selected Topics in Signal Processing* 5 (1) (2010) 5–23.
- [62] Miia Mustonen, et al., An evolution toward cognitive cellular systems: Licensed shared access for network optimization, *IEEE Communications Magazine* 53 (5) (2015) 68–74.
- [63] Sebastian Herbert, Diana Marculescu, Analysis of dynamic voltage/frequency scaling in chip-multiprocessors, in: *Proceedings of the 2007 international symposium on Low power electronics and design*, 2007, pp. 38–43.

Sustainable hardware and software design challenges for Green IoT devices

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3.1 Introduction

The Internet of Things (IoT) can be defined as a network of interconnected devices capable of sensing the world around them, taking actions, and communicating with each other without human intervention [1,2]. This interconnected ecosystem encompasses sensors, cameras, and computing devices, reshaping industries, enhancing operational efficiency, and improving the quality of life [3]. From smart homes and cities to supply chains and transportation, IoT applications are ubiquitous and rapidly expanding [4]. By 2025, it is estimated that 42 billion IoT devices will be deployed globally, underscoring the vast scale of this technology [3].

However, this remarkable growth of IoT is accompanied by significant environmental challenges. The energy consumption of billions of devices, including their production, operation, and eventual disposal, raises critical concerns about their carbon footprint and sustainability [5]. As IoT adoption accelerates, addressing its environmental impact becomes imperative to ensure a sustainable future. Green IoT emerges as a solution to this challenge by focusing on reducing the energy consumption and carbon footprint of IoT systems throughout their lifecycle. This involves designing energy-efficient hardware, optimizing software, and implementing sustainable practices that align with the United Nations (UN) sustainability goals. By prioritizing energy efficiency and sustainability, green IoT aims to balance technological advancement with ecological responsibility [6].

One of the key areas influencing energy consumption in IoT systems is the processing unit, which serves as the computational heart of these systems. Single-Board Computers (SBCs), such as the Raspberry Pi, offer comprehensive computational capabilities, making them suitable for high-performance applications. However, their

relatively high energy demands can strain energy resources, particularly in resource-constrained deployments [7,8]. On the other hand, Single-Board Microcontrollers (SBMs) like Arduino and ESP32 are optimized for low-power operations, making them ideal for task-specific, energy-constrained applications [9]. Striking a balance between computational performance and energy efficiency is critical for advancing green IoT, necessitating the design of hardware that minimizes energy usage without compromising functionality. This ensures that IoT systems can meet application-specific requirements sustainably.

In addition to hardware considerations, communication technologies, which form the backbone of IoT systems—present another critical area for energy optimization. These technologies enable devices to transmit and receive data, but their energy consumption varies depending on the protocol and the deployment context. For instance, Long Range (LoRa) and Bluetooth Low Energy (BLE) are tailored for energy-constrained devices, making them suitable for low data-rate communication scenarios [10,11]. Conversely, Wi-Fi and Millimeter Wave (mmWave) technologies offer high-speed data transfer capabilities at the cost of increased energy usage [12,13]. Achieving energy-efficient communication requires selecting the appropriate technology based on application needs and implementing optimization techniques to minimize unnecessary data transmission and idle power consumption.

Another innovative approach to address the energy challenges of IoT is Energy Harvesting (EH), which harnesses ambient energy sources such as sunlight, radio waves, mechanical vibrations, or temperature gradients [14–16]. IoT devices can use these sources to generate their own power, reducing dependency on traditional batteries and external power supplies. For example, solar EH is particularly well-suited for outdoor applications with consistent sunlight availability [17], while piezoelectric EH utilizes mechanical vibrations to power devices in dynamic environments [18]. These self-sustaining energy solutions extend device lifespans, lower maintenance requirements, and reduce electronic waste. Despite their potential, EH technologies face challenges, such as variability in energy availability and the need for efficient storage systems to ensure consistent device operation. By integrating advanced EH technologies into IoT systems, energy-resilient solutions can be created, aligning with the objectives of green IoT.

Moreover, advances in edge and fog computing have further revolutionized the potential of green IoT. These paradigms address the energy inefficiencies of traditional cloud-centric IoT systems by bringing computational resources closer to the devices that generate data [19]. Edge computing processes data locally at the device or network level, significantly reducing the energy consumed in transmitting large volumes of data to the cloud and back. This also improves system responsiveness and supports real-time applications [20]. Fog computing extends the cloud model by leveraging intermediate nodes to distribute cloud resources and tasks across multiple locations closer to IoT systems, enabling scalable and energy-efficient operations [19]. Together, these technologies enable green IoT systems to minimize energy costs while maintaining high performance and reliability [21].

The integration of Artificial Intelligence (AI) and Machine Learning (ML) is also integral to realizing the full potential of green IoT. By analyzing the vast amounts of

data generated by IoT devices, AI and ML can enable intelligent decision-making and optimize energy consumption [22]. For example, edge intelligence leverages AI at the device level to process data locally, reducing transmission energy and latency. Furthermore, Deep Learning (DL) models enhance capabilities such as image and video recognition, while predictive ML algorithms improve system performance through functions like anomaly detection, predictive maintenance, and resource allocation [23,24].

Despite its promising potential, green IoT faces several challenges that must be addressed for widespread adoption. One significant obstacle is the trade-off between energy efficiency and performance. Designing energy-efficient hardware and software often involves compromises that limit computational capabilities, particularly in resource-intensive applications. Additionally, integrating sustainable technologies, such as EH and advanced communication protocols, can increase initial costs, posing economic barriers to large-scale implementation. Moreover, the variability of renewable energy sources, such as solar or Radio Frequency (RF) harvesting, introduces reliability concerns that require innovative storage and energy management solutions [25]. Security concerns also arise, as distributed computing approaches like edge and fog computing increase the attack surface of IoT systems [19]. Addressing these challenges requires holistic approaches that integrate technological innovation, cost-effective designs, and robust security measures.

In conclusion, the successful implementation of green IoT will play a pivotal role in building a sustainable and environmentally responsible technological ecosystem. By prioritizing energy efficiency, minimizing carbon footprints, and leveraging innovative technologies, green IoT can drive a paradigm shift toward a greener future, ensuring that the benefits of IoT are realized without compromising the health of our planet.

The remainder of this chapter is structured as follows: Section 3.2 surveys the current landscape of green IoT, focusing on hardware and software challenges. Section 3.3 discusses EH techniques. Section 3.4 explores the role of edge and fog computing in supporting green IoT. Section 3.5 showcases the use of AI and ML in fulfilling the promise of green IoT. Finally, Section 3.6 concludes the chapter.

3.2 Energy efficient hardware

Energy-efficient hardware has become a crucial area of focus in the pursuit of green IoT, emphasizing the development of devices that minimize power consumption without compromising performance [26]. This section explores the foundational elements of energy-efficient hardware, with a particular focus on advanced processing units, innovative communication technologies, and their integration into IoT systems [27]. By examining state-of-the-art solutions such as SBCs, SBMs, and optimized communication protocols, this section underscores the importance of sustainable hardware design in promoting eco-friendly IoT deployments [3,9].

Table 3.1 Comparison of SBM and SBC.

	SBM	SBC
Primary Purpose	Automation, real-time tasks, control	General-purpose computing
Operating System (OS)	Minimal to no firmware	Full OS (Linux, Android)
Performance	Lower performance, task-focused	Higher performance, more versatile
Power consumption	Lower, usually less than 500 mW	Higher, usually 0.5 W to 1.5 W
Cost	Lower	Higher

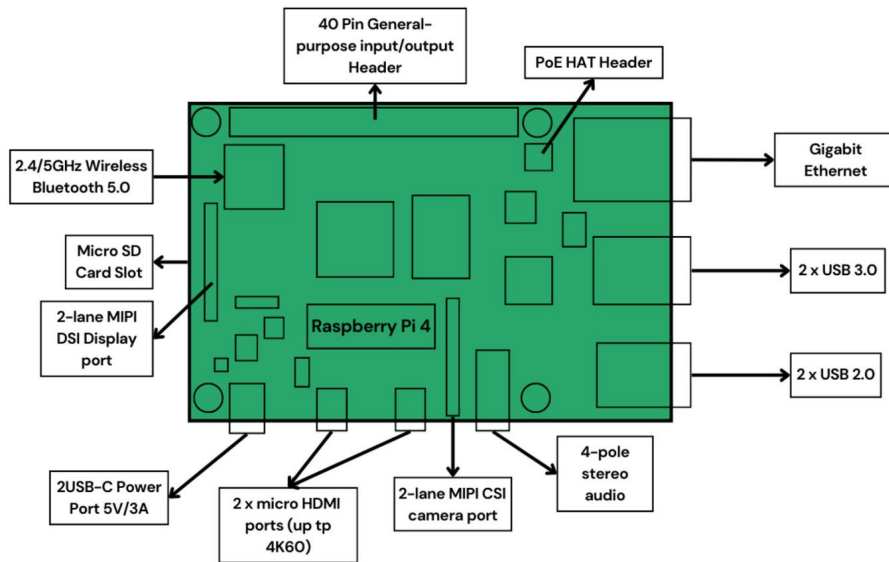
3.2.1 Energy-efficient processing units

Processing units form the core of IoT systems, responsible for performing computational tasks and often serving as the primary consumers of energy. Sustainable hardware design emphasizes energy-efficient processors to balance computational capabilities with power consumption. The two main types of processing units used in IoT devices are SBCs and SBMs [3]. On one hand, SBCs are fully functional modern computers built on a single circuit board, integrating all necessary components such as the Central Processing Unit (CPU), Random Access Memory (RAM), input/output interfaces, storage, and sometimes even a power supply, all onto one board [3]. On the other hand, SBMs are compact devices that includes a Microcontroller Unit (MCU) and essential components (such as RAM and storage) on a single board, designed specifically for controlling tasks or systems in embedded applications [9]. Unlike an SBC, which is a full-fledged computer, an SBM is focused on control and automation rather than computational performance. SBM have gained popularity in the IoT industry due to their ultra-low power consumption and integrated Wi-Fi and Bluetooth functionality [28]. Their low power consumption and small size make them ideal for real-time monitoring devices [28]. A comparison between SBC and SBM is shown in Table 3.1.

Raspberry Pi

The Raspberry Pi is a low-cost SBC widely used for its versatility and modular design. Although originally developed for educational purposes, its adaptability and computational power have made it a popular choice in IoT deployments. It supports a range of IoT applications, including industrial automation and smart homes, though its power requirements are higher compared to simpler microcontrollers. Fig. 3.1 illustrates the components of a standard Raspberry Pi 4 model. Energy efficiency is a critical consideration when using Raspberry Pi devices, as it is a key priority in green IoT initiatives.

The Raspberry Pi also offers extensive library support, such as RPi.GPIO for controlling General Purpose Input/Output (GPIO) pins and Adafruit's CircuitPython for simplified interaction with hardware components. These libraries, along with support for popular programming languages like Python, C, and Java, make the Raspberry

**FIGURE 3.1**

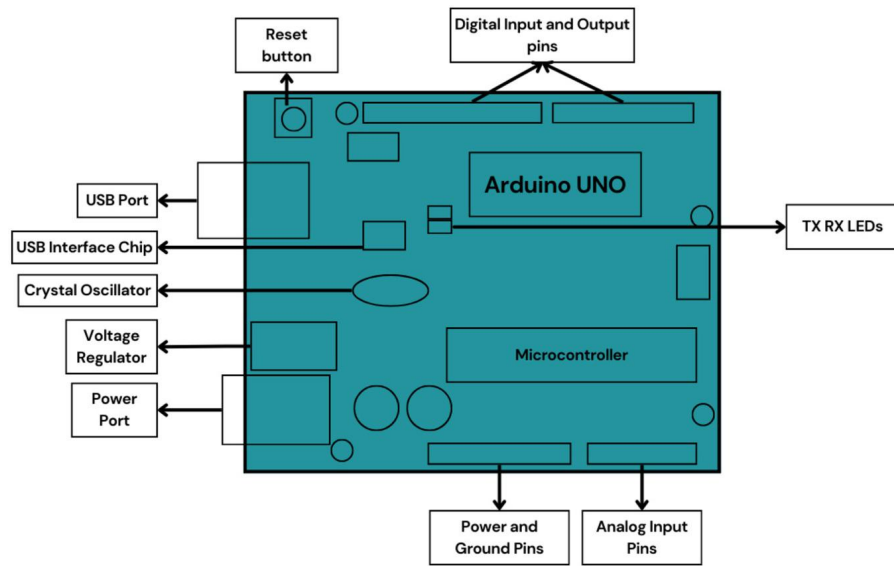
An illustration of Raspberry Pi 4.

Pi highly accessible to developers building energy-efficient IoT solutions [29]. Additionally, its robust community ecosystem provides access to open-source resources, facilitating rapid prototyping and development. While Raspberry Pi models like the Raspberry Pi 3 offer significant computational capabilities, their power consumption (1.5 W) may not be suitable for battery-powered IoT deployments [7]. To address this, the Raspberry Pi Zero, an energy-efficient variant, offers power consumption as low as 0.5 W during operation, while still featuring a quad-core processor and Wi-Fi and Bluetooth connectivity. This makes it an ideal choice for sustainable IoT applications. The Raspberry Pi's balance of computational performance, flexibility, and energy efficiency positions it as a valuable tool for achieving green IoT objectives [30].

Arduino

Arduino is a widely used open-source SBM platform, renowned for its simplicity, affordability, and versatility. Unlike full-fledged SBCs, Arduino is designed for tasks that require minimal computational power, making it an ideal choice for energy-efficient IoT applications. Arduino's extensive library ecosystem simplifies the development of such solutions. For example, the Arduino low-power library enables the use of sleep modes, allowing devices to enter extremely low-power states when idle, significantly reducing energy consumption [31].

Additionally, there are libraries specifically tailored for low-power features, such as the Arduino low-power library for SAMD21-based boards, which helps extend battery life and enhance sustainability [31]. By providing tools that streamline energy-conscious development and integrating low-power functionalities with ease, Arduino

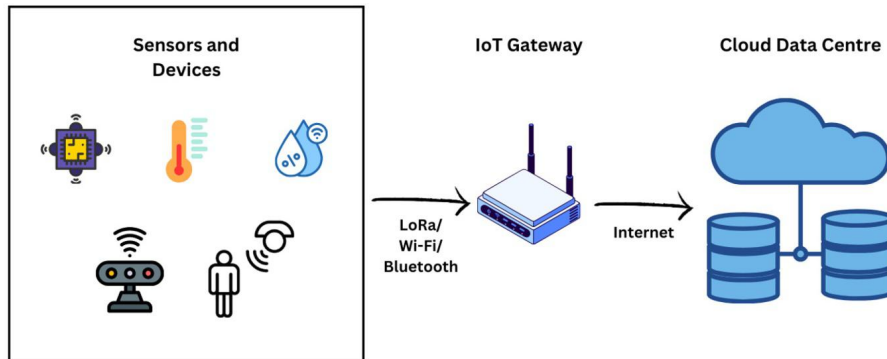
**FIGURE 3.2**

An illustration of Arduino Uno.

empowers developers to create solutions that align with green IoT principles. This reduces environmental impact and conserves energy resources, particularly in battery-powered and remote deployments [9]. Fig. 3.2 illustrates the components of a standard Arduino Uno.

ESP32 and STM32

The ESP32 and STM32 are prominent examples of energy-efficient SBM that have gained significant traction in the IoT industry. Like Arduino, both are compact and optimized for low power consumption. However, the ESP32 stands out with its built-in Wi-Fi and Bluetooth capabilities, making it ideal for IoT applications. In contrast, the STM32 focuses on high performance and a wide range of peripherals, making it better suited for industrial and complex systems that typically require external modules for wireless connectivity [32,33]. The ESP32 is particularly well-suited for applications like smart homes and wearable devices due to its ultra-low power consumption and dual-core processor, which enables efficient multitasking [32]. Similarly, STM32 microcontrollers, based on the ARM Cortex-M architecture, are known for their energy efficiency and versatility, making them popular in industrial automation and precision control systems [33]. These characteristics position the ESP32 and STM32 as excellent choices for sustainable IoT solutions, especially in battery-powered or off-grid deployments [32]. Their blend of computational capability, connectivity, and energy efficiency aligns with the goals of green IoT.

**FIGURE 3.3**

Communication between IoT devices and the cloud.

3.2.2 Communication technologies

IoT devices are typically small, wireless, and battery-powered units that must operate for extended periods without requiring frequent battery replacements. These devices also need to communicate regularly with a base station or gateway to send and receive data, as illustrated in Fig. 3.3. As a result, energy-efficient wireless communication is crucial for the development of effective IoT networks for future applications. In this section, we will explore some of the communication technologies commonly used in IoT deployments.

LoRa

LoRa is a communication protocol specifically designed for low-power, low-bitrate, and long-range communication in IoT applications [10]. It is particularly well-suited for deployments involving energy-constrained devices that transmit or receive small amounts of data, typically just a few bytes per transaction. Operating mainly in the 800 MHz frequency band, LoRa can transmit data over distances of up to 15 kilometers. These characteristics make LoRa an attractive solution for a wide range of IoT applications, especially those requiring broad coverage and minimal energy consumption.

Bluetooth

Originally introduced in 1994, Bluetooth technology has undergone significant development over the years [34], culminating in the release of Bluetooth 6.0 in September 2024. The versions most commonly used in industry today include Bluetooth 4, Bluetooth 5, and BLE. BLE, a variant introduced by the Bluetooth special interest group, is specifically designed for low energy consumption, making it particularly well-suited for IoT applications that require efficient data exchange between smartphones and energy-constrained peripheral devices [11]. Notably, most modern smartphones are equipped with BLE capabilities, offering an advantage over other low-power

wireless communication standards such as ZigBee and Thread [11]. A comparative analysis reported in [35] demonstrates that Bluetooth 4.2 and Bluetooth 5 consume significantly less energy than the IEEE 802.15.4 standard. Specifically, these Bluetooth versions use approximately one-third of the energy required by IEEE 802.15.4 in indoor environments and less than half in outdoor settings [35].

Wi-Fi

Wi-Fi is a technology that allows devices to connect to the internet or communicate wirelessly with one another using radio waves. It operates under the IEEE 802.11 family of standards and is commonly used in Local Area Networks (LAN). Wi-Fi is widely utilized in homes, businesses, and public spaces to connect devices such as smartphones, laptops, tablets, and other internet-enabled gadgets to the internet, typically through a wireless router. Wi-Fi generally operates on the 2.4 GHz and 5 GHz frequency bands and can transfer data at gigabit speeds, making it significantly faster than technologies like LoRa and Bluetooth. However, Wi-Fi typically consumes more energy than these alternatives. This higher energy consumption poses a significant challenge for IoT devices, which often rely on small, battery-powered units. To preserve energy efficiency in such devices, minimizing power consumption during wireless communication is critical. Simply embedding conventional Wi-Fi chipsets in IoT devices is not a viable solution, as it would lead to excessive energy consumption [12]. To address this issue, Hossein Pirayesh and colleagues propose an asymmetric physical design that enables substantial power reduction in IoT devices [12]. Furthermore, the IEEE 802.11 standard includes a power-saving mode, which allows mobile devices to enter a low-power state by turning off the transmitter and receiver when not in use, thus conserving energy [36].

Millimeter wave

The introduction of mmWave technology in 5G New Radio (NR) is expected to play a critical role in future 6G networks [37]. mmWave refers to extremely high-frequency RF signals, typically ranging from 24 GHz to 300 GHz. Compared to legacy RF technologies operating below 6 GHz, mmWave significantly expands the available bandwidth by using higher carrier frequencies, which far exceed the bandwidth allocated to today's Wi-Fi and cellular networks [13,37]. mmWave systems enhance transmission efficiency by leveraging beam directivity, which improves antenna performance for both transmitters and receivers [5]. Additionally, the shorter wavelength of mmWave signals allows for smaller antennas, enabling the deployment of large Multiple-Input Multiple-Output (MIMO) antenna arrays. This improves communication performance, particularly in IoT environments [5]. However, several challenges persist. The shorter wavelength also results in higher path loss, limiting transmission range [38]. Atmospheric and molecular absorption exacerbate this problem, especially in the 60 GHz, 120 GHz, and 180 GHz bands, where significant propagation loss occurs [37]. On the other hand, certain frequency bands, such as 35 GHz, 94 GHz, 140 GHz, and 220 GHz, experience lower attenuation, enabling longer-range communication [37]. Due to these limitations, mmWave communication often requires line-of-sight transmission and is highly susceptible to obstruction by vehicles,

Table 3.2 Comparison of LoRa, Bluetooth, Wi-Fi, and mmWave technologies.

Technologies	LoRa	Bluetooth	Wi-Fi	mmWave
Range	4.8 km–16 km	10 m–240 m	20 m–45 m	80 m–200 m
Data transfer rate	250 Kbps	2Mbps	1Gbps–9Gbps	1Gbps–10Gbps
Energy consumption	10 mW to 50 mW	10 mW–1 W	2 W–20 W	320 W–450 W
Frequency bands	433 MHz–928 MHz	2.4 GHz	2.4 GHz–6 GHz	24 GHz–300 GHz

pedestrians, and even the human body [37]. This line-of-sight dependency, along with the short transmission range, makes mmWave systems highly sensitive to mobility and fading effects, which can degrade signal quality [37]. Another significant challenge for mmWave systems is energy consumption. The technology demands substantial power for transmission and beamforming, making it unsuitable for low-power IoT devices [13]. Additionally, the complexity of phased array systems, which are used to focus mmWave signals into narrow beams, further increases power consumption and hardware costs [13]. These factors limit mmWave’s applicability in IoT applications, where cost and energy efficiency are crucial. Table 3.2 compares various communication technologies.

3.3 Energy harvesting

One approach to achieving energy efficiency in IoT, as previously discussed, is the use of energy-efficient IoT devices. Another method for promoting green IoT is the generation or harvesting of renewable and sustainable energy through EH techniques to power IoT devices. In the following section, we will explore these EH techniques in detail.

3.3.1 Photovoltaic/solar energy harvesting

Photovoltaic or solar EH is a clean and affordable energy source that can help address energy shortages in IoT networks by converting light into electricity through the photovoltaic effect [5]. Among all EH techniques, it is one of the most effective due to its efficiency and high power density of 100 mW/cm² during daylight hours [17]. This process uses solar cells to generate power from light shining on semiconducting materials, making it particularly suitable for locations with abundant sunlight. Outdoor IoT devices can directly utilize solar energy during periods of sufficient sunlight, while indoor devices can benefit from trickle charging in well-lit environments [5]. However, the technique faces limitations in areas with inconsistent light availability, and transporting harvested energy to other locations can result in significant energy losses, emphasizing the need for further research and improvements [39].

3.3.2 Radio-frequency harvesting

RF EH is a technique used to power IoT devices and charge batteries by capturing energy from radio waves. It operates based on magnetic inductive coupling, where a time-varying current in a transmitter loop generates an open-circuit voltage in a nearby receiver loop [18]. The induced voltage, typically around 0.5 V, can power passive devices like Radio Frequency Identification (RFID) tags or be stored in batteries for active battery-powered devices [18]. This technology is currently applied in systems such as electronic ID tags and smart cards, which activate when exposed to RF-rich environments. However, scaling this solution for large-scale IoT deployments may require significant RF radiation, which could potentially pose health risks to humans [18,40].

Despite the relatively low power density of ambient RF energy (ranging from 0.2 nW/cm² to 1 W/cm²), it is increasingly available due to the widespread presence of wireless communication infrastructures like Wi-Fi, cellular networks, and broadcasting systems, especially in urban areas [17]. This technology is particularly advantageous for wirelessly charging batteries or powering electronics in hard-to-reach locations, such as bridges, chemical plants, or aircraft, and can operate continuously with minimal ambient power [17].

3.3.3 Thermoelectric harvesting

Thermoelectric harvesting is an EH technique that generates electricity from temperature gradients or differences. The thermoelectric effect allows the conversion of temperature gradients into electrical energy by diffusing charge carriers, which creates a voltage difference [5]. This principle can be used to power IoT devices by harnessing thermal energy from sources such as hot beverages, the human body, or environmental temperature variations [5]. Efficient energy generation is essential to fully leverage the potential of thermal EH for powering IoT devices. The human body, in particular, is an excellent source for thermoelectric harvesting and is especially valuable for powering wearable devices [41].

3.3.4 Piezoelectric harvesting

Piezoelectric materials have the ability to convert mechanical energy into electrical energy. The direct piezoelectric effect, where mechanical strain generates an electric field proportional to the applied stress, is the primary mechanism used for EH from vibrations [18]. This principle enables the powering of IoT devices, such as roadside sensors and smart traffic lights, by harnessing vibrations from human motion or vehicles. Piezoelectric devices can also act as backup energy sources for smartphones and other electronics by capturing energy from movements like shaking [5].

Piezoelectric energy harvesters are more reliable and efficient compared to other EH methods [18]. These materials can be optimized for specific applications and are available in various shapes and sizes, offering considerable flexibility [18]. As the cost of piezoelectric materials decreases, their high energy density and adaptability make them ideal for IoT devices requiring long lifespans. By integrating piezoelectric units for energy harvesting and storage, device lifetimes can be significantly extended [18].

3.4 Edge & fog computing

IoT devices typically lack the processing power needed to analyze the data they collect. These devices are primarily designed to gather data and transmit it to remote cloud centers for processing. However, this centralized cloud-based approach can be inefficient or infeasible in certain situations. For instance, in real-time systems, the latency caused by transmitting data to distant cloud servers may exceed the application's requirements. Additionally, in remote areas with poor or no connectivity, sending data to the cloud may not be possible. In such cases, local processing becomes essential, making edge and fog computing a viable solution [42].

Edge computing involves performing computational tasks at the network's edge, closer to the IoT devices themselves [43], [44], [23]. Edge computing offers energy savings in scenarios where the cost of processing locally is lower than transmitting data to remote cloud centers. This can contribute to more energy-efficient and sustainable IoT systems [45]. While cloud computing setups are highly effective for handling large-scale systems with multiple users or devices per server [46], [47], their energy efficiency decreases significantly under low loads. In cases like small-scale IoT deployments, where devices transmit data infrequently, the static energy costs of running a cloud server often outweigh the benefits of centralized processing [48]. In contrast, edge computing proves more energy-efficient in such situations. Even with increased sensor density, the energy cost of edge infrastructure scales more linearly than that of centralized cloud systems, due to the distributed nature of edge networks, which minimizes bottlenecks and the need for extensive cooling [48].

Similar to edge computing, fog computing brings cloud computing resources closer to the network edge. However, rather than placing computation directly on the edge devices, fog computing divides traditional centralized cloud resources and data centers into smaller centers located at strategic geographical points, bringing cloud capabilities nearer to the endpoints [19]. While edge computing relies on local resources within the target network, fog computing functions as an intermediary between the cloud and the edge. Essentially, fog computing is akin to having a cloud center closer to the network, often provided as Infrastructure as a Service (IaaS). Although fog computing cannot fully replace cloud computing, nor replicate the extensive functionality of a complete cloud computing center, it extends and complements the cloud's capabilities [19].

3.4.1 Challenges

Despite the numerous advantages offered by edge and fog computing, there are several drawbacks that must be considered. Since edge and fog centers are distributed across various locations at the edge of networks, they increase the overall attack surface by introducing more potential points of vulnerability for hackers to exploit [44,49]. If one center is compromised, attackers can use it as a gateway to target other centers or services [44,50,51]. Furthermore, because edge and fog centers are smaller and less resourceful than full-scale cloud centers, they lack the hardware capabilities to implement robust security measures [44]. This makes them more susceptible to attacks, which can, in turn, create vulnerabilities that hackers might use to breach the larger cloud infrastructure.

3.5 Artificial intelligence for Green IoT

AI can enable machines to learn and solve problems similarly to humans, and have gained significant popularity across various disciplines [22] due to its ability to handle large amounts of data, a task where traditional systems often fall short [22]. As the number of IoT devices continues to grow, the volume of data generated has increased dramatically, making it challenging for traditional systems to manage. AI can play crucial roles in the future of IoT, potentially enabling smart decision-making that can help save energy, in alignment with the green IoT concept [3].

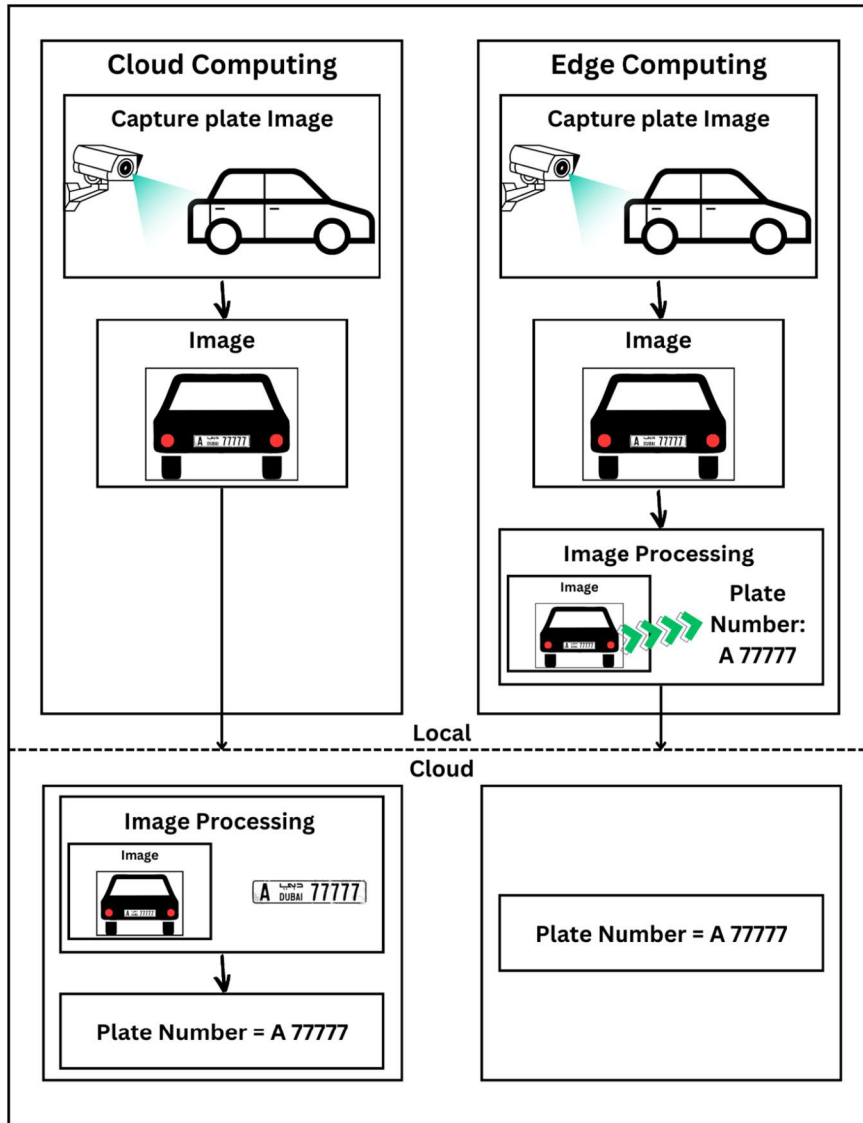
IoT devices produce substantial amounts of data, which is typically transferred to the cloud for further processing. These devices incorporate various types of sensors that collect both structured and unstructured data. While structured data can be easily processed by traditional systems, unstructured data, such as videos, images, and sounds, requires significant computational power—resources that IoT devices generally lack [23]. Whereas DL (an AI variant) enhances the efficiency of processing unstructured data [23], saving time, computation, and energy.

Cloud computing relies on centralized data centers to handle large-scale tasks, such as training DL models and performing complex data analytics. However, these data centers are energy-intensive. The power usage effectiveness of large data centers is typically around 1.2, meaning that 20% of their energy consumption supports infrastructure, like cooling systems and power distribution [52]. This static power cost contributes significantly to the overall energy consumption of cloud systems.

For AI applications, cloud computing provides efficient scaling and parallel processing. However, as the traffic and computational load increase, so does the dynamic energy consumption of the cloud systems. Furthermore, transmitting data from IoT devices to the cloud increases network energy consumption. For example, a study showed that static power consumption from idle servers and routers, combined with the dynamic costs of data transmission, creates inefficiencies, especially in low-bandwidth IoT applications [48].

On the other hand, deploying AI on edge computing can amplify the benefits provided by edge networks. Edge AI reduces latency further and filters unnecessary data, ensuring that only relevant information is transmitted to the cloud, thus saving transmission energy [3]. With the AI model running locally, the IoT system can continue to function without connectivity, and the AI system can troubleshoot and predict potential issues before they cause system failure, improving both availability and uptime [3].

Video sensing and image recognition are key applications within the IoT domain that deal with unstructured data. These technologies combine image processing and computer vision to enhance IoT networks [22]. However, accurately recognizing objects in low-quality video data captured by IoT devices remains a significant challenge [22]. Given the impressive accuracy of DL techniques in video recognition tasks, this area exemplifies how DL can be leveraged in IoT applications [22]. An example of this is the license plate recognition system as illustrated in Fig. 3.4 [53]. In traditional cloud-based architectures, images captured by cameras are transmitted to the cloud for processing, recognition, and storage, leading to high data

**FIGURE 3.4**

An illustration of license plate recognition process [53].

transfer and bandwidth consumption, which results in excessive energy usage. However, when implemented with edge intelligence, the recognition software runs locally on the camera system, meaning only the license plate number and associated meta-data need to be sent to the cloud. This significantly reduces bandwidth requirements and energy consumption.

Minimizing energy consumption in DL is essential for battery-powered edge devices in IoT systems. Reducing computational complexity naturally lowers energy use, but further research into how DL computations interact with battery management mechanisms—such as CPU throttling and sensor hardware optimizations—could reveal additional opportunities for energy savings [54]. Techniques like change detection, implemented either in software or hardware, can reduce the frequency of DL executions, lowering the overall energy demand [54]. While optimizing energy efficiency in hardware is important, a comprehensive understanding of how these hardware optimizations interact with broader system mechanisms, such as battery management and edge server resource trade-offs, is crucial for achieving overall energy optimization [54]. Another strategy for improving energy efficiency in edge intelligence involves reducing the size and complexity of neural networks deployed on edge devices [55]. In [55], the authors propose a neural network compression method called DeepIoT, which is applicable to common architectures, including fully connected, convolutional, and recurrent neural networks. This technique can reduce the size of deep neural networks by up to 98.9%, leading to a 72.2% to 95.7% decrease in energy consumption, all without sacrificing accuracy [55].

3.6 Conclusion

Green IoT represents a transformative approach to the development and deployment of IoT systems, aiming to minimize their environmental impact while maintaining functionality and efficiency. By addressing key challenges such as energy consumption, resource optimization, and sustainability, green IoT seeks to align technological advancement with ecological responsibility. The core principles of green IoT emphasize the use of energy-efficient hardware, sustainable communication technologies, and EH methods that reduce reliance on traditional power sources. Alongside hardware improvements, advancements in edge and fog computing bring computational resources closer to IoT devices, thereby lowering the energy demands associated with data transmission and cloud processing. These decentralized approaches not only improve energy efficiency, but also enhance system responsiveness, supporting real-time applications. Moreover, the integration of AI, ML, and DL technologies further optimizes IoT operations by enabling intelligent decision-making, predictive analytics, and efficient resource allocation, ensuring minimal energy waste. Despite the promising potential of green IoT, several challenges persist, including trade-offs between energy efficiency and performance, economic feasibility, and security concerns. Overcoming these barriers requires collaborative efforts from researchers, developers, and policymakers to create cost-effective, secure, and sustainable IoT ecosystems. By focusing on energy-efficient design, sustainable practices, and the integration of advanced technologies, green IoT can pave the way for a sustainable digital future, ensuring that the growth of IoT contributes positively to both society and the environment.

References

- [1] S. Li, L.D. Xu, S. Zhao, The Internet of Things: a survey, *Information Systems Frontiers* 17 (2015) 243–259.
- [2] M.A. Jamshed, K. Ali, Q.H. Abbasi, M.A. Imran, M. Ur-Rehman, Challenges, applications, and future of wireless sensors in Internet of Things: a review, *IEEE Sensors Journal* 22 (6) (2022) 5482–5494.
- [3] M.A. Albreem, A.M. Sheikh, M.H. Alsharif, M. Jusoh, M.N.M. Yasin, Green Internet of Things (GIoT): Applications, practices, awareness, and challenges, *IEEE Access* 9 (2021) 38833–38858.
- [4] R. Arshad, S. Zahoor, M.A. Shah, A. Wahid, H. Yu, Green IoT: an investigation on energy saving practices for 2020 and beyond, *IEEE Access* 5 (2017) 15667–15681.
- [5] X. Liu, N. Ansari, Toward Green IoT: energy solutions and key challenges, *IEEE Communications Magazine* 57 (3) (2019) 104–110.
- [6] A.A. Shah, A software-defined networking based simulation framework for Internet of space things, in: 2023 IEEE 97th Vehicular Technology Conference (VTC2023-Spring), IEEE, 2023, pp. 1–4.
- [7] C.A. Okigbo, A. Seeam, S.P. Guness, X. Bellekens, G. Bekaroo, V. Ramsurrun, Low cost air quality monitoring: comparing the energy consumption of an Arduino against a raspberry pi based system, in: *Proceedings of the 2nd International Conference on Intelligent and Innovative Computing Applications*, 2020, pp. 1–8.
- [8] T. Karkashina, A.A. Shah, D.P. Pezaros, In-network real-time flow classification using hierarchical decision trees, in: 2024 20th International Conference on Network and Service Management (CNSM), IEEE, 2024, pp. 1–5.
- [9] M.M. Al-Kofahi, M.Y. Al-Shorman, O.M. Al-Kofahi, Toward energy efficient microcontrollers and Internet-of-Things systems, *Computers & Electrical Engineering* 79 (2019) 106457.
- [10] A. Augustin, J. Yi, T. Clausen, W.M. Townsley, A study of LoRa: long range & low power networks for the Internet of Things, *Sensors* 16 (9) (2016) 1466.
- [11] J. Fürst, K. Chen, H.-S. Kim, P. Bonnet, Evaluating bluetooth low energy for IoT, in: 2018 IEEE Workshop on Benchmarking Cyber-Physical Networks and Systems (CPSBench), IEEE, 2018, pp. 1–6.
- [12] H. Pirayesh, P.K. Sangdeh, H. Zeng, Coexistence of Wi-Fi and IoT communications in wlns, *IEEE Internet of Things Journal* 7 (8) (2020) 7495–7505.
- [13] M.H. Mazaheri, S. Ameli, A. Abedi, O. Abari, A millimeter wave network for billions of things, in: *Proceedings of the ACM Special Interest Group on Data Communication*, 2019, pp. 174–186.
- [14] M.A. Jamshed, W.U. Khan, H. Pervaiz, M.A. Imran, M. Ur-Rehman, Emission-aware resource optimization framework for backscatter-enabled uplink noma networks, in: 2022 IEEE 95th Vehicular Technology Conference:(VTC2022-Spring), IEEE, 2022, pp. 1–5.
- [15] M.A. Jamshed, B. Haq, M.A. Mohsin, A. Nauman, H. Yanikomeroglu, Artificial intelligence, ambient backscatter communication and non-terrestrial networks: a 6 g commixture, *arXiv preprint, arXiv:2501.09405*, 2025.
- [16] M.A. Jamshed, Y.A. Qadri, A. Nauman, H. Jung, Electromagnetic field exposure-aware AI framework for integrated sensing and communications-enabled ambient backscatter wireless networks, *IEEE Internet of Things Journal* (2024).
- [17] S. Kim, R. Vyas, J. Bito, K. Niotaki, A. Collado, A. Georgiadis, M.M. Tentzeris, Ambient rf energy-harvesting technologies for self-sustainable standalone wireless sensor platforms, *Proceedings of the IEEE* 102 (11) (2014) 1649–1666.

- [18] M. Shirvanimoghaddam, K. Shirvanimoghaddam, M.M. Abolhasani, M. Farhangi, V.Z. Barsari, H. Liu, M. Dohler, M. Naebe, Towards a green and self-powered Internet of Things using piezoelectric energy harvesting, *IEEE Access* 7 (2019) 94533–94556.
- [19] F. Jalali, S. Khodadustan, C. Gray, K. Hinton, F. Suits, Greening IoT with fog: a survey, in: 2017 IEEE International Conference on Edge Computing (EDGE), IEEE, 2017, pp. 25–31.
- [20] R. Cziva, D.P. Pezaros, On the latency benefits of edge NFV, in: 2017 ACM/IEEE Symposium on Architectures for Networking and Communications Systems (ANCS), 2017, pp. 105–106.
- [21] I. Alghamdi, C. Anagnostopoulos, D.P. Pezaros, On the optimality of task offloading in mobile edge computing environments, in: 2019 IEEE Global Communications Conference (GLOBECOM), 2019, pp. 1–6.
- [22] H. Hua, Y. Li, T. Wang, N. Dong, W. Li, J. Cao, Edge computing with artificial intelligence: a machine learning perspective, *ACM Computing Surveys* 55 (9) (2023) 1–35.
- [23] H. Li, K. Ota, M. Dong, Learning IoT in edge: deep learning for the Internet of Things with edge computing, *IEEE Network* 32 (1) (2018) 96–101.
- [24] M. Kuzlu, C. Fair, O. Guler, Role of artificial intelligence in the Internet of Things (IoT) cybersecurity, *Discover Internet of Things* 1 (1) (2021) 7.
- [25] H.H.R. Sherazi, D. Zorbas, B. O’Flynn, A comprehensive survey on rf energy harvesting: applications and performance determinants, *Sensors* 22 (8) (2022).
- [26] M.A. Jamshed, M.F. Khan, K. Rafique, M.I. Khan, K. Faheem, S.M. Shah, A. Rahim, An energy efficient priority based wireless multimedia sensor node dynamic scheduler, in: 2015 12th International Conference on High-Capacity Optical Networks and Enabling/Emerging Technologies (HONET), IEEE, 2015, pp. 1–4.
- [27] M.A. Jamshed, F. Ayaz, A. Kaushik, C. Fischione, M. Ur-Rehman, Green uav-enabled Internet-of-Things network with AI-assisted noma for disaster management, in: 2024 IEEE 35th International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), IEEE, 2024, pp. 1–6.
- [28] M. Babiuch, P. Foltýnek, P. Smutný, Using the esp32 microcontroller for data processing, in: 2019 20th International Carpathian Control Conference (ICCC), IEEE, 2019, pp. 1–6.
- [29] K. Kesrouani, H. Kalso, A. Nouredine, A preliminary study of the energy impact of software in raspberry pi devices, in: 2020 IEEE 29th International Conference on Enabling Technologies: Infrastructure for Collaborative Enterprises (WETICE), 2020, pp. 231–234.
- [30] F. Holik, M.M. Cook, X. Li, A.A. Shah, D. Pezaros, Programmable data planes for increased digital resilience in ot networks, *IEEE Communications Magazine* (2025).
- [31] Y. Kabir, Y.M. Mohsin, M.M. Khan, Automated power factor correction and energy monitoring system, in: 2017 Second International Conference on Electrical, Computer and Communication Technologies (ICECCT), 2017, pp. 1–5.
- [32] C. Srun, S. Siren, V. Ny, S. Ive, S. Mao, S. Phal, Efficient energy usage monitoring system with esp32 technology, in: 2024 7th International Conference on Green Technology and Sustainable Development (GTSD), 2024, pp. 56–61.
- [33] N. Kshirsagar, S. Shinde, A. Rajeevan, S. Srivastava, R. Harikrishnan, P. Shahane, S. Dudam, Stm32-based home automation and energy monitoring system with tft display, *Lecture Notes in Networks and Systems* 948 (2024) 45–57.
- [34] K.-H. Chang, Bluetooth: a viable solution for IoT?[industry perspectives], *IEEE Wireless Communications* 21 (6) (2014) 6–7.
- [35] M. Collotta, G. Pau, T. Talty, O.K. Tonguz, Bluetooth 5: a concrete step forward toward the IoT, *IEEE Communications Magazine* 56 (7) (2018) 125–131.

- [36] S. Tozlu, M. Senel, W. Mao, A. Keshavarzian, Wi-Fi enabled sensors for Internet of Things: a practical approach, *IEEE Communications Magazine* 50 (6) (2012) 134–143.
- [37] W. Jiang, B. Han, M.A. Habibi, H.D. Schotten, The road towards 6 g: a comprehensive survey, *IEEE Open Journal of the Communications Society* 2 (2021) 334–366.
- [38] C.-X. Wang, J. Huang, H. Wang, X. Gao, X. You, Y. Hao, 6 g wireless channel measurements and models: trends and challenges, *IEEE Vehicular Technology Magazine* 15 (4) (2020) 22–32.
- [39] S. Benhamaid, A. Bouabdallah, H. Lakhlef, Recent advances in energy management for Green-IoT: an up-to-date and comprehensive survey, *Journal of Network and Computer Applications* 198 (2022) 103257.
- [40] M.A. Jamshed, F. Heliot, T.W. Brown, A survey on electromagnetic risk assessment and evaluation mechanism for future wireless communication systems, *IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology* 4 (1) (2019) 24–36.
- [41] A. Nozariasbmarz, H. Collins, K. Dsouza, M.H. Polash, M. Hosseini, M. Hyland, J. Liu, A. Malhotra, F.M. Ortiz, F. Mohaddes, et al., Review of wearable thermoelectric energy harvesting: from body temperature to electronic systems, *Applied Energy* 258 (2020) 114069.
- [42] R. Meng, A.A. Shah, M.A. Jamshed, D. Pezaros, Federated learning-based intrusion detection framework for Internet of things and edge computing backed critical infrastructure, in: 2024 IEEE International Conference on Communications Workshops (ICC Workshops), IEEE, 2024, pp. 810–815.
- [43] I. Leyva-Pupo, C. Cervelló-Pastor, C. Anagnostopoulos, D.P. Pezaros, Dynamic scheduling and optimal reconfiguration of upf placement in 5G networks, in: Proceedings of the 23rd International ACM Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems, MSWiM '20, Association for Computing Machinery, New York, NY, USA, 2020, pp. 103–111.
- [44] Z. Xu, W. Liu, J. Huang, C. Yang, J. Lu, H. Tan, Artificial intelligence for securing IoT services in edge computing: a survey, *Security and Communication Networks* 2020 (1) (2020) 8872586.
- [45] J. Azar, A. Makhoul, M. Barhamgi, R. Couturier, An energy efficient IoT data compression approach for edge machine learning, *Future Generations Computer Systems* 96 (2019) 168–175.
- [46] F.P. Tso, G. Hamilton, R. Weber, C.S. Perkins, D.P. Pezaros, Longer is better: exploiting path diversity in data center networks, in: 2013 IEEE 33rd International Conference on Distributed Computing Systems, 2013, pp. 430–439.
- [47] L. Cui, R. Cziva, F.P. Tso, D. Pezaros, Synergistic policy and virtual machine consolidation in cloud data centers, 2016.
- [48] L. Guegan, A.-C. Orgerie, Estimating the end-to-end energy consumption of low-bandwidth IoT applications for Wi-Fi devices, in: 2019 IEEE International Conference on Cloud Computing Technology and Science (CloudCom), IEEE, 2019, pp. 287–294.
- [49] A. Ullah, A.A. Shah, J.S. Khan, M. Sajjad, W. Boulila, A. Akgul, J. Masood, F.A. Ghaleb, S.A. Shah, J. Ahmad, An efficient lightweight image encryption scheme using multi-chaos, *Security and Communication Networks* 2022 (1) (2022) 5680357.
- [50] F. Nocera, S. Demilito, P. Ladisa, M. Mongiello, A.A. Shah, J. Ahmad, E. Di Sciascio, A user behavior analytics (uba)-based solution using lstm neural network to mitigate ddos attack in fog and cloud environment, in: 2022 2nd International Conference of Smart Systems and Emerging Technologies (SMARTTECH), IEEE, 2022, pp. 74–79.

- [51] F. Nocera, S. Abascià, M. Fiore, A.A. Shah, M. Mongiello, E. Di Sciascio, G. Acciani, Cyber-attack mitigation in cloud-fog environment using an ensemble machine learning model, in: 2022 7th International Conference on Smart and Sustainable Technologies (SpliTech), IEEE, 2022, pp. 1–6.
- [52] E. Ahvar, A.-C. Orgerie, A. Lebre, Estimating energy consumption of cloud, fog, and edge computing infrastructures, *IEEE Transactions on Sustainable Computing* 7 (2) (2019) 277–288.
- [53] G. Plastiras, M. Terzi, C. Kyrkou, T. Theocharides, Edge intelligence: challenges and opportunities of near-sensor machine learning applications, in: 2018 IEEE 29th International Conference on Application-Specific Systems, Architectures and Processors (ASAP), IEEE, 2018, pp. 1–7.
- [54] J. Chen, X. Ran, Deep learning with edge computing: a review, *Proceedings of the IEEE* 107 (8) (2019) 1655–1674.
- [55] S. Yao, Y. Zhao, A. Zhang, L. Su, T. Abdelzaher, Deepiot: compressing deep neural network structures for sensing systems with a compressor-critic framework, in: Proceedings of the 15th ACM Conference on Embedded Network Sensor Systems, 2017, pp. 1–14.

Role of non-terrestrial networks in achieving sustainability in IoT devices

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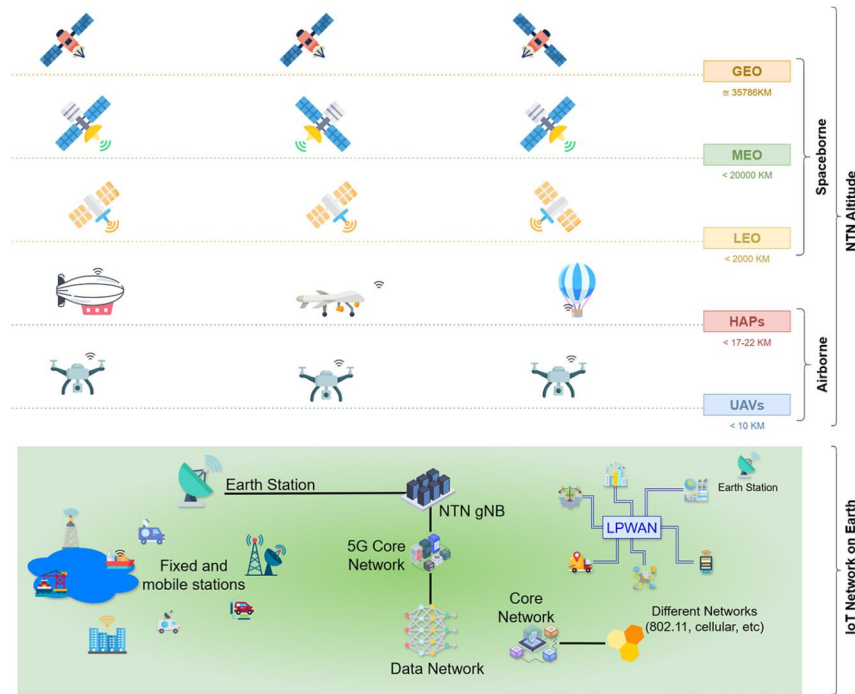
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4.1 Introduction to NTN

NTNs are an incomparable advancement in communication technologies. They extend complex connections beyond terrestrial borders with a constellation of specialized airborne and space-borne platforms. The space-borne platforms consist of satellites and are divided into three primary types: Geostationary Earth Orbit (GEO) satellites, Medium Earth Orbit (MEO) satellites, and Low Earth Orbit (LEO) satellites. GEO satellites are about 35,786 km from Earth and always occupy the same position above the equator. The best utility of this type of satellite is for continuous, wide-area coverage. GEO satellites are widely used in television broadcasting and meteorological monitoring applications. MEO satellites travel at distances from 2,000 km to 35,786 km above the equator. Mostly, MEO satellites are used in global positioning and navigation systems. MEO satellites offer a great compromise between the area over which coverage is provided and the delay in signal strength. LEO satellites operate above Earth in the range between 180 km and up to 2,000 km, providing much lower latency and increased bandwidth that are essential for real-time, data-intensive IoT communication [1–3].

Besides satellites, NTNs consist of airborne platforms consisting of High-Altitude Platforms (HAPs) and Unmanned Aerial Vehicles (UAVs), which are an essential part of NTNs [4,5]. HAPs encompass objects such as balloons or airships within the stratosphere, which can provide localized communications coverage that is close to that of a satellite. In addition, HAPs offer more operational flexibility and reduce the necessary operational costs. These platforms are particularly used to provide temporary solutions for connectivity during live events, emergency response situations, or other transient conditions that demand extra coverage with lower latency [4]. UAVs or drones augment the high flexibility of NTNs with their quick deployability to ensure

**FIGURE 4.1**

NTN layers supporting IoT connectivity.

disaster areas receive immediate ad-hoc network support. UAVs are also deployed to provide support in wide areas hosting important events, ensuring network availability in critical situations [5]. Fig. 4.1 shows the hierarchical arrangement of NTN components comprising GEO, MEO, LEO satellites, HAP, and UAV interconnected with terrestrial and core networks to enable seamless data exchange and Low-Power Wide-Area Network (LPWAN) for sustainable IoT applications.

The integration of NTN is critical in geographical or underdeveloped regions, where laying physical cables in the ground or installing cell towers and terrestrial infrastructure is not possible or economically viable [6]. NTNs in these regions catalyze the expansion of robust communication services, driving the world closer to seamless global connectivity. The integration of NTNs becomes especially important with respect to IoT, where seamless connectivity in a wide range of locations is essential for continuous data collection and delivery between devices [7]. IoT applications that support environmental monitoring in remote wilderness or real-time data management with offshore oil platforms are highly dependent on the wide coverage and support of NTNs. NTNs are also highly beneficial in enhancing network resiliency, as they provide alternative data routes, useful when the terrestrial network fails, particularly during calamities. In case of such natural disasters, readily available NTNs

provide continued communication, aiding the key emergency services and coordination [8].

The strategic deployment of NTNs immensely relieves the congestion that exists on terrestrial networks by managing the excess overflow of information traffic. The network overburden is imperative given the exponential growth in the number of IoT devices, which tends to exert a strain on the existing network infrastructure. Through the use of NTNs, diversification of the data path occurs, hence enhancing the overall network performance. NTNs not only guarantee increased service quality, but also ensure that the network attains sustainability through optimized performance of the energy resources as well as minimized usage of extensive physical infrastructural expansions that cater to the modern-day challenges of network demand, connectivity reliability, and inclusivity on a geographically wide scale. As we move forward, the combination of terrestrial and NTNs would, without a doubt, be one of the pillars around which the revolution in the global communication landscape unravels, especially in the vast and variably connected space of the IoT [7] [9].

4.2 NTNs and IoT connectivity

The integration of NTNs with existing terrestrial and IoT infrastructure is a step forward in achieving full global connectivity. This is important to create a connectivity mesh around the world that welcomes both traditional ground-based networks and advanced aerial and satellite systems [10]. To ensure the seamless operation of global IoT systems, it is important to have such a connected mesh, especially in providing reliable service delivery in areas with a sparse or non-existent terrestrial network. By providing stable internet connectivity, the NTNs enable these areas to be connected to the internet, allowing these populations to participate more positively in the global digital economy. This is not only for accessing information, but also for varied services including advanced health, education, and disaster management, in which the data exchange is of great importance [1] [11].

The integration of NTNs extends the capability of IoT to support massive deployments across a range of sectors. This promise of IoT technology for the transformation of industrial operations, agriculture, and urban management relies heavily on handling a big network of devices that work smoothly and efficiently. Here, NTNs are providing a major solution for increased bandwidth and wider coverage [10]. An example is in large agricultural lands, where traditional terrestrial connectivity can hardly cover all the areas, leading to the formation of blind spots. NTNs remove these gaps by offering farmers detailed real-time data from sensors. These sensors are spread across large fields and enable farmers to achieve an optimized irrigation system, including pest management, and crop health monitoring [12]. Similarly, in urban scenarios, where the density of devices and data demand is massive, NTNs take the load off the terrestrial networks by spreading the data traffic across the available spectrum [13]. This will not only make the operation of the IoT applications run smoother, but also enable the urban network service providers to achieve optimized infrastructure, and obtain higher spectrum efficiency and greater reliability [14].

Table 4.1 Comparison of NTN and terrestrial networks for IoT connectivity.

Parameter	Terrestrial Networks	NTNs
Coverage Area	Limited to urban and suburban areas	Global, including remote and underserved areas
Bandwidth	High	Varies, typically lower than terrestrial
Latency	Low	Higher due to signal travel distance
Deployment Cost	High initial cost, lower maintenance	Lower initial cost, higher operational cost
Scalability	Limited by infrastructure	Highly scalable across vast regions
Reliability	High in covered areas	Consistent, even in challenging environments
Data Handling Capacity	High	Can handle large volumes from numerous devices

The NTNs support massive data from a large number of devices, a game changer for IoT deployments. It not only has the potential to support the current scale of IoT implementations, but also has to support future network expansions. The expandability that NTNs have in place ensures the network's growth with technological advances in the IoT and the expected resultant growth in data traffic, while maintaining service performance at full speed and quality [15]. In addition, NTNs improved connectivity, paving the way for the use of more sophisticated IoT applications. One such example is in industrial IoT applications, which require precision and efficiency, where the use of NTNs ensures that complex automated processes and machinery operate continuously [16]. NTNs significantly improve productivity and safety and reduce downtime due to connection issues, allowing real-time monitoring and maintenance. The merger of NTN with industrial IoT networks represents simply an incremental value addition to the existing system and is a step toward a global IoT infrastructure that is more accessible, more connected, and finally more capable [17]. Table 4.1 provides a comparison of NTNs and terrestrial networks for IoT Connectivity, highlighting differences in coverage, bandwidth, latency, deployment costs, scalability, reliability, and data handling, showcasing NTNs' strengths in global and remote IoT applications.

4.3 NTNs sustainability challenges and opportunities

The deployment and maintenance of NTNs inherently involve significant environmental and sustainability challenges, largely due to the energy-intensive nature of their lifecycle. The process begins with the manufacturing of components, such as satellites, UAVs, and HAPs, which require substantial amounts of various raw materials, including metals and composite materials that are often procured through environmentally taxing mining practices. Many of these materials, such as lithium for

Table 4.2 Life cycle of NTNs, environmental impacts, and sustainable solutions.

Life Cycle Stage	Environmental Impact	Sustainable Solutions
Manufacturing	Raw material extraction (e.g., lithium, rare earth elements)	Use of recycled materials, eco-friendly mining practices, material substitution
Launch	High carbon emissions from rocket propellants	Development of reusable rockets, green propellants, more efficient launch schedules
Operation	Energy consumption (satellites in orbit, ground stations)	Increased use of solar power, energy-efficient ground station designs
End-of-Life Management	Space debris, decommissioned satellites	Recycling/re-purposing satellites, safe de-orbit technologies, space debris mitigation
Broad Impact	Disruption from terrestrial infrastructure (e.g., deforestation)	Reducing terrestrial reliance through NTN connectivity
Resource Management	Efficient water and fertilizer use, renewable energy management	IoT applications for agriculture, real-time data collection for remote installations

batteries and rare earth elements crucial for electronic components, often have complex extraction processes associated with high environmental costs, such as habitat destruction, water pollution, and high carbon emissions [1]. Next, the launch phase of the satellites introduces another layer of environmental impact. The rocket launching process used to place satellites into orbit is the most carbon-intensive aspect of NTN operations. These launches utilize rocket propellants that release significant amounts of carbon dioxide and other pollutants into the atmosphere, contributing to both localized air pollution and global greenhouse gas emissions [18]. There is another environmental impact due to the satellite constellation that needs to be maintained by launching new satellites, especially as more and more satellites reach their end of life and require replacement [19]. Once operational, NTNs continue to consume energy, predominantly to power the satellites in orbit and the ground stations that control them. Although solar power provides much of the in-orbit energy needs, ground operations often rely on conventional energy sources that may not be sustainable. Furthermore, the end-of-life management of these technologies poses a critical sustainability challenge, as decommissioned satellites can contribute to the growing problem of space debris. Space debris not only poses a threat to other satellites and space missions, but also represents a long-term environmental concern in near-Earth space [20,21]. Table 4.2 illustrates the environmental impact throughout the NTN lifecycle and the solutions that support this with an effective green approach that supports sustainability across every stage in their life cycle, from manufacturing through to end-of-life management, to enable positive contributions towards overall global sustainability.

4.3.1 Opportunities for sustainable solutions

Despite these challenges, NTN holds substantial potential for fostering sustainable IoT systems and reducing the environmental footprint of global connectivity infrastructure. One of the most pronounced benefits is their ability to minimize reliance on terrestrial infrastructure, which is often more invasive and resource-intensive to build and maintain. Terrestrial network components such as cell towers and ground cables necessitate extensive physical disruption, including deforestation and landscape alteration, to establish network coverage, especially in rural or environmentally sensitive areas. By providing connectivity from the sky, NTNs can drastically reduce these intrusions, thereby preserving natural habitats and decreasing the carbon footprint associated with constructing and maintaining terrestrial networks [14]. The expanded coverage offered by NTNs enables more effective management and utilization of natural resources, especially for IoT applications powered by NTNs in agriculture can optimize the use of water and fertilizers, reducing waste and environmental impact. Similarly, NTNs can support efficient renewable energy management by facilitating real-time data collection and control of remote installations, like wind farms, located in offshore or hard-to-reach areas. The remote connectivity achieved through NTNs ensures energy is harnessed and distributed more efficiently, aligning with goals for reducing greenhouse gas emissions [22].

There is also a growing trend towards incorporating sustainability into the design and operation of NTNs themselves. Innovations in technology are gradually reducing the size and weight of satellite components, which lowers the materials required and also decreases the fuel requirement needed for launches and daily operations. The advancements in propulsion and materials science are improving the lifespan of satellites and ultimately reducing the frequency of launches. There is a need to recycle older satellites and use them for different applications. The safe de-orbiting of satellites, when they reach their end of life, is also a promising avenue to explore for the reduction of space debris, and it also minimizes the environmental footprint of NTNs [23,24]. The integration of sustainable practices in NTNs reduces their ecological impact, and encourages eco-friendly IoT adoption. Since NTNs reduce dependence on terrestrial infrastructure and address sustainability challenges, they support global environmental goals and will, therefore, form a vital role in the road to greener, long-term strategies for a hyperconnected world [25].

4.4 Energy efficiency in NTNs

Energy efficiency is critical for all communication systems, especially for NTNs where the lifespan of the equipment is highly energy-constrained. The NTNs' energy dependency is driven by innovations in different technological domains. Solar energy is the most important domain for the NTNs as it drives the space-born and usually drives the air-born equipment. All the satellites and most of the HAPs and UAVs are equipped with state-of-the-art solar panels that convert sunlight directly into electrical energy to meet the power requirements of these systems [14]. Recent advancements in photovoltaic cell technology have led to increased efficiency and reduced weight, resulting in ultra-light materials. These innovations have significantly

improved the power-to-weight ratio, enhancing the operational longevity and overall efficiency of NTN platforms [26].

The advanced signal processing algorithms achieved better energy efficiency for both uplink and downlink data [27]. These innovative error detection and correction solutions provide better signal integrity with minimum power consumption. Although the complexity of the system is often increased, the low power requirement makes them ideal for IoT and NTNs as both sides of the network are energy-constrained [28]. There are several modulation schemes available in the literature that demonstrate promising results in achieving energy efficiency, and if they can be implemented, they have the potential to improve the energy efficiency of NTN networks [14,29,30]. The adaptive communication protocols used in IoT and NTN dynamically adjust the energy used based on the quality of the communication link and data demands, and also conserve the energy on both the IoT and NTN side of the network [31]. The novel designs of UAVs also help them achieve better energy efficiency. Modern UAVs are usually designed with superior aerodynamics and equipped with lighter materials to reduce drag and energy consumption. The integration of AI results in intelligent navigation systems that allow for optimized travel paths, and reduce unnecessary maneuvers, thereby extending the battery life and operational duration [32]. In the following subsections, we will dive deep into the technologies enabling NTNs to achieve energy efficiency.

4.4.1 Advanced technologies for energy efficiency

Several emerging technologies, such as beamforming and massive Multiple-Input and Multiple-Output (MIMO) possess the potential to enhance the energy efficiency of NTNs. Beamforming is a technology that focuses the concentration of wireless signals toward a specific direction, resulting in a directional gain. Beamforming possesses the potential to improve the transmission and reception of signal energy, which not only improves signal quality but also reduces power wastage in other directions [33]. Beamforming, when combined with massive MIMO technology, further enhances the performance of the communication system. Massive MIMO is a technology where a large number of antennas are embedded in the base station. The base station serves the different devices simultaneously through spatial multiplexing, leveraging beamforming for focused signals, and also results in reduced interference for other nearby devices. The combination of massive-MIMO and beamforming enhances the energy efficiency of NTN and IoT networks by focusing the signal power on the intended users, minimizing energy wastage, and improving the coverage of the network in the remote areas [34,35].

4.4.2 Energy harvesting

The role of NTNs in enabling IoT devices to leverage energy harvesting technologies opens a new dimension of sustainability, especially in energy-constrained environments. Energy harvesting refers to the process by which energy is derived from external sources and converted to electricity to power IoT devices. These sources are easily available in the environment, and utilizing them reduces the dependency

on conventional power sources. Energy harvesting improves the autonomy of devices and improves the self-sustainability of the devices and the overall network as well [14,36]. Table 4.3 provides a concise comparison of the solar, kinetic, and thermal energy harvesting options for NTN-IoT devices, including typical application areas, advantages, and implementation challenges.

Table 4.3 Comparison of energy harvesting methods.

Energy Source	Application Area	Advantages	Challenges
Solar Energy	Agricultural fields, remote areas	Sustainable power source, easy to deploy	Weather-dependent, initial setup cost
Kinetic Energy	Urban settings, roads, bridges	Utilizes ambient energy, reduces external power need	Low energy yield, device complexity
Thermal Energy	Industrial environments	Uses temperature gradients, reliable in high-temp areas	Initial setup cost, efficiency varies by environment

Solar energy harvesting

In remote areas, where IoT devices are deployed, such as agricultural fields or wildlife monitoring areas, solar energy provides a sustainable power source that can keep devices running indefinitely, depending on weather conditions. The solar panels on these devices capture sunlight, which is then converted into electrical energy to power sensors and communication modules [37]. The dependence on solar reduces battery and fossil fuel-based energy consumption and overall reduces the carbon footprint of the overall network. The longer life of high-quality solar panels, which is around twenty years, is a huge contributing factor towards the sustainability of this solution.

Kinetic energy harvesting

Kinetic energy harvesting is the process of converting motion or mechanical vibration into electrical energy. Most kinetic energy harvesters depend on mechanical-to-electrical energy converters. Typically, this process consists of three stages. The first stage, energy capture, involves coupling externally provided motion or vibration to a mechanical structure, such as a spring or mass, to facilitate energy conversion. The second stage, energy conversion, transduces the captured mechanical energy into electrical energy using mechanisms such as electromagnetic induction, piezoelectricity, or electrostatic methods. The third and final stage, energy conditioning and storage, processes and stores the harvested energy in batteries or supercapacitors, ensuring a stable power supply for IoT devices. Several key components are involved in this process. The important ones among them are energy transducers. Energy transducers are classified as mechanical, magnetic, and electrostatic. Piezoelectric materials fall into the first category, converting mechanical stress into electricity using quartz or ceramic elements. Coming to electromagnetic generators utilize the motion of a magnet through a coil in order to induce an electric current, using Faraday's law. Finally, the electrostatic generators work on the principle of converting changes in capacitance

caused by mechanical motion to generate power. The second constituent in this interaction is the source of vibration, such as ambient vibrations from machinery or wind, even from user activity in wearable devices, and it provides mechanical energy to actuate the system. Mechanical structures, such as cantilever beams, resonators, or springs, amplify the mechanical vibration to improve the capture efficiency of vibrational energy. Power management circuits will finally regulate the output voltage and current to match IoT devices for energy storage in batteries or supercapacitors. Kinetic energy harvesting is suitable for IoT in NTN scenarios, like satellites, UAVs, and remote sensors, where ambient motion is rich, such as wind, vibration, or body movement. It provides a renewable and sustainable power source to reduce the frequency of battery replacement and enhance the reliability of IoT networks [38].

Thermal energy harvesting

Thermal energy conversion is also an emerging trend in which temperature differences are used to generate electricity. Thermal energy harvesting works by converting heat into electrical energy using thermoelectric materials and leveraging the temperature difference between two surfaces or regions. The process is primarily based on the Seebeck effect, a phenomenon where a voltage is generated across two dissimilar conductors or semiconductors that experience a temperature gradient.

The thermal energy harvesting process is divided into several steps. First, the heat absorption, where a heat source, such as solar radiation, electronic devices, or natural geothermal heat, generates thermal energy. Heat collectors capture this energy and transfer it to the thermoelectric generator (TEG). Second, the creation of a temperature gradient. The TEG has two sides, one exposed to the heat source (hot side) and the other connected to a heat sink (cold side). A temperature difference is established between the two sides, which is crucial for generating electricity. Third, the electron movement via thermoelectric materials. Inside the TEG, thermoelectric materials such as bismuth telluride or silicon-germanium alloys facilitate the conversion of the temperature difference into an electric current. The hot side excites electrons, causing them to move towards the cooler side, creating a flow of charge. Fourth is the energy output stage. The resulting voltage from the temperature difference generates Direct Current (DC) electricity. The amount of electricity is proportional to the material's thermoelectric efficiency and the magnitude of the temperature gradient. The fifth step is power regulation, where the harvested electricity is typically low in voltage and requires regulation to be usable by IoT devices. A power management circuit, including voltage regulators and converters, ensures the output is stable and matches the device's energy requirements. The last step is energy storage, which is to provide continuous power, especially when the temperature gradient fluctuates. The harvested energy is stored in batteries or supercapacitors. This ensures IoT devices have a reliable energy supply even during periods of minimal heat availability.

Over the years, there have been several enhancements in thermal energy harvesting systems however there are several open research challenges that can further improve these systems, like the advanced thermoelectric materials with higher Seebeck coefficients and thermal conductivities improve conversion efficiency. The

integration of Phase Change Materials (PCMs) which store excess thermal energy during peak heat and release it during cooler periods, maintains a steady temperature gradient. The development of hybrid harvesting systems combines thermal energy harvesting with other energy sources, such as solar or kinetic energy, for higher reliability and efficiency in NTN-IoT networks.

This seamless energy harvesting process ensures that IoT devices in NTNs operate autonomously in remote or harsh environments, reducing dependency on traditional power sources and supporting sustainable energy practices [39].

4.4.3 Optimization through low-energy protocols

Beyond enhancing hardware efficiency and incorporating energy harvesting strategies, energy efficiency in NTNs is achieved through the implementation of low-energy protocols. These protocols are designed to minimize energy consumption during data transmission and reception. This is crucial for the longevity and sustainability of NTN communication platforms [40–43].

An example of such protocol optimization is the use of LPWAN technologies in NTNs. LPWAN technologies are specifically designed for long-range communication between IoT devices while consuming very little power. Integrating LPWAN technology with NTN infrastructures significantly prolongs the operational life of individual IoT devices deployed in remote areas, reduces maintenance frequency due to battery depletion, and ensures continuous data collection and monitoring, all while maintaining minimal energy usage [44]. There are several subcategories of Low-Energy Protocols, and we will explore them in detail in the following sections. Complementing these protocol-level strategies, Table 4.4 summarizes representative energy-efficient signal-processing techniques, outlining their purposes and the benefits they offer in NTN deployments.

Table 4.4 Energy efficiency techniques in signal processing.

Technique	Purpose	Benefits
Error Correction Codes	Maintain signal integrity	Reduces power use, improves reliability
Power-saving Modulation	Minimize power requirement for data transmission	Increases energy efficiency, reduces power waste
Adaptive Communication Protocols	Adjust energy use based on link quality	Optimizes energy consumption, conserves power

Dynamic Power Management (DPM)

These strategies are very important and are considered an integral portion of the NTN power management system. DPM involves the use of software and hardware techniques that dynamically adjust the power state of network components based on current network load and performance requirements. The DPM is used to switch certain parts of a satellite payload to a low-power state during periods of low communication activity, thus conserving energy without impacting the overall performance of the networks [45].

Efficient network routing

Enhanced routing protocols also contribute significantly to energy conservation in NTN. Efficient routing algorithms ensure that data packets sent from source to destination follow the most energy-efficient path, thus minimizing the power consumed during transmission across networks. The path-finding algorithms, such as Dijkstra's algorithm or Bellman-Ford algorithm, are among the most popular in obtaining the most suitable paths. Suitable route exploration, route selection, and dynamic route updates are the stages of these algorithms. These routes are calculated not only based on the shortest path but also take into account current network conditions and energy profiles of the nodes, optimizing energy use across the network architecture [46,47].

Energy-aware system design

Beyond protocols, the complete design philosophy for NTN has the potential to embed energy-aware strategies at various levels of abstraction, which range from hardware design to operational and management strategies; this includes the use of materials or components that allow saving energy, or system designs that make more efficient heat dispersal possible, and leveraging software techniques, which reduce computational burdens, thus slashing the energy input required by a processing unit mounted on an NTN platform [48,49].

Implementation of smart sleep schedules

Smart sleep protocols are also employed across IoT and NTN. These protocols are especially viable for satellite and UAV-operated networks. The smart sleep protocols intelligently determine inactive periods of the devices and put these devices into sleep mode or low-power modes. The sleep mode significantly reduces the power usage of devices and it is only used when full operation is unnecessary. Smart sleep schedules are dynamically adjusted based on real-time data usage patterns and predictions of network demand, optimizing energy utilization [14].

All these techniques, such as low-power protocols, dynamic power management, efficient network routing, energy-conscious system design, and smart sleep schedules, offer an avenue for NTN to further their sustainability. The sustainability results in improved power savings and the improvement of network component life. Such strategies align with the United Nations' sustainability vision, but also provide a guarantee for NTN to increase their reliability. The economic impact of sustainability is huge and results in further deployment and extension of services for IoT networks. By emphasizing low-energy software and network management techniques, a critical opportunity is opened to significantly enhance the environmental sustainability of next-generation network technologies, enabling a more resource-efficient future in the realm of global communications.

4.5 Case studies and real-world applications

The transformative impact of NTN in sustainable IoT applications can be best understood through specific case studies that illustrate their deployment and functionality in various sectors. Each case study showcases the practicability and benefits of NTN and contextualizes their role in enhancing IoT-driven sustainability.

4.5.1 Environmental monitoring

Rainforest Connection (RFCx)¹ is a San Francisco-based organization that develops a solution that utilizes innovative hardware, NTN, and cutting-edge software to enable effective wildlife and forest conservation. RFCx built hardware, at the core of their innovative solution, termed “*Guardians*”, which is fundamental in detection and data transmission. The Guardian is fabricated from recycled smartphones, making them very viable, cost-effective solutions that are sustainable. Smartphones have been converted to microphones, picking up sounds like chainsaws, gunshots, or even the call of animals in the forest. Guardians are also fitted out with extra hardware components: solar panels that allow the devices to continuously supply power from remote locations using renewable sources when traditional energy sources are not available. These solar panels are very efficient and, therefore, can allow these devices to operate 24/7 without maintenance, even in adverse weather conditions.

It combines NTN-based connectivity solutions, including satellites and HAPs, whichever solution is geographically feasible to facilitate communication in areas bereft of terrestrial network coverage. Guardians use terrestrial networks where available, but, in case of their absence, rely on satellite communication to transmit real-time audio data to the cloud. The NTNs form a critical link from these remote forest monitoring systems to the centralized data processing centers. This makes RFCx reliably transmit the data from locations considered so out of reach through satellites to have continuous monitoring in large-scale areas of the forests. By routine, a forest guard patrols through an area by vehicle or on foot. The work of these guard personnel was thus made smooth and effective since one need not patrol physically on the ground through the areas assigned.

Once the audio reaches the cloud, it is further analyzed on advanced ML and AI algorithms. The algorithms are engineered to identify shots, chainsaw sounds, or other animal distress calls associated with specific illegal logging, poaching, or other harms. The NTN supports this by allowing low-latency data transmission from Guardians to processing centers, so that possible threats can be identified quickly and a rapid response facilitated. It does this by distinguishing between all the natural sounds of the rainforest and those that are artificial, such as chainsaws, gunshots, or vehicles; thus, the alerts given are highly accurate.

The satellite-based communication system also contributes to RFCx being scalable and adaptable. Since NTNs mean an organization could deploy Guardians across diverse regions — from the dense Amazonian rainforests to isolated areas in Africa and Southeast Asia — without the use of any ground-based communications infrastructure, it enables RFCx to reach large swaths of forests while adjusting their systems according to varied environments. Incorporating IoT-enabled Guardians with any NTN creates an ecosystem with a powerful platform for making actionable insights using connectivity and data processing. RFCx works with local authorities, governments, and communities by giving them access to real-time alerts created

¹ <https://RFCx.org/>.

by the Guardians. This is further facilitated through the use of cloud computing services linked to NTN systems. NTNs fill in the gap in connectivity for conservationists to take quick action and contain deforestation, poaching, and other dangers to biodiversity. This seamless integration of hardware, NTNs, and AI-driven analytics underlines the technological sophistication and environmental impact of the RFCx method. Their work epitomizes how NTNs and IoT could shape the future in the name of global conservation, offering a replicable, sustainable model for the protection of natural ecosystems.

4.5.2 Precision agriculture

CropX² is a leading digital agronomy platform that integrates advanced hardware and software solutions to provide comprehensive farm management. Founded in 2013 in New Zealand, the company has expanded its expertise globally, offering tools that aggregate data from various sources to monitor field and crop health effectively. The CropX system comprises several key components like Soil Sensors, which are patented spiral-designed sensors that measure soil moisture, temperature, and electrical conductivity, providing real-time data essential for informed irrigation decisions. Telemetry devices facilitate the wireless data transmission from the sensors to the cloud-based platform, ensuring seamless integration and accessibility. The Actual Evapotranspiration (ETa) sensors of CropX measure and monitor the water use of crops daily in real-time, enabling precise irrigation planning. The rain gauges are precisely the tipping-spoon rain gauges that capture accurate precipitation data, contributing to effective water management strategies.

The combined data collected is synthesized into a specially designed, user-friendly application capable of managing multiple farms and fields from a single account. This holistic approach allows farmers to make data-driven decisions about irrigation, disease control, nutrition monitoring, and effluent management. While CropX primarily utilizes terrestrial IoT devices for data collection and transmission, the integration of NTNs, such as satellite communications, holds the potential for enhancing connectivity, especially in remote agricultural areas. NTNs can provide reliable data transmission where traditional cellular networks are unavailable, ensuring continuous monitoring and management capabilities. The CropX solution is promoting sustainable agricultural practices. By incorporating advanced technology, the company has achieved a 36% reduction in greenhouse gas emissions and a 47% decrease in water usage compared to traditional irrigation methods. These efforts contribute to environmental conservation and support the long-term viability of farming operations. CropX's innovative agronomy platform exemplifies how the integration of IoT technologies can drive sustainable and efficient farming practices. The potential incorporation of NTNs further enhances these capabilities, offering robust solutions for modern agriculture.

² <https://cropx.com/>.

4.5.3 Disaster management

The American Red Cross³ requires no introduction. It has enormously upgraded its response to disasters by introducing advanced technologies that allow it to intervene at the quickest possible time in disaster situations. This technological advancement has been headlined by the Disaster Services Technology (DST) team that installs and operates communication networks in disaster areas. The DST team deploys various equipment, including radios, computer networks, cell phones, tablets, and laptops, and manages to keep connectivity for the Red Cross operations. This integrated arrangement thus provides great coordination among the response teams and timely dissemination of information to people in need. The Red Cross uses Geographic Information Systems (GIS), and UAVs, where the GIS allows analysis and visualization of data on disaster impact, resource allocation, and logistical planning for better decision-making during relief operations. These UAVs provide immediate aerial views of affected areas, thus enabling responders to gauge the extent of damages, locate areas inaccessible, and effectively marshal assistance efforts.

Central to the Red Cross's technological framework is the disaster management system — previously RC View, which was recently replaced by Arc GIS Online⁴ developed by Esri — an innovative IT support system that integrates real-time data into a unified platform, offering a comprehensive view of disaster situations. This system enables the Red Cross and its partners to share visual situational awareness, manage disaster operations more effectively, and coordinate responses with greater precision. The organization is also exploring the use of AI to further streamline disaster response. By automating tasks and analyzing data swiftly, AI has the potential to reduce the need for extensive on-ground personnel, accelerate response times, and allow teams to focus on mission-critical activities.

Satellites feature in several different initiatives within the disaster response and preparedness activities of the American Red Cross. Current weather and forecast monitors, including observations, watches, warnings, and radar graphics from satellite imagery, are available through the organization's Map, Weather, and Hazard Catalogs. The Red Cross uses satellite images in its effort to map the most vulnerable communities using a project called Missing Maps⁵ for risk reduction planning and assistance. The Red Cross Volunteers examine massive satellite imagery to locate rural hamlets and villages, then ensure humanitarian organizations reach those in need; Humanitarian Organizations at the Red Cross encourage each one to join disaster preparedness through the Humanitarian OpenStreetMap Team (HOT)⁶ to utilize satellite imagery for developing newer, more complete and accurate geographic data. These initiatives show the commitment of the Red Cross to taking up space technology in effective disaster management and humanitarian assistance.

³ <https://redcross.org/>.

⁴ <https://www.esri.com/en-us/arcgis/products/arcgis-online/overview>.

⁵ <https://www.missingmaps.org/>.

⁶ <https://www.hotosm.org/>.

Through the integration of these advanced technologies and volunteer efforts, the American Red Cross has developed a robust system capable of delivering rapid and effective disaster response. The integration of NTN and IoT technologies empowers organizations like the Red Cross to enhance disaster management through real-time connectivity, rapid response, and improved resource allocation, even in the most remote and underserved regions.

4.6 Technological innovations and future directions

In this section, we delve into the dynamic interfacing between NTNs and the IoT, investigating recent technological innovations and studies developed to improve NTN and IoT networks. We also discuss promising future research directions aimed at further integrating and improving NTN into eco-friendly IoT solutions.

4.6.1 Review of current technologies

Recent technological developments have been gradually improving the integration of NTNs with IoT devices. These improvements are focused on energy optimization and increased robustness in communications between terrestrial IoT networks and their non-terrestrial counterparts. We will discuss a few of these solutions in the following section.

Innovative antenna designs

Antennas in wireless communication play a vital role in both IoT and NTN systems for data transmission and reception using electromagnetic waves. Compact and energy-efficient antennas are used in IoT to support low-power devices, while NTNs require high-gain, directional antennas that maintain reliable communication over long distances or in remote areas [50]. Recent developments in antenna technology represent a significant step forward. Antennas with improved energy efficiency not only reduce the power requirements for maintaining communications but also help enhance signal quality with superior directionality [51]. phased-array antennas, known for their ability to electronically steer the direction of their beam without moving parts, ensure focused communication that dramatically cuts down the energy lost in signal spread [52]. This technology is ideal for dynamic environments, like those encountered in satellite or UAV-based communications, where traditional directional antennas would require constant mechanical adjustments [53].

Advancements in low-power communication protocols

The low-power communication protocol has been a driver of much development in IoT and NTN energy efficiency by enabling device communication with minimum energy consumption. Long-range protocols such as LoRa [54] and Sigfox [55] enable IoT devices to send limited amounts of data over long distances and, hence, are particularly appropriate for NTN applications such as satellite-enabled remote monitoring. LoRaWAN [56] has enabled the realization of bidirectional wireless

communication with very low energy consumption, which allows sensors in agricultural fields to communicate information toward NTN-connected gateways. Another example is Bluetooth Low Energy (BLE) [57], which enables short-range IoT applications, such as wearable health devices, to reduce power usage while maintaining reliable connectivity. Another important development in this regard is Narrowband IoT (NB-IoT) [58], which enables huge IoT deployment at low power consumption, allowing devices like smart meters and environmental sensors to function efficiently for several years on a single replacement of batteries. These protocols are particularly advantageous in supporting IoT applications in remote or difficult-to-access areas, because they enable reliable connectivity and long battery life by transmitting small amounts of data over long distances without demanding much power and ensuring sustainability [59].

4.6.2 Future research directions

As we look to the future, several research initiatives are poised to further cement the role of NTNs in sustainable IoT applications. These efforts focus on enhancing network intelligence, reducing environmental impacts, and extending the capabilities and application scopes of NTN systems.

Integration of AI

Future research is increasingly focusing on harnessing AI to enhance the efficiency and functionality of NTNs in IoT applications. AI could lead to smarter data processing algorithms that predict network loads and adjust energy use accordingly. Moreover, AI can enhance decision-making processes within IoT devices, allowing for autonomous operations based on real-time data, which would be particularly useful in dynamic or unpredictable environments [60].

Exploration of advanced materials and technologies

The ongoing fascination with reducing the cost and improving the lifespan of NTNs has led to research into next-generation materials and battery technologies. Innovations such as graphene-based materials for lighter and stronger satellite structures, or cutting-edge energy storage solutions like solid-state batteries, are expected to redefine the operational parameters of NTNs. These advancements could lead to smaller, lighter, and more efficient satellites, UAVs, and IoTs that are cheaper to launch and operate and have a longer service life [61].

Satellite mega-constellations

The concept of deploying large numbers of smaller satellites in carefully planned constellations offers the potential for global coverage and resilient connectivity for IoT devices anywhere on the planet. Research into managing these mega-constellations effectively—and sustainably—concerns both the optimal design for coverage and the development of sustainable practices for dealing with satellite end-of-life scenarios, such as through automated deorbiting systems to prevent space debris [62].

Emerging applications in deep-sea and remote monitoring

The potential for NTN extends into novel applications such as deep-sea IoT connectivity and real-time environmental monitoring in geographically isolated regions. Developing communication technologies that can withstand harsh underwater environments or provide consistent performance in polar regions represents a leading edge of current research efforts [14].

As NTNs continue to evolve, their role in enabling a connected, sustainable world appears increasingly crucial. The ongoing advancements in antenna technology, communication protocols, and the integration of AI, along with the explorations into new materials and satellite constellation management, underscore a future where NTNs are pivotal in deploying extensive, eco-friendly IoT solutions globally. This progressive trajectory highlights the importance of continued innovation and research in overcoming the existing challenges and unlocking the full potential of NTNs and IoT networks.

4.7 Policy and regulatory considerations

We now delve into the complicated landscape of policy and regulatory considerations that surround the deployment and operation of NTNs. These networks are indeed facing a host of regulatory hurdles that need to be negotiated with care in order to make sure the solutions are effective and compliant. This section debates specific policy recommendations that could facilitate the sustainable development of NTNs.

4.7.1 Regulatory challenges

The implementation of NTNs introduces several regulatory challenges, such as spectrum management, space traffic management, and cross-border coordination. We will discuss each one in the following section.

Spectrum management

One of the most critical regulatory challenges for the NTNs has to do with the efficient management of the radio frequency spectrum, which is extremely limited and hotly contested. Ensuring that NTNs operate seamlessly, causing no interference to the terrestrial networks nor any other types of non-terrestrial communications, is highly important [63]. Regulatory bodies like the International Telecommunication Union spearhead this cause by overseeing how the spectrum will be allocated, among other factors, and building global standards into place. These are measures put in place to avoid conflicts, ensure coexistence, and make the spectrum resource available to all stakeholders equitably [64].

Space traffic management

It is important to cope with the growing need for effective space traffic management while satellites continue to multiply, especially under large-scale constellations

already under deployment by different organizations like SpaceX,⁷ OneWeb,⁸ and many others. This creates great necessities regarding setting and observing robust regulatory frameworks that would sort out a few of the critical aspects involving satellite operations. Key issues also include satellite deorbiting protocols that make sure non-functional or end-of-life satellites are taken out of orbit safely and sustainably to reduce collision risks and further the creation of debris. Besides, collision avoidance can be ensured only if safe orbital operations are maintained, which again requires highly developed tracking systems, reliable communication between satellite operators, and adherence to predefined maneuvering standards.

All these go hand in hand with regulatory frameworks provided by relevant bodies such as the International Telecommunication Union and other national space agencies involved in their development and enforcement to encourage the sustainable use of space. It is critical to their enforcement, not only in terms of mitigating most of the immediate risks that come with space debris, but also to safeguard the usability of this environment as a common heritage. It follows that without an adequate management regime, there will probably be cascading collision events in effect, something often termed Kessler syndrome, where such orbits could well become unavailable to later missions. Rigorous management of space traffic will go hand in glove with sustainable space operation, especially with continuing growth into the satellite-based application, including NTN and IoT solutions-appropriately looking after the environment for space into the future [65].

Cross-border coordination

The NTNs operate within many different national jurisdictions; any meaningful cross-border coordination must handle these regulatory and operational challenges robustly. Some of the central issues include data sovereignty: many nations require data collected within their borders to be stored, processed, and managed subject to that nation's laws and regulations. It will be particularly hard on NTNs since often they deal with data transferring between satellites, ground stations, and users in different countries. The environmental regulations also have many differences depending on the nation; hence, going into making NTNs compliant with several different standards over sustainability, emissions, and environmental impacts.

Comprehensive international agreements on the operations of NTN make for smooth operations. Organizations such as the International Telecommunication Union (ITU) and regional regulation bodies are very important in making these regulations agree on a set of global standards. These will help in conflict resolution, smoothing out data management policies, and enforcing interoperability across borders as NTNs remain operationally effective and sustainable in their manner [66].

⁷ <https://www.spacex.com/>.

⁸ <https://oneweb.net/>.

4.7.2 Policy recommendations

This section elaborates on some policy recommendations that can effectively address regulatory challenges to NTN while contributing to their sustainable development. The following recommendations seek to achieve a proper balance between technological development and environmental concerns through innovation and global coordination.

Incentives for green technology

The policy frameworks by governments have to be worked out that would incentivize firms to adopt or develop green technologies within NTNs; these incentives, in the form of tax breaks, grants for research and development, and subsidies, act to encourage them to integrate their NTN infrastructure using energy-efficient technologies. It is expected that incentives or special regulatory treatment will be given to the companies deploying satellites or building renewable energy-powered ground stations using solar, wind, or hybrid systems. Energy-efficient communication protocols, sustainable manufacturing, and advanced recycling for satellite components are also encouraged by the policies. If there is an increased innovation in renewable energy technologies and environmentally friendly design of equipment for NTN, the carbon footprint from NTN can be reduced. These will be instrumental in bringing in an environment that will make technological growth keep up with global sustainability objectives to help NTNs become greener and more efficient in communication [67].

Guidelines for Environmental Impact Assessments (EIAs)

The development of detailed, specific, and standardized guidelines for EIAs concerning NTNs will be very important for the sustainable development of NTNs. The EIAs should be made to cover all the possible environmental impacts of NTN activities, including atmospheric pollution from rocket launches, which would involve the emission of Greenhouse Gases (GHGs) and particulate matter, and impacts on local ecosystems from ground stations, including land use change, noise pollution, and interference with wildlife habitats. EIAs should contain lifecycle analyses of NTN infrastructure manufacturing, operation, and end-of-life phases, which will allow regulators and companies to find the most critical environmental risks. The implementation of mitigation strategies is allowed, for instance, by the adoption of greener propellants, renewable energy used in ground stations, or the design of deorbiting systems that reduce space debris. Incorporating EIAs as a mandatory regulatory requirement will align NTN deployments with global sustainability goals and foster responsible innovation in the satellite and IoT ecosystem [68,69].

Frameworks for international cooperation

Since the coverage and impact of NTNs are global, robust international frameworks will be vital for policy harmonization and effective cross-border collaboration. International frameworks should, therefore, aim at data sharing and joint monitoring of environmental and operational impacts of NTNs to make the stakeholders operating NTNs more transparent and responsible. Unified standards should be set to

manage fundamental issues such as radiofrequency spectrum allocation, space debris mitigation, and safe deorbiting of defunct satellites. The same would also apply to internationally collaborative research undertakings, combining resources and expertise in advanced development toward sustainable NTN technology. This could be achieved by jointly working on low-impacting propulsion, optimization of energy efficiency in NTN operations, and elaboration on a global protocol related to space debris. An effective regulatory approach that aligns worldwide should foster NTNs working well while being environmentally friendly, and it creates one path toward sustainability in satellite communication [70].

The regulatory landscape is complex, and the implementation of effective policy frameworks will be crucial to make NTN deployment successful and sustainable. The main regulatory challenges, such as spectrum allocation, space traffic management, and cross-border coordination, require comprehensive and forward-looking strategies. Simultaneously, incentivizing the adoption of green technologies, rigorous environmental impact assessments, and international collaboration in policy recommendations are critical for embedding sustainability into NTN operations. In that way, with early mitigations of such challenges, along with the integration of sustainable practices, NTNs could be designed to handle ever-increasing global demand for connectivity without having to make compromises in environmental responsibility and long-term viability.

4.8 Conclusion

This chapter has examined the role of NTNs in providing a sustainable and greener future for IoT technologies. NTNs are revolutionizing connectivity and playing a critical role in the expansion of IoT access into remote and underserved areas, while promoting environmentally conscious technological deployments. They become major enablers of transformation in IoT, offering connectivity solutions that enable very important applications: environmental monitoring, precision agriculture, disaster management, urban air quality assessment, and maritime surveillance. These use cases strengthen the real impact that NTNs may have on global goals for sustainable development by scaling up our capability to collect, analyze, and act on environmental data. The technological development in NTNs is highly committed to sustainability, ranging from the integration of NTNs with IoT technologies does not come without challenges. The regulatory complexities involve spectrum management, space traffic control, and cross-border coordination. High costs and technical difficulties in deploying and maintaining NTNs also stand in the way of widespread adoption. Such challenges require collaborative efforts in engineering, environmental science, information technology, law, and international relations. Only collaborative approaches can overcome these obstacles while ensuring ethical, sustainable, and effective NTN implementations. Such challenges require collaborative efforts in engineering, environmental science, information technology, law, and international relations. It is only

through collaborative approaches that these obstacles can be overcome while ensuring ethical, sustainable, and effective NTN implementations. NTNs hold immense promise for changing the paradigm of IoT connectivity and fostering global sustainability. However, their eventual success will depend upon sustained innovation, robust policy frameworks, and international cooperation in accordance with environmental imperatives. NTNs are indeed a technological milestone, but they also form a cornerstone in framing IoT strategies that are ecologically sensitive and globally impactful. The NTNs, supporting various IoT applications while integrating sustainability, have opened ways toward a much more connected, equitable, and efficient future. Further innovation, interdisciplinary collaboration, and policy alignment are all required in the context of realizing full NTN potential and assuring that IoT advances contribute toward a sustainable and prosperous future for generations to come.

References

- [1] M. Centenaro, C.E. Costa, F. Granelli, C. Sacchi, L. Vangelista, A survey on technologies, standards and open challenges in satellite IoT, *IEEE Communications Surveys and Tutorials* 23 (3) (2021) 1693–1720.
- [2] B. Al Homssi, A. Al-Hourani, K. Wang, P. Conder, S. Kandeepan, J. Choi, B. Allen, B. Moores, Next generation mega satellite networks for access equality: opportunities, challenges, and performance, *IEEE Communications Magazine* 60 (4) (2022) 18–24.
- [3] G. Geraci, D. López-Pérez, M. Benzaghta, S. Chatzinotas, Integrating terrestrial and non-terrestrial networks: 3d opportunities and challenges, *IEEE Communications Magazine* 61 (4) (2023) 42–48.
- [4] S. Euler, X. Lin, E. Tejedor, E. Obregon, High-altitude platform stations as international mobile telecommunications base stations: a primer on hibs, *IEEE Vehicular Technology Magazine* 17 (4) (2022) 92–100.
- [5] P. Elechi, K.E. Onu, Unmanned aerial vehicle cellular communication operating in non-terrestrial networks, in: *Unmanned Aerial Vehicle Cellular Communications*, Springer, 2022, pp. 225–251.
- [6] M. Giordani, M. Zorzi, Non-terrestrial networks in the 6g era: challenges and opportunities, *IEEE Network* 35 (2) (2021) 244–251.
- [7] M. Marchese, A. Moheddine, F. Patrone, IoT and UAV integration in 5g hybrid terrestrial-satellite networks, *Sensors* 19 (17) (2019) 3704.
- [8] F. De Trizio, G. Sciddurlo, I. Cianci, D. Striccoli, G. Piro, G. Boggia, Surviving disaster events via dynamic in-network processing assisted by network digital twins, in: *2023 International Conference on Information and Communication Technologies for Disaster Management (ICT-DM)*, 2023, pp. 1–6.
- [9] W. Abderrahim, O. Amin, M.-S. Alouini, B. Shihada, Latency-aware offloading in integrated satellite terrestrial networks, *IEEE Open Journal of the Communications Society* 1 (2020) 490–500.
- [10] A. Iqbal, A. Shakeel, A. Rashid, S.W. Kim, in: *IoT and M2M Applications in Satellite Networks*, Springer Nature Switzerland, Cham, 2025, pp. 17–45.
- [11] A. Rashid, T. Pecorella, Is 6lowpan-nd necessary? (spoiler alert: Yes), *Computer Networks* 250 (2024) 110535.

- [12] Q. Liu, Z. Feng, D. Chen, F. Tan, C. He, Empowering 6g non-terrestrial networks with intelligent reflection technologies for IoT applications, *IEEE Network* (2024).
- [13] A. Machumilane, A. Gotta, P. Cassarà, G. Amato, C. Gennaro, Learning-based traffic scheduling in non-stationary multipath 5g non-terrestrial networks, *Remote Sensing* 15 (7) (2023) 1842.
- [14] S. Plastras, D. Tsoumatidis, D.N. Skoutas, A. Rouskas, G. Kormontzas, C. Skianis, Non-terrestrial networks for energy-efficient connectivity of remote IoT devices in the 6g era: a survey, *Sensors* 24 (4) (2024) 1227.
- [15] O. Liberg, S.E. Löwenmark, S. Euler, B. Hofström, T. Khan, X. Lin, J. Sedin, Narrow-band Internet of Things for non-terrestrial networks, *IEEE Communications Standards Magazine* 4 (4) (2020) 49–55.
- [16] M.F. Khan, A. Iqbal, A. Shakeel, A. Rashid, D. Pesch, Enhancing industrial 4.0 connectivity: a d2d-based algorithm for blind spot mitigation in 5g future networks enabled smart industry, in: *2023 IEEE Globecom Workshops (GC Wkshps)*, 2023, pp. 2012–2017.
- [17] H. Cui, J. Zhang, Y. Geng, Z. Xiao, T. Sun, N. Zhang, J. Liu, Q. Wu, X. Cao, Space-air-ground integrated network (sagin) for 6g: requirements, architecture and challenges, *China Communications* 19 (2) (2022) 90–108.
- [18] W.E. Forum, Environmental impact of space debris and how to solve it, 2022. Last visited on November 29, 2024.
- [19] W.E. Forum, What's the climate impact of space exploration? 2021. Last visited on November 29, 2024.
- [20] Astroscale, Sweeping up space: the end-of-life solution, 2022. Last visited on November 29, 2024.
- [21] L. Chen, G. Msigwa, M. Yang, A.I. Osman, S. Fawzy, D.W. Rooney, P.-S. Yap, Strategies to achieve a carbon neutral society: a review, *Environmental Chemistry Letters* 20 (4) (2022) 2277–2310.
- [22] A. Tomar, A. Pattnaik, Smart energy management in renewable energy systems, *Smart Energy Management Systems and Renewable Energy Resources* (2021) 1.
- [23] J. Smith, J. Doe, Miniaturization of satellite technology advancements, *Journal of Space Technology* 10 (2) (2023) 123–135. Last visited on November 29, 2024.
- [24] NASA, Advanced propulsion technology and development, 2024. Last visited on November 29, 2024.
- [25] A.S.I. KN, A. Nallasivam, S. Madan, S. Kautish, Internet of things and sustainability: opportunities and challenges, *Digital Technologies to Implement the UN Sustainable Development Goals* (2024) 257–273.
- [26] M. News, Paper-thin solar cell can turn any surface into a power source, 2022. Last visited on November 29, 2024.
- [27] E. Björnson, J. Hoydis, L. Sanguinetti, et al., Massive mimo networks: spectral, energy, and hardware efficiency, *Foundations and Trends in Signal Processing* 11 (3–4) (2017) 154–655.
- [28] F. Gregorio, G. González, C. Schmidt, J. Cousseau, *Signal Processing Techniques for Power Efficient Wireless Communication Systems, Practical Approaches for RF Impairments Reduction*, Springer, 2020.
- [29] H.S. Hussein, M. Elsayed, M. Fakhry, U. Sayed Mohamed, Energy and spectrally efficient modulation scheme for IoT applications, *Sensors* 18 (12) (2018) 4382.
- [30] H. Gao, Y. Lu, S. Yang, J. Tan, L. Nie, X. Qu, Energy consumption analysis for continuous phase modulation in smart-grid Internet of Things of beyond 5g, *Sensors* 24 (2) (2024) 533.

- [31] D. Dhahliya, R. Soundararajan, P. Selvarasu, M.S. Balasubramaniam, A.S. Rajawat, S. Goyal, M.S. Raboaca, T.C. Mihaltan, C. Verma, G. Suci, Energy-efficient network protocols and resilient data transmission schemes for wireless sensor networks—an experimental survey, *Energies* 15 (23) (2022) 8883.
- [32] X. Pang, J. Tang, N. Zhao, X. Zhang, Y. Qian, Energy-efficient design for mmwave-enabled noma-uav networks, *Science China. Information Sciences* 64 (2021) 1–14.
- [33] M. Caus, A. Perez-Neira, E. Mendez, Smart beamforming for direct Leo satellite access of future IoT, *Sensors* 21 (14) (2021) 4877.
- [34] M. Girnyk, H. Jidhage, S. Faxér, Broad beamforming technology in 5g massive mimo, *Ericsson Technology Review* 2023 (10) (2023) 2–6.
- [35] F. Qi, W. Xie, Enhancing IoT services in 6g non-terrestrial networks with multicast massive mimo, *IEEE Network* (2024).
- [36] GSMA, IoT guide: Hybrid cellular/non-terrestrial network (ntn), 2024. Last visited on November 29.
- [37] P. Patel, A. Kishor, G. Mehta, Smart solar-powered smart agricultural monitoring system using Internet of Things devices, AI and IOT in Renewable Energy (2021) 101–109.
- [38] M. Thompson, Energy harvesting: Capturing ambient energy for everyday use, 2024. Last visited on November 29, 2024.
- [39] P. Barmavatu, S.K. Kothapalli, A. Radhakrishnan, D.J. Railis, Designing sustainable thermal energy system with electro-photo conversion, *Journal of Thermal Science* 33 (5) (2024) 1642–1656.
- [40] A.K. Dwivedi, H. Chougrani, S. Chaudhari, N. Varshney, S. Chatzinotas, Efficient transmission scheme for Leo satellite-based nb-IoT: a data-driven perspective, *arXiv preprint, arXiv:2406.14107*, 2024.
- [41] C. Sengul, A. Kirby, Message Queuing Telemetry Transport (MQTT) and Transport Layer Security (TLS) Profile of Authentication and Authorization for Constrained Environments (ACE) Framework, RFC 9431, July 2023.
- [42] Z. Shelby, K. Hartke, C. Bormann, The Constrained Application Protocol (CoAP), RFC 7252, June 2014.
- [43] M. Bishop, HTTP/3, RFC 9114, June 2022.
- [44] O. Ledesma, P. Lamo, J.A. Fraire, Trends in lpwan technologies for Leo satellite constellations in the newspace context, *Electronics* 13 (3) (2024) 579.
- [45] H. Alam, A. de Domenico, D. López-Pérez, F. Kaltenberger, Optimizing integrated terrestrial and non-terrestrial networks performance with traffic-aware resource management, *arXiv preprint, arXiv:2410.06700*, 2024.
- [46] T. Korikawa, C. Takasaki, K. Hattori, H. Oowada, A routing method with link information-based rule selection in non-terrestrial networks, in: 2024 International Conference on Computing, Networking and Communications (ICNC), IEEE, 2024, pp. 850–855.
- [47] A. Nauman, H.M. Alshahrani, N. Nemri, K.M. Othman, N.O. Aljehane, M. Maashi, A.K. Dutta, M. Assiri, W.U. Khan, Dynamic resource management in integrated noma terrestrial–satellite networks using multi-agent reinforcement learning, *Journal of Network and Computer Applications* 221 (2024) 103770.
- [48] M. Awais, H. Pervaiz, M.A. Jamshed, W. Yu, Q. Ni, Energy-aware resource optimization for improved urllc in multi-hop integrated aerial terrestrial networks, *IEEE Transactions on Green Communications and Networking* (2023).
- [49] Y. Özçevik, B. Canberk, Energy aware endurance framework for mission critical aerial networks, *Ad Hoc Networks* 96 (2020) 101992.

- [50] A.C. Rhodes, Handset Antenna Design Optimisation and Considerations for NTN Applications, IET 6G and Future Networks Conference (IET 6G 2024), vol. 2024, IET, 2024, pp. 72–78.
- [51] Innovantennas, Home of the low noise lfa Yagi – ham radio antennas. Last visited on December 7, 2024.
- [52] R.J. Mailloux, Phased Array Antenna Handbook, Artech House, 2017.
- [53] T. Tandel, S. Trapasiya, Reconfigurable antenna for wireless communication: recent developments, challenges and future, *Wireless Personal Communications* 133 (2) (2023) 725–768.
- [54] A. Zourmand, A.L.K. Hing, C.W. Hung, M. AbdulRehman, Internet of things (IoT) using lora technology, in: 2019 IEEE International Conference on Automatic Control and Intelligent Systems (I2CACIS), IEEE, 2019, pp. 324–330.
- [55] C. Gomez, J.C. Veras, R. Vidal, L. Casals, J. Paradells, A sigfox energy consumption model, *Sensors* 19 (3) (2019) 681.
- [56] M. Devare, Low power communication protocols for IoT-enabled applications, in: *Protocols and Applications for the Industrial Internet of Things*, IGI Global, 2018, pp. 64–94.
- [57] S.M. Darroudi, C. Gomez, Bluetooth low energy mesh networks: a survey, *Sensors* 17 (7) (2017) 1467.
- [58] J. Xu, J. Yao, L. Wang, Z. Ming, K. Wu, L. Chen, Narrowband Internet of Things: evolutions, technologies, and open issues, *IEEE Internet of Things Journal* 5 (3) (2017) 1449–1462.
- [59] 3GPP, 3gpp release 17: Understanding nb-IoT over ntn, 2022. Last visited on November 30, 2024.
- [60] E.T. Michailidis, S.M. Potirakis, A.G. Kanatas, Ai-inspired non-terrestrial networks for iiot: review on enabling technologies and applications, *IoT* 1 (1) (2020) 3.
- [61] T. Scalia, L. Bonventre, M.L. Terranova, From protosolar space to space exploration: the role of graphene in space technology and economy, *Nanomaterials* 13 (4) (2023) 680.
- [62] L. Jia, Y. Zhang, J. Yu, X. Wang, Design of mega-constellations for global uniform coverage with inter-satellite links, *Aerospace* 9 (5) (2022) 234.
- [63] J. Choi, B. Li, B. Al Homssi, J. Park, S.-L. Kim, Spectrum sharing through marketplaces for o-ran based non-terrestrial and terrestrial networks, *IEEE Internet of Things Magazine* 7 (5) (2024) 128–134.
- [64] H. Martikainen, M. Majamaa, J. Puttonen, Coordinated dynamic spectrum sharing between terrestrial and non-terrestrial networks in 5g and beyond, in: 2023 IEEE 24th International Symposium on a World of Wireless, Mobile and Multimedia Networks (WoWMoM), IEEE, 2023, pp. 419–424.
- [65] K.-U. Schrogl, C. Jorgenson, J. Robinson, A. Soucek, Space traffic management towards a roadmap for implementation, 2020. UNOOSA Space Law Conference Presentation. Last visited on December 7, 2024.
- [66] I.T.U. (ITU), Cross-border coordination for fixed and mobile services, 2024. Last visited on December 7, 2024.
- [67] A. Umunnakwe, H. Huang, K. Oikonomou, K. Davis, Quantitative analysis of power systems resilience: standardization, categorizations, and challenges, *Renewable and Sustainable Energy Reviews* 149 (2021) 111252.
- [68] N. IAS, Environmental impact assessment (eia), 2024. Last visited on December 7, 2024.
- [69] NTEPA, Environmental impact assessment guidelines, 2020. Last visited on December 7, 2024.
- [70] E.S.A. (ESA), European space agency launches non-terrestrial network forum, 2024. Last visited on December 7, 2024.

Secure and privacy-aware solutions for sustainable IoT

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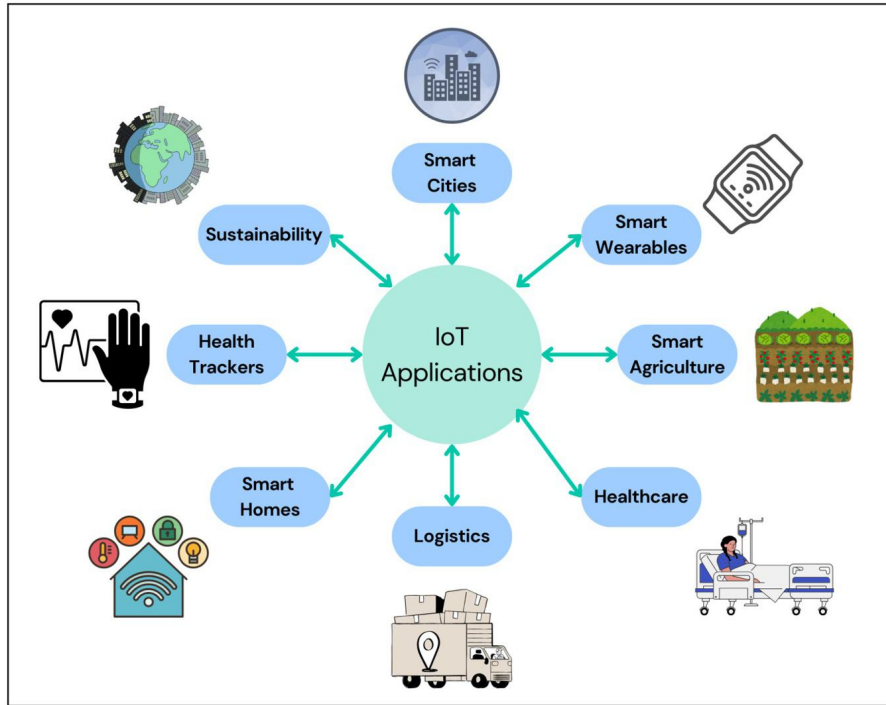
5.1 Introduction

The technological advances in the Internet of Things (IoT) domain are transforming modern society by introducing new technologies that improve efficiency across industries and quality of life [1–5]. IoT refers to a vast network of interconnected devices that collect, exchange, and process data without human intervention [6]. IoT devices, ranging from simple household items like smart thermostats and fitness trackers to complex systems such as autonomous vehicles and critical healthcare, as shown in Fig. 5.1, are deeply embedded in our daily lives. These devices enhance efficiency and quality of life by automating home environments, tracking vital signs, and optimizing traffic flow and energy consumption in smart city infrastructures [7,8].

However, as IoT adoption grows, so do the associated security challenges. IoT devices, essentially resource-constrained computers, significantly widen the attack surface for cyber threats [9–12]. As a result, cyberattacks targeting IoT systems have surged in frequency and impact. One notable example is the Mirai botnet attack, which exploited weak IoT security, compromising thousands of devices to orchestrate one of the largest Distributed Denial of Service (DDoS) attacks in history [13]. Even seemingly harmless smart devices, like a connected smart coffee machine, can have vulnerabilities that allow attackers to infiltrate a home network. Once inside, hackers could manipulate other connected devices, steal sensitive data, or even endanger lives by tampering with critical medical equipment like pacemakers [14].

Beyond household security risks, IoT vulnerabilities can escalate into large-scale national threats. Critical infrastructure, such as power grids and oil pipelines, relies on thousands of interconnected sensors and actuators. A cyberattack on these systems could cause catastrophic disruptions comparable to the impact of conventional weapons [15]. Even indirect attacks, such as exploiting vulnerabilities in automated thermostats, could have the same effect. Malicious actors could simultaneously increase heating in millions of homes and overload the power grid, leading to widespread power outages.

Given the far-reaching implications of IoT security breaches, robust and efficient security solutions are essential at every level. One foundational pillar is lightweight

**FIGURE 5.1**

IoT Applications.

encryption techniques. While traditional cryptographic methods offer strong protection, they impose high computational and energy costs that resource-constrained IoT devices cannot afford. Lightweight encryption techniques address this challenge by optimizing security for embedded and battery-powered applications without significantly degrading device performance [16,17].

Beyond encryption, secure data transmission and aggregation play a crucial role in IoT security, particularly in data-sensitive environments like healthcare and industrial automation. IoT-generated data must be protected during transit to prevent unauthorized access or tampering. Innovative approaches such as fog computing and blockchain-based data aggregation help secure real-time communication while improving efficiency and reducing latency [18,19]. The integration of privacy-preserving encryption techniques, such as homomorphic encryption and secure multi-party computation, allows IoT devices to transmit and analyze encrypted data without exposing sensitive information [20]. By implementing secure transmission frameworks, IoT ecosystems can mitigate cyber threats while optimizing network performance [21–23].

Another important aspect of IoT security is privacy-preserving data analytics. The increasing reliance on IoT-generated data for decision-making has raised concerns

regarding user privacy and data exposure. Conventional centralized data processing models expose raw data to potential breaches and unauthorized surveillance. To counteract this, decentralized and privacy-preserving analytics methods have been proposed, including homomorphic encryption, federated learning, and anonymization techniques [24,25]. These methods enable IoT devices to process and analyze data securely without compromising privacy. As Artificial Intelligence (AI) and Machine Learning (ML) become more integrated with IoT, ensuring secure and private data analytics is imperative for sustainable IoT adoption.

While encryption and secure data handling are crucial, secure authentication methods form the foundation of reliable IoT security frameworks. Authentication mechanisms ensure that only legitimate devices and users can access IoT networks, preventing unauthorized intrusions and attacks. Traditional password-based authentication methods are often insufficient due to scalability and security limitations. Advanced authentication techniques, including blockchain-based authentication, delegated authentication, and Radio Frequency Identification (RFID)-based authentication, have been introduced to enhance identity verification while maintaining minimal computational overhead [26–28]. Secure authentication methods are vital in preventing impersonation attacks and ensuring the integrity of IoT networks.

As the IoT ecosystem continues to expand, addressing security and privacy challenges remains a priority. A comprehensive security framework must incorporate lightweight encryption, secure data transmission, privacy-preserving analytics, and strong authentication mechanisms. By integrating these solutions, we can create a secure, privacy-aware IoT landscape that supports sustainable innovation while mitigating cyber threats.

The remainder of this chapter is structured as follows: Section 5.2 explores lightweight encryption techniques, highlighting cryptographic solutions optimized for resource-constrained IoT environments. Section 5.3 discusses secure data transmission techniques, including blockchain-based aggregation, to enhance communication security. Section 5.4 examines privacy-preserving data analytics, focusing on decentralized approaches such as federated learning and homomorphic encryption. Section 5.5 delves into secure authentication mechanisms, evaluating advanced identity verification techniques such as blockchain-based authentication and RFID-based authentication. Finally, Section 5.6 concludes the chapter.

5.2 Lightweight encryption techniques

The increasing adoption of IoT devices in diverse applications ranging from healthcare and smart cities to industrial automation necessitates the development of efficient cryptographic solutions that address security challenges while maintaining the resource constraints of these devices. With IoT devices operating under constrained resources such as limited battery life, low processing power, and minimal memory capacity, traditional encryption methods are often too computationally expensive. Standard cryptographic algorithms like RSA, AES and DES require significant processing

Table 5.1 Comparison of different lightweight encryption techniques [31–33].

Encryption Technique	Key Size (bits)	Block Size (bits)	Structure	Rounds	Encryption Strength	Computational Cost
AES	128/192/256	128	SPN	10/12/14	High	High
HIGHT	128	64	GFS	32	Medium	Low
PRESENT	80/128	64	SPN	31	Medium	Low
RC5	0-2048	32/64/128	Feistel	1-255	Variable	Variable
TEA	128	64	Feistel	64	Medium	Medium
XTEA	128	64	Feistel	64	Medium	Medium
LEA	128-256	128	Feistel	24-32	High	High
DES	54	64	Feistel	16	Medium	Medium
TWINE	80/128	64	Feistel	32	Medium	Low
Humming-bird	256	16	SPN	4	Low	Very Low
Iceberg	128	64	SPN	16	Medium	Medium
SIMON	64-256	32-128	Feistel	32-72	High	Low
SPECK	64-256	32-128	Feistel	22-34	Medium	Low
Chaskey	128	128	Feistel	8/16	Medium	Low

resources, making them impractical for small IoT devices that must balance security with energy efficiency [29]. Lightweight cryptography is specifically designed to reduce computational overhead while maintaining adequate security levels for IoT applications. These encryption techniques enable secure communication while minimizing power consumption, making them ideal for deployment in resource-constrained IoT environments [14].

Lightweight cryptographic algorithms are primarily classified into block ciphers, stream ciphers, homomorphic encryption, and chaotic encryption. Block ciphers such as PRESENT, SIMON, SPECK, Chaskey, and optimized versions of AES-128 for constrained environments by reducing the key size, block size, and number of rounds, making encryption operations feasible for battery-powered devices [14,29]. These algorithms are widely used in IoT security due to their balance between security and performance. Stream ciphers such as Grain, MICKEY, and Trivium provide real-time encryption of data streams, making them suitable for IoT applications requiring minimal latency and computational overhead like wireless sensor networks and embedded systems [29]. Table 5.1 shows a comparison of different encryption techniques, including key sizes, block sizes, structures, rounds, relative encryption strengths, and relative computational costs [30].

Homomorphic encryption enables computations to be performed on encrypted data without requiring decryption, thereby preserving privacy in applications such as healthcare and secure data aggregation. The Paillier cryptosystem supports additive homomorphic encryption and is commonly used for privacy-preserving computations in IoT healthcare environments [34]. Lattice-based homomorphic encryption offers

additional security advantages by providing resistance against quantum attacks, making it a promising technique for future post-quantum IoT security implementations. The applicability of lattice-based cryptography in IoT environments is particularly significant due to its computational efficiency and resilience against quantum threats. The Learning With Errors (LWE) and Ring-Learning With Errors (R-LWE) techniques form the foundation of many lattice-based encryption schemes, offering worst-case security guarantees [31]. These techniques ensure that cryptographic primitives remain computationally feasible while providing robust security for IoT applications, including secure authentication, key exchange, and data encryption [31]. Moreover, LWE-based encryption schemes have been shown to efficiently support homomorphic operations, allowing secure computation on encrypted data without revealing plaintext information. These properties make lattice-based encryption a viable choice for securing sensitive data in resource-constrained IoT devices [31].

In addition to homomorphic encryption, chaotic encryption techniques provide lightweight security solutions for resource-constrained IoT devices. The IEPSBP framework is a cost-efficient image encryption algorithm based on a parallel chaotic system that enhances both security and energy efficiency in Green IoT applications [35]. It utilizes a 16-bit precision-limited chaotic system, known as PSBP, which combines Piecewise Linear Chaotic Map (PWLCM), Skew Tent Map (STM), and Bernoulli Map in a parallel configuration. This approach allows for the generation of high-quality pseudo-random sequences suitable for encryption while maintaining low computational complexity. Unlike conventional encryption methods that operate at the bit or byte level, IEPSBP employs row- and column-based permutation and diffusion techniques, significantly reducing the computational overhead required for secure data transmission in IoT networks [35]. The algorithm is optimized for low-power devices, enabling secure image transmission while minimizing energy consumption, making it particularly suitable for Green IoT applications.

Despite their advantages, several implementation challenges must be addressed. The trade-off between security strength and resource constraints means that lightweight cryptographic algorithms must be carefully designed to resist common attacks such as differential cryptanalysis, side-channel attacks, and man-in-the-middle attacks [29]. For instance, while PRESENT (a lightweight SP-network cipher) provides strong security with a 31-round encryption process, its small key size (80-bit) makes it vulnerable to brute-force attacks over time [36]. To address this, hybrid encryption techniques that combine lightweight symmetric and asymmetric encryption have been proposed. For example, Elliptic Curve Cryptography (ECC) provides a lightweight asymmetric encryption alternative with smaller key sizes than RSA while maintaining comparable security levels. The combination of AES and ECC in hybrid encryption models ensures faster processing for bulk data encryption, while leveraging ECC for secure key exchange, thereby balancing security and efficiency in IoT systems [14]. Such lightweight algorithms and hybrid models provide a scalable approach to securing large-scale IoT networks, reducing latency while maintaining end-to-end encryption.

The development of lightweight cryptographic methods must focus on optimizing energy consumption, enhancing security resilience, and standardizing cryptographic evaluation metrics. Research into AI-driven security adaptation can enable the dynamic selection and adjustment of cryptographic schemes based on available computational resources, ensuring optimal performance in diverse IoT environments. Additionally, post-quantum cryptography is gaining attention as a potential solution to future security threats posed by quantum computing advancements. Establishing universal standards for lightweight encryption techniques will facilitate greater adoption and interoperability, ultimately strengthening the security and sustainability of IoT systems [19].

5.3 Secure data transmission and aggregation

In modern Internet of Medical Things (IoMT) applications, ensuring the secure transmission and aggregation of healthcare data is a critical challenge due to the sensitive nature of patient records and the necessity for real-time monitoring. Traditional cloud-centric architectures introduce high latency, bandwidth consumption, and security risks, making them less suitable for real-time and privacy-sensitive applications. To address these challenges, Fog-assisted data aggregation has emerged as a promising solution [18]. Fig. 5.2 shows the different layers in the IoT architecture

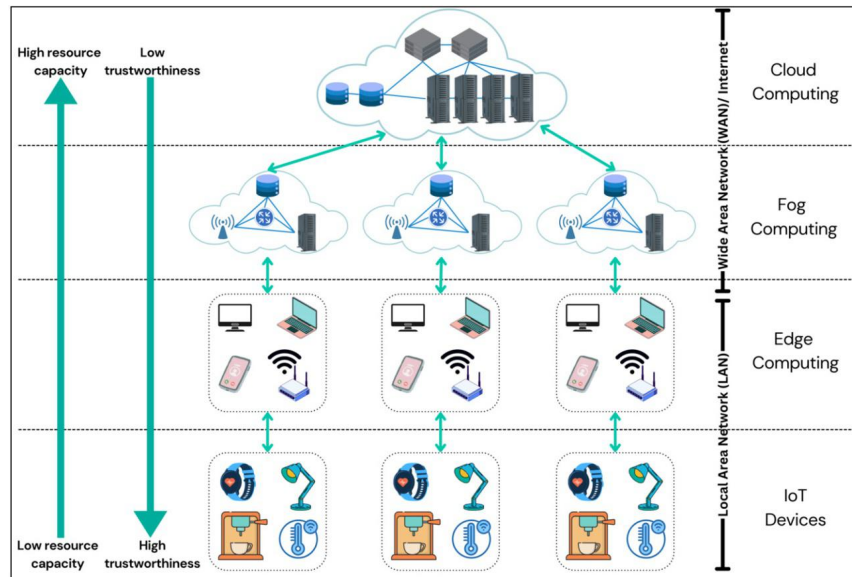


FIGURE 5.2

Illustration of data transmission between IoT devices, Edge Computing, Fog Computing and Cloud Computing.

and the data transmission between the layers. Fog computing acts as an intermediary between edge devices [37] and cloud servers, enabling local processing, encryption, and compression before transmitting data to the cloud. This approach significantly reduces transmission delays, improves efficiency, and minimizes exposure to security threats. In secure IoT-based healthcare networks, data is often aggregated at the edge nodes, such as smartphones, wearable devices, or local fog servers, where encryption techniques like Homomorphic Encryption, Attribute-Based Encryption (ABE), and Secure Multiparty Computation (SMC) ensure privacy-preserving aggregation [18].

Privacy-preserving aware data aggregation (EPPADA), as proposed by Othman et al. [38], integrates Homomorphic Encryption to secure medical data aggregation while minimizing communication overhead and energy consumption. The system ensures that medical sensors transmit encrypted data, which can be aggregated by intermediate nodes without decryption, thus maintaining end-to-end confidentiality. This approach effectively mitigates the risk of data interception and unauthorized access during transmission. Furthermore, dual-prediction mechanisms are employed to reduce the number of transmissions by only sending data when deviations from predicted values occur, significantly lowering bandwidth consumption and energy usage [38]. This aligns with green computing principles, ensuring sustainability while enhancing security in IoT-driven healthcare applications.

In IoT-driven healthcare networks, blockchain-based mechanisms for secure data aggregation enhance privacy, integrity, and scalability. Ahmed et al. propose an Energy-Efficient Data Aggregation Mechanism (EEDAM) secured by blockchain [19], which leverages fuzzy similarity clustering and sleep scheduling to optimize network traffic, reduce data redundancy, and enhance security. This approach groups sensor nodes with high data similarity to minimize redundant transmissions, while blockchain technology is used to authenticate and validate aggregated data before it is stored in the cloud. By integrating edge computing and decentralized architectures, EEDAM enhances scalability, reduces computational overhead, and prevents single points of failure [8,19,39,40]. Moreover, the use of blockchain-enabled smart contracts ensures tamper-proof data storage and automated access control, preventing unauthorized modifications while allowing secure, real-time data retrieval by medical professionals.

Efficient data compression and deduplication techniques further enhance secure data aggregation by reducing redundant transmissions and storage costs. As healthcare IoT devices continuously generate vast amounts of real-time data, it is crucial to employ lightweight and scalable compression techniques such as TTTD-Huffman hybrid encoding, Secure Deduplication and Data Dissemination (S-DDD), and Slepian-Wolf coding-based methods [18]. These techniques allow data to be efficiently compressed at fog nodes, ensuring that only relevant and non-redundant information is transmitted to the cloud. This approach not only reduces energy consumption and bandwidth usage, but also enhances real-time analytics and decision-making for critical healthcare applications. Furthermore, priority-based data transmission frameworks such as those designed for non-delay-tolerant medical emergencies, allow urgent data to be transmitted immediately, while non-critical data is compressed and stored for later retrieval [18]. These strategies optimize network efficiency, reduce unnecessary data loads, and contribute to the scalability and sustainability of IoT-driven healthcare ecosystems.

5.4 Privacy-preserving data analytics

With the increasing reliance on IoT-enabled healthcare systems, preserving data privacy while enabling efficient analytics remains a pressing challenge. Traditional cloud-based architectures centralize IoT data, making them susceptible to privacy breaches and high latency issues. Liang Zhao introduced a fog computing framework that distributed data analytics across edge devices and fog nodes, reducing reliance on the cloud and enhancing privacy [24]. Unlike centralized approaches, this method keeps raw data at the edge, only sharing encrypted gradients and model parameters, thereby preventing data leakage. A key component of this approach is the homomorphic encryption-based privacy-preserving protocol, ensuring that sensitive IoT data remains secure during analytics processing. The security analysis in the study demonstrates that an honest-but-curious adversary cannot infer raw data from encrypted updates, ensuring privacy without compromising analytical accuracy [24].

The kHealth framework, an IoT-based healthcare system, demonstrates how personalized health analytics models can be built while maintaining privacy [41]. In such frameworks, Cryptographic Service Providers (CSP) are proposed as intermediary entities that manage secret keys and intermediate computations, reducing the risk of data exposure to potentially honest but curious service providers. Another promising approach is SMC, which allows multiple parties (such as hospitals or research institutions) to jointly train machine learning models without revealing their private datasets [41]. However, SMC requires extensive computational resources and synchronized participation, limiting its scalability.

Another significant advancement in privacy-preserving IoT analytics comes from deep learning-based methods. Bi et al. introduced a privacy-isolation zone at the user end to separate Personally Identifiable Information (PII) from health-related sensor data before uploading to the cloud [25]. This method ensures that only anonymized health metrics are processed in the cloud, while privacy-sensitive behavioural data such as gait patterns or voice characteristics are filtered locally. A non-privacy data extraction algorithm, implemented via Convolutional Neural Networks (CNNs), enhances the security of extracted data while maintaining accuracy in health assessments. The proposed approach is particularly useful in wearable healthcare technologies, such as smart earphones for posture monitoring, where head motion data must be separated from identifiable gait signals to prevent unauthorized re-identification [25]. The combination of deep learning and data isolation mechanisms provides a scalable, privacy-enhanced framework for sustainable IoT analytics.

While encryption and anonymization techniques offer privacy benefits, they often introduce computational overhead. The papers reviewed suggest a hybrid approach, combining lightweight encryption, fog-based distributed analytics, and AI-driven privacy protection to balance efficiency and security [24,25]. Edge computing and fog-based privacy-preserving analytics provide a decentralized solution that minimizes data exposure risks while improving real-time processing for sustainable IoT systems. By reducing reliance on third-party cloud services and implementing secure, distributed data-sharing protocols, these approaches significantly enhance privacy protection in real-world IoT applications, particularly in healthcare, smart cities, and industrial IoT ecosystems [41].

5.5 Secure authentication methods

Authentication is a fundamental requirement in sustainable IoT systems to ensure secure and reliable communication between devices, especially in privacy-sensitive environments like healthcare [42]. Since medical sensor nodes are often deployed in untrusted environments, they are vulnerable to data tampering, identity spoofing, and man-in-the-middle attacks. To mitigate these risks, cryptographic schemes like HMAC-based authentication, mutual authentication protocols, and session key generation techniques are implemented to validate the integrity of data before aggregation [18]. Another approach is mutual authentication using hash functions and shared secrets, as explored in the Hybrid Logical Security Framework (HLSF), which employs a three-phase authentication process involving device registration, mutual authentication, and secure data communication [27]. When a device joins the network, its credentials are securely registered with a central Inventory Server (IS). During authentication, the client device generates a hash of its identity combined with a nonce and a shared key before sending an authentication request [27]. The IS verifies the request and responds with its own hash-based verification, ensuring a bidirectional authentication mechanism that prevents replay and impersonation attacks [27].

Another promising authentication method for green IoT is blockchain-based authentication, which enhances security through decentralization. The BENIGREEN authentication scheme uses blockchain technology to validate the legitimacy of sensor nodes before allowing them to participate in data transactions [26]. Instead of relying on a centralized authentication authority, this scheme assigns each node a pseudo-identity and dynamically updates authentication keys at predefined time intervals. The authentication process ensures that only verified nodes can communicate with others, mitigating risks such as Sybil attacks and identity spoofing. Additionally, the system employs certificate revocation to prevent compromised nodes from accessing the network, further enhancing security [26].

RFID-based authentication is another mechanism that can be integrated into IoT ecosystems to facilitate secure access control. RFID technology enables automatic identification and tracking of devices or assets within IoT networks, including smart agriculture and green IoT applications. A lightweight anonymous RFID authentication scheme has been proposed to enhance privacy by using pseudo-identities, emergency keys, and cryptographic hash functions [28]. This scheme effectively defends against common security threats such as replay, cloning, and location-tracking attacks. Moreover, RFID authentication can be combined with cloud-based verification to ensure scalability and seamless device management across large IoT deployments [28].

Delegated authentication is another key strategy for securing IoT-based communication, particularly when data is transported via untrusted public networks [28]. A Semi-outsourcing Privacy-Preserving authentication scheme allows authentication tasks to be offloaded to intermediate cloud nodes while ensuring the integrity and confidentiality of IoT data [28]. This scheme leverages ECC to enable non-interactive authentication, significantly reducing computational overhead for resource-constrained IoT devices. By delegating authentication responsibilities to trusted public clouds, the approach provides a balance between security and efficiency, ensuring that only legitimate devices gain access to IoT networks while mitigating unauthorized access attempts [28].

5.6 Conclusion

The increasing adoption of IoT has enhanced efficiency and connectivity across various domains while also introducing security and privacy challenges. Addressing these concerns requires a combination of robust encryption, secure data transmission, privacy-preserving analytics, and strong authentication mechanisms.

As discussed in this chapter, effective security strategies include lightweight encryption to balance security and computational efficiency, secure transmission methods such as fog computing and blockchain-based solutions to protect data integrity, and privacy-preserving analytics using federated learning and homomorphic encryption to enable safe data processing. Authentication mechanisms, including blockchain-based authentication, RFID-based solutions, and delegated authentication, play a crucial role in preventing unauthorized access and ensuring trust within IoT ecosystems.

A comprehensive approach to IoT security involves integrating these measures while adapting to emerging technologies. Future research should focus on scalable security frameworks, AI-driven threat detection, and post-quantum cryptography to strengthen IoT resilience. Implementing these strategies will support the sustainable and secure expansion of IoT applications across industries.

References

- [1] M.A. Jamshed, K. Ali, Q.H. Abbasi, M.A. Imran, M. Ur-Rehman, Challenges, applications, and future of wireless sensors in Internet of Things: a review, *IEEE Sensors Journal* 22 (6) (2022) 5482–5494.
- [2] A.A. Shah, G. Piro, L.A. Grieco, G. Boggia, A qualitative cross-comparison of emerging technologies for software-defined systems, in: 2019 Sixth International Conference on Software Defined Systems (SDS), IEEE, 2019, pp. 138–145.
- [3] A.A. Shah, G. Piro, L.A. Grieco, G. Boggia, A review of forwarding strategies in transport software-defined networks, in: 2020 22nd International Conference on Transparent Optical Networks (ICTON), IEEE, 2020, pp. 1–4.
- [4] M.A. Jamshed, M.F. Khan, K. Rafique, M.I. Khan, K. Faheem, S.M. Shah, A. Rahim, An energy efficient priority based wireless multimedia sensor node dynamic scheduler, in: 2015 12th International Conference on High-Capacity Optical Networks and Enabling/Emerging Technologies (HONET), IEEE, 2015, pp. 1–4.
- [5] M.A. Jamshed, F. Ayaz, A. Kaushik, C. Fischione, M. Ur-Rehman, Green UAV-enabled Internet-of-Things network with AI-assisted noma for disaster management, in: 2024 IEEE 35th International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), IEEE, 2024, pp. 1–6.
- [6] S. Li, L.D. Xu, S. Zhao, The Internet of Things: a survey, *Information Systems Frontiers* 17 (2015) 243–259.
- [7] R. Arshad, S. Zahoor, M.A. Shah, A. Wahid, H. Yu, Green IoT: an investigation on energy saving practices for 2020 and beyond, *IEEE Access* 5 (2017) 15667–15681.
- [8] A.A. Shah, A software-defined networking based simulation framework for Internet of space things, in: 2023 IEEE 97th Vehicular Technology Conference (VTC2023-Spring), IEEE, 2023, pp. 1–4.

- [9] F. Nocera, S. Abascià, M. Fiore, A.A. Shah, M. Mongiello, E. Di Sciascio, G. Acciani, Cyber-attack mitigation in cloud-fog environment using an ensemble machine learning model, in: 2022 7th International Conference on Smart and Sustainable Technologies (SpliTech), IEEE, 2022, pp. 1–6.
- [10] F. Nocera, S. Demilito, P. Ladisa, M. Mongiello, A.A. Shah, J. Ahmad, E. Di Sciascio, A user behavior analytics (uba)-based solution using lstm neural network to mitigate ddos attack in fog and cloud environment, in: 2022 2nd International Conference of Smart Systems and Emerging Technologies (SMARTTECH), IEEE, 2022, pp. 74–79.
- [11] R. Meng, A.A. Shah, M.A. Jamshed, D. Pazaros, Federated learning-based intrusion detection framework for Internet of Things and edge computing backed critical infrastructure, in: 2024 IEEE International Conference on Communications Workshops (ICC Workshops), IEEE, 2024, pp. 810–815.
- [12] A. Ullah, A.A. Shah, J.S. Khan, M. Sajjad, W. Boulila, A. Akgul, J. Masood, F.A. Ghaleb, S.A. Shah, J. Ahmad, An efficient lightweight image encryption scheme using multi-chaos, *Security and Communication Networks* 2022 (1) (2022) 5680357.
- [13] G. Kambourakis, C. Kolias, A. Stavrou, The mirai botnet and the IoT zombie armies, in: MILCOM 2017-2017 IEEE Military Communications Conference (MILCOM), IEEE, 2017, pp. 267–272.
- [14] M.N. Khan, A. Rao, S. Camtepe, Lightweight cryptographic protocols for IoT-constrained devices: a survey, *IEEE Internet of Things Journal* 8 (6) (2020) 4132–4156.
- [15] T.H. Szymanski, Security and privacy for a green Internet of Things, *IT Professional* 19 (5) (2017) 34–41.
- [16] M.A. Jan, F. Khan, S. Mastorakis, M. Adil, A. Akbar, N. Stergiou, Lightiot: lightweight and secure communication for energy-efficient IoT in health informatics, *IEEE Transactions on Green Communications and Networking* 5 (3) (2021) 1202–1211.
- [17] X.-W. Wu, E.-H. Yang, J. Wang, Lightweight security protocols for the Internet of Things, in: 2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC), IEEE, 2017, pp. 1–7.
- [18] A. Ullah, M. Azeem, H. Ashraf, A.A. Alaboudi, M. Humayun, N.Z. Jhanjhi, Secure healthcare data aggregation and transmission in IoT—a survey, *IEEE Access* 9 (2021) 16849–16865.
- [19] A. Ahmed, S. Abdullah, M. Bukhsh, I. Ahmad, Z. Mushtaq, An energy-efficient data aggregation mechanism for IoT secured by blockchain, *IEEE Access* 10 (2022) 11404–11419.
- [20] S. Gupta, R. Garg, N. Gupta, W.S. Alnumay, U. Ghosh, P.K. Sharma, Energy-efficient dynamic homomorphic security scheme for fog computing in IoT networks, *Journal of Information Security and Applications* 58 (2021) 102768.
- [21] F.P. Tso, G. Hamilton, R. Weber, C.S. Perkins, D.P. Pazaros, Longer is better: exploiting path diversity in data center networks, in: 2013 IEEE 33rd International Conference on Distributed Computing Systems, IEEE, 2013, pp. 430–439.
- [22] I. Leyva-Pupo, C. Cervelló-Pastor, C. Anagnostopoulos, D.P. Pazaros, Dynamic scheduling and optimal reconfiguration of upf placement in 5g networks, in: Proceedings of the 23rd International ACM Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems, 2020, pp. 103–111.
- [23] I. Alghamdi, C. Anagnostopoulos, D.P. Pazaros, On the optimality of task offloading in mobile edge computing environments, in: 2019 IEEE Global Communications Conference (GLOBECOM), IEEE, 2019, pp. 1–6.
- [24] L. Zhao, Privacy-preserving distributed analytics in fog-enabled IoT systems, *Sensors* 20 (21) (2020) 6153.

- [25] H. Bi, J. Liu, N. Kato, Deep learning-based privacy preservation and data analytics for IoT enabled healthcare, *IEEE Transactions on Industrial Informatics* 18 (7) (2021) 4798–4807.
- [26] R. Goyat, G. Kumar, M. Conti, T. Devgun, R. Saha, R. Thomas, Benigreen: blockchain-based energy-efficient privacy-preserving scheme for green IoT, *IEEE Internet of Things Journal* 10 (18) (2023) 16480–16493.
- [27] I. Batra, S. Verma, A. Malik Kavita, U. Ghosh, J.J. Rodrigues, G.N. Nguyen, A.S. Hosen, V. Mariappan, Hybrid logical security framework for privacy preservation in the green Internet of Things, *Sustainability* 12 (14) (2020) 5542.
- [28] M.A. Ferrag, L. Shu, X. Yang, A. Derhab, L. Maglaras, Security and privacy for green IoT-based agriculture: review, blockchain solutions, and challenges, *IEEE Access* 8 (2020) 32031–32053.
- [29] S. Singh, P.K. Sharma, S.Y. Moon, J.H. Park, Advanced lightweight encryption algorithms for IoT devices: survey, challenges and solutions, *Journal of Ambient Intelligence and Humanized Computing* (2024) 1–18.
- [30] A.A. Shah, A. Adeel, J. Ahmad, A. Al-Dubai, M. Gogate, A. Bishnu, M. Diyan, T. Hussain, K. Dashtipour, T. Ratnarajah, et al., A novel chaos-based light-weight image encryption scheme for multi-modal hearing aids, in: *2022 IEEE Conference on Dependable and Secure Computing (DSC)*, IEEE, 2022, pp. 1–6.
- [31] R. Chaudhary, G.S. Aujla, N. Kumar, S. Zeadally, Lattice-based public key cryptosystem for Internet of Things environment: challenges and solutions, *IEEE Internet of Things Journal* 6 (3) (2018) 4897–4909.
- [32] R. Beaulieu, D. Shors, J. Smith, S. Treatman-Clark, B. Weeks, L. Wingers, The Simon and speck lightweight block ciphers, in: *Proceedings of the 52nd Annual Design Automation Conference*, 2015, pp. 1–6.
- [33] D. Dinu, Y.L. Corre, D. Khovratovich, L. Perrin, J. Großschädl, A. Biryukov, Triathlon of lightweight block ciphers for the Internet of Things, *Journal of Cryptographic Engineering* 9 (2019) 283–302.
- [34] A. Salim, W. Osamy, A. Aziz, A.M. Khedr, Seedgt: secure and energy efficient data gathering technique for IoT applications based wsns, *Journal of Network and Computer Applications* 202 (2022) 103353.
- [35] Z. Gu, H. Li, S. Khan, L. Deng, X. Du, M. Guizani, Z. Tian, Iepspb: a cost-efficient image encryption algorithm based on parallel chaotic system for green IoT, *IEEE Transactions on Green Communications and Networking* 6 (1) (2021) 89–106.
- [36] A. Bogdanov, L.R. Knudsen, G. Leander, C. Paar, A. Poschmann, M.J. Robshaw, Y. Seurin, C. Vikkelsøe, Present: an ultra-lightweight block cipher, in: *Cryptographic Hardware and Embedded Systems-CHES 2007: 9th International Workshop*, Vienna, Austria, September 10–13, 2007, in: *Proceedings 9*, Springer, 2007, pp. 450–466.
- [37] J. Yang, A.A. Shah, D. Pezaros, A survey of energy optimization approaches for computational task offloading and resource allocation in mec networks, *Electronics* 12 (17) (2023) 3548.
- [38] S.B. Othman, F.A. Almalki, C. Chakraborty, H. Sakli, Privacy-preserving aware data aggregation for IoT-based healthcare with green computing technologies, *Computers & Electrical Engineering* 101 (2022) 108025.
- [39] A. Petrosino, G. Sciddurlo, G. Grieco, A.A. Shah, G. Piro, L.A. Grieco, G. Boggia, Dynamic management of forwarding rules in a t-sdn architecture with energy and bandwidth constraints, in: *Ad-Hoc, Mobile, and Wireless Networks: 19th International Conference on Ad-Hoc Networks and Wireless, ADHOC-NOW 2020*, in: *Proceedings 19*, Springer, Bari, Italy, October 19–21, 2020, pp. 3–15, 2020.

- [40] A. Shah, M. Mussini, F. Nicassio, G. Parladori, F. Triggiani, G. Grieco, G. Iaffaldano, G. Piro, A real-time simulation framework for complex and large-scale optical transport networks based on the sdn paradigm, in: 2020 IEEE/ACM 24th International Symposium on Distributed Simulation and Real Time Applications (DS-RT), IEEE, 2020, pp. 1–4.
- [41] S. Sharma, K. Chen, A. Sheth, Toward practical privacy-preserving analytics for IoT and cloud-based healthcare systems, *IEEE Internet Computing* 22 (2) (2018) 42–51.
- [42] S. Son, Y. Park, Y. Park, A secure, lightweight, and anonymous user authentication protocol for IoT environments, *Sustainability* 13 (16) (2021) 9241.

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Achieving the sustainability in IoT network using software defined radios and virtualization

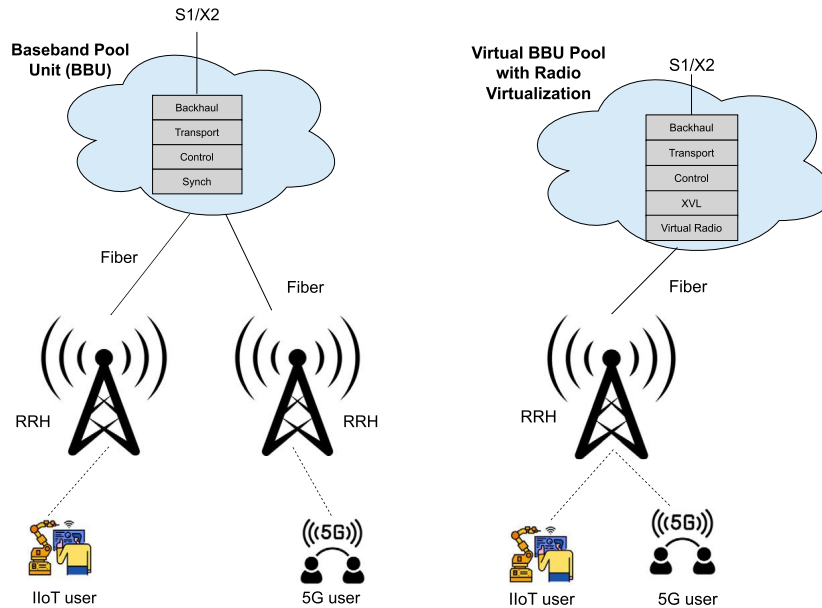
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6.1 Introduction

In the 6G era, there is vast growth in industrial applications, smart cities, Intelligent Transportation Systems (ITS), smart agriculture, and smart healthcare [1]. All these applications are governed under the umbrella of Internet of Things (IoT) networks. For the seamless operation of each application, the IoT ecosystem must ensure both scalability and sustainability to accommodate the increasing connectivity demands and long-term efficiency. Traditional IoT architectures rely on fixed, hardware-centric infrastructures that lead to inefficient power usage, increased operational costs, and a high carbon footprint. As a next-generation communication paradigm, 6G strides toward addressing these sustainability concerns by leveraging Artificial Intelligence (AI), Network Function Virtualization (NFV), Software-defined Networking (SDN), and Software-defined Radios (SDRs) to build a more energy-efficient, scalable, and adaptive IoT ecosystem [2].

One of the main challenges in IoT sustainability is high energy consumption. Many IoT applications, particularly in remote, rural, and industrial environments, rely on battery-operated devices. These devices need to function for extended periods with minimal energy usage. Such devices should be capable of operating for long periods while consuming less energy. Consequently, the widespread deployment of IoT sensors, edge devices, and gateways necessitates an effective approach to power management. Inefficient energy utilization increases maintenance costs and compromises environmental integrity. Additionally, spectrum scarcity and inefficient resource allocation further limit the potential of IoT networks, especially Multi-Radio Access Technologies (Multi-RATs) [3]. Multi-RATs include Narrow Band IoT (NB-IoT), Long Term Evolution for Machines (LTE-M), Long Range (LoRa), and 5G, operating simultaneously one or more. Traditional hardware-related network solutions are rigid and do not efficiently allocate resources on demand across different IoT applications, leading to inefficient spectrum usage and hardware redundancy [4].



(a) Radio Access Network without Virtual Radio Implementation

(b) Radio Access Network with Virtual Radio Implementation

FIGURE 6.1

Radio access network with (right) and without (left) virtual radio implementation.

To tackle these sustainability challenges, 6G-enabled AI-driven SDRs and virtualization techniques are the potential alternatives. The integration of 6G and AI in the domain of virtualization offers adaptive, programmable, and energy-efficient IoT network solutions. SDRs replace traditional fixed-function radio hardware with re-configurable, software-controlled systems, enabling seamless adaptation to different IoT communication standards without requiring separate hardware infrastructures for each RAT. As a result, it reduces power consumption, enhances spectral efficiency, and minimizes infrastructure costs. Additionally, NFV and SDN enable the dynamic allocation of network resources, ensuring that IoT connectivity remains sustainable, cost-effective, and scalable.

SDR-based virtualization benefits in reducing hardware redundancy. Since a virtual logical network could be created over a single hardware platform. The physical layer parameters could be adaptive based on the RAT through an SDN. In traditional IoT deployments, multiple base stations or gateways are required to support different RATs, leading to hardware redundancy and excessive energy consumption. By virtualizing SDRs, a single Remote Radio Head (RRH) can dynamically switch between multiple RATs (e.g., NB-IoT, LTE, 5G, V2X) based on network demand. Fig. 6.1 depicts the SDR-based virtualization to enable each standard. This eliminates the need

for separate infrastructure for different RATs. AI-driven dynamic resource allocation further enhances the sustainability of IoT networks by intelligently managing spectrum allocation, transmission power, and network slicing in real time. This enables IoT applications to efficiently balance energy efficiency, latency, and data throughput based on contextual requirements [5].

The need for Multi-RAT support in IoT networks is becoming increasingly hot as heterogeneous IoT network users demand diverse services. These diverse services include High-Definition (HD) streaming, Virtual Reality (VR), Augmented Reality (XR), and remote driving. Each service has its own Key Performance Indicators (KPIs), such as throughput, guaranteed bandwidth, transmission power, and reliability. To enable such diverse services, different physical layer technologies are required, such as Orthogonal Frequency Division Multiplexing (OFDM) / Non-Orthogonal Frequency Multiple Access (NOMA). Each RAT has its own physical layer design tailored to its specific requirements [6]. In a typical smart city or industrial IoT deployment, different IoT applications may require low-power connectivity (e.g., NB-IoT, LTE-M), broadband access (e.g., 5G), Ultra-Reliable Low-Latency Communication (URLLC), or integration with satellite-based Non-Terrestrial Networks (NTN) solutions. However, traditional networking architectures struggle to efficiently accommodate these diverse requirements. Traditionally, each RAT has its dedicated physical infrastructure, leading to unnecessary hardware deployment and scalability issues. For example, fixed infrastructure allocation can be inefficient, as demand for specific services fluctuates over time. Some services may require more resources at certain times, while others remain underutilized. By leveraging SDR-based virtualization, IoT networks can achieve seamless multi-RAT support through AI-driven spectrum management, dynamic RAT selection, and intelligent power optimization [7].

In this chapter, we explore how SDR-based virtualization can revolutionize IoT sustainability by enabling dynamic, software-driven network architectures. We begin by discussing the fundamentals of SDRs and network virtualization in the context of IoT, followed by an in-depth analysis of AI-driven multi-RAT support, energy-efficient resource allocation, and network slicing for sustainable IoT networks. Additionally, we examine the role of AI in optimizing virtualized SDR networks, ensuring low power consumption, seamless connectivity, and intelligent spectrum management. Finally, we highlight key challenges and future research directions for achieving a green and sustainable IoT ecosystem in 6G and beyond.

6.2 Fundamentals of Software-Defined Radios (SDRs) and virtualization

The advent of wireless communication has opened the gates for the creation of more flexible, multidimensional, and power-effective networking techniques. SDRs are instrumental in bringing about such a change by substituting the conventional hardware-based radio systems with software-defined reconfigurable architectures [8].

Whereas traditional radios are designed to work on pre-configured frequency and modulation modes, SDRs offer the flexibility to modify parameters like frequency bands, transmit power, and modulation schemes in real-time via software updates. Such programmability renders SDRs as the perfect choice for multi-RAT use cases, where one hardware platform can cater to various communication standards like 5G, NB-IoT, LTE-M, V2X, NTN, and Wi-Fi.

The requirement of sustainability in IoT networks is promoting the use of SDRs since they lessen the dependency on hardware, decrease infrastructure expenditure, and enhance spectral efficiency. Through the cognitive radio feature, SDRs can intelligently sense free frequency bands and dynamically assign resources, hence guaranteeing maximum spectrum usage while reducing energy consumption. This is especially important in large-scale IoT deployments, where billions of interconnected devices demand energy-efficient and scalable communications [9]. SDRs provide on-demand reconfiguration of IoT networks, adjusting to evolving network conditions and traffic loads without the cost of hardware upgrades.

To enhance the performance of SDR networks, virtualization technologies such as NFV and SDN have been proposed as facilitators of sustainable IoT paradigms. NFV allows the implementation of traditional network functions as software-based services on standard hardware, thus reducing the need for specialized physical infrastructure. By virtualizing network elements like firewalls, routers, and base stations, IoT networks become more scalable, cost-effective, and energy efficient. Similarly, SDN decouples the control plane and data plane, managing the networks in a centralized way and intelligently steer the traffic [10].

Employing virtualization, an SDR can support multi-RAT environments in a single hardware deployment. By combining virtualized SDRs, NFV, and SDN, network operators can deploy one RRH that can switch dynamically between various communication standards. This feature provides end-to-end connectivity for IoT use cases demanding low-power wide-area connectivity (LoRa, NB-IoT), broadband connectivity (5G), or URLLC.

Virtualized SDRs provide several key benefits for green IoT networks, with power-efficient spectrum utilization being one of the most significant. AI-powered cognitive networking techniques enable dynamic spectrum allocation, optimizing the use of frequency resources. Traditional wireless networks often suffer from inefficient spectrum utilization, where some frequency bands remain underused while others become overcrowded. Virtualized SDRs address this limitation by sensing real-time spectrum demand and dynamically allocating bandwidth, allowing IoT devices to transmit at optimal energy levels.

IoT service demand-based dynamic reconfiguration is another key aspect of SDR virtualization. IoT applications pose varying communications demands, from low-power periodic data transfer (smart metering, environmental monitoring) to high-bandwidth real-time processing (industrial control, autonomous vehicles). Virtualized SDRs can dynamically adapt transmission parameters, power levels, and RAT selection according to the demands of each IoT application. This flexibility makes smart cities, healthcare systems, and industrial Internet of Things systems operate more effectively, consume less power, and lower operational costs.

Additionally, SDR virtualization enables network slicing and multi-tenancy, in which multiple IoT service providers use a shared virtualized infrastructure. Each provider has an isolated, independent network slice tailored to their specific application. This enables a cost-effective deployment of IoT networks as the infrastructure investments can be shared and optimized across various applications and industries [11].

6.3 Sustainable IoT networks with SDR virtualization

The sustainability of IoT networks depends upon optimized resource utilization. Virtualized SDRs significantly reduce energy consumption through adaptive power control and intelligent waveform selection. Unlike traditional networks, where radio transmitters work with fixed-power levels. Further, the integration of AI allows IoT devices to utilize resources more efficiently. AI-enabled framework distribute the radio resources fairly among the virtual radios employed over the SDR [12].

SDR virtualization, coupled with AI, supports green network slicing to enhance IoT sustainability. Demand-oriented IoT resource allocation can be enabled, ensuring that low-power IoT applications receive the minimum bandwidth required, while high-performance applications obtain sufficient resources without excessive energy consumption [13].

6.4 Multi-RAT virtualized Remote Radio Head (RRH) for 6G IoT

The rising demand for scalable, energy-efficient, and flexible wireless communication infrastructure has driven the evolution of Multi-RAT virtualized RRHs [14]. Unlike traditional networks, where each RAT—for instance, NB-IoT, LTE-M, 5G, V2X, and NTN requires its dedicated radio access infrastructure, thereby leading to considerable hardware redundancy, high power consumption, and poor spectrum utilization, software-defined radios (SDRs) and virtualization technologies enable a single virtualized RRH to flexibly switch multiple RATs to enhance the efficiency, sustainability, and cost efficiency in networking. Such shifts will form the basis for the development of 6G-enabled IoT networks, where the requirements for heterogeneous connectivity must be fulfilled with the least possible energy usage and costs [15].

6.4.1 Concept of a virtualized RRH for IoT

A virtualized RRH is characterized as a flexible radio access unit operating over multiple RATs and dynamically responsive to the communication requirements of IoT applications [16]. Traditionally, dedicated base stations are designed for certain wireless standards, each works on a fixed frequency band and protocol. This often results

in energy wastage and severely limited scalability. Using SDR-based virtualization, any RRH can provide support for multiple RATs efficiently, thereby allowing IoT devices to connect whenever needed by using the most efficient connectivity standard [17].

An IoT sensor network for smart city development, for example, can very well use NB-IoT and LTE-M for low-power, long-range communication. Real-time video surveillance or autonomous vehicles could be supported with 5G or 6G millimeter-wave communications by switching RRH. The RRH can also incorporate NTN-based satellite communication for remote communication and to enable continuous connectivity for IoT. This unique capability to dynamically allocate RATs enables the operators to optimize infrastructure costs and spectrum efficiency.

AI-driven dynamic RAT selection

The AI-oriented RAT selection is one of the very powerful features of a virtualized RRH [18]. Different IoT applications have diverse requirements for data rate, latency, reliable delivery, and energy consumption. AI-based decision-making frameworks could analyze the network condition, node mobility, traffic load, and existing power availability and select the most suitable RAT in real time. For example, AI can classify IoT traffic into different categories:

- Low-power, delay-tolerant applications (e.g., smart meters, environmental sensors) characterized under NB-IoT or LTE-M.
- Ultra-reliable low-latency applications (e.g., autonomous vehicles, remote surgery) characterized under 5G URLLC.
- High-bandwidth applications (e.g., drone-based video streaming, XR/VR for IoT) characterized under 6G mmWave or Terahertz bands.
- IoT deployments in remote areas (e.g., maritime IoT, disaster recovery) characterized under NTN (LEO satellites, HAPs, UAV relays).

The adaptive selection of the RAT ensures sustainability towards IoT networks while giving resilience and scalability for a variety of applications, each configured through scalable QoS, without wasting energy or over-provisioning resources.

6.4.2 Hardware and architecture of virtualized SDR-based RRH

The implementation of virtualized RRHs involves both SDR hardware along with AI-enabled network management and virtualization on cloud computing. Unlike traditional RRHs, which rely on dedicated, static radio hardware, the virtualized SDR-based RRH consists of flexible radio front-end, reconfigurable baseband processing, and intelligent spectrum management [19].

Virtualized RRH with dynamic waveform adaptation

Another fundamental capability of a virtualized RRH is its direct adaptability of the waveforms instantaneously based on the RAT in operation. In a legacy centralized system, distinct RAT uses different waveform structures (OFDM in 5G, Single

Carrier Frequency Division Multiple Access (SC-FDMA) in LTE, and narrowband modulations in NB-IoT). The RRH, through the use of SDR technology, is free to dynamically modulate and demodulate the signal, thereby allowing for the use of many different standards and without a need for hardware modifications [20].

Along with AI-based waveform adaptation, this ensures that higher energy efficiency is maintained, as the most power-efficient transmission mode is selected in real time according to prevailing network conditions. For example, during low-traffic conditions, the RRH can adopt low-power waveforms with reduced transmission bandwidth, conserving energy before resuming normal operational settings when needed [21].

Efficient spectrum sharing and low-power SDR base stations

Spectrum efficiency is crucial for sustainability in IoT networks. The conventional usage of pre-allocated spectrum bands in cellular networks leads to inefficient spectrums and interference problems. The virtualized RRH allows the dynamic spectrum access, where idle frequency bands could be reallocated to active IoT devices, thus reducing the wastage of spectrum while enhancing the overall efficiency of networks [22].

Low-power software-defined radio base stations can also be established within the virtualized RRH structure to serve a localized IoT cluster such as smart factories, connected transportation hubs, and industrial automation zones. These light-weight, software-defined base stations work from optimized power to severely limit the carbon footprint of traditional cell towers while providing custom network slices for IoT applications.

6.4.3 Use cases of virtualized multi-RAT RRH in IoT

Dynamic NB-IoT and 6G network allocation

Smart cities rely on various heterogeneous deployments of IoT, involving environmental sensor, traffic management systems, public safety networks, and energy grids [23]. To fully utilize the resources efficiently, virtualized RRH enables NB-IoT connectivity to the low-data applications and 5G connectivity to high-data applications such as real-time surveillance.

Multi-RAT support for vehicular communication

To support autonomous vehicles connectivity two major technologies have been introduced such as IEEE 802.11P in 2010 and Cellular Standard C-V2X in 2017. Later, 802.11P evolved to 802.11bd and C-V2X to NR-V2X. To provide interoperability, a virtualized RF end could be utilized [24]. Also, based on the applications the network traffic load could be shifted among the technologies. These heterogeneous technologies could be enabled by virtualization over a single hardware. By enabling dynamic RAT switching, virtualized RRHs significantly enhance road safety and network sustainability.

Satellite-based NTN for IoT

Many IoT applications demand connectivity in areas that are remote, offshore, or disaster-prone where terrestrial networks are unavailable. NTN-based IoT communication, facilitated by LEO satellites, HAPs, and UAV relays, plays a vital role in ensuring global IoT coverage [25]. A virtualized RRH may integrate satellite-based RATs that complement terrestrial networks 5G and NB-IoT to allow IoT devices to seamlessly switch from terrestrial to satellite communication links, as depicted in Fig. 6.2. As an example, this includes an IoT-enabled maritime monitoring system. Using NB-IoT connectivity while near coastal areas and switching to satellite-based NTN when in deep-sea locations. This type of model guarantees continuous connectivity, reduced satellite bandwidth costs, and enhanced power conservation.

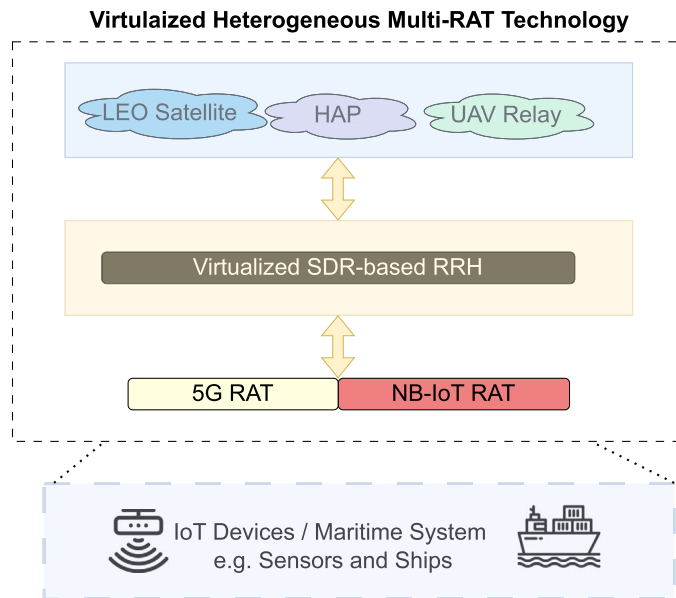


FIGURE 6.2

Virtualized heterogeneous Multi-RAT to support low-latency space–air–ground communication.

6.5 AI-driven dynamic resource allocation for sustainable IoT SDR networks

The use of artificial intelligence and machine learning in the virtualization of software-defined radio is an essential step toward energy-efficient, adaptive intelligent resource allocation in sustainable IoT networks. Conventional resource allocation techniques in wireless networks depend on pre-fixed rules and static policies,

which yield suboptimal performance, resulting in ineffective spectrum utilization and high-power consumption [26]. The enormous growth of 6G IoT networks encompasses AI-driven dynamic resource allocation, offering real-time optimization, efficient network slicing, and maximum security, with low-latency, high-reliability for various IoT applications.

AI techniques such as Reinforcement Learning (RL), Federated Learning (FL), and deep neural networks further enhance the SDR-based virtualized networks [27]. IoT networks learn from data, adapt to changes, and dynamically deploy resources, enabling multiple RAT-based SDR networks to be efficient and sustainable. In addition, AI-based anomaly detection and blockchain-based security framework further enhance virtualized IoT networks considering reliability and security.

6.5.1 Machine learning for efficient SDR virtualization

Reinforcement Learning (RL) for adaptive radio resource management

RL refers to a machine learning paradigm wherein an agent learns how to achieve its objective through trial and error by interacting with the environment. Based on real-time network conditions, SDN-based IoT networks can dynamically allocate radio resources, like spectrum management and power optimization in real time [27], [28].

Unlike traditional scheduling algorithms that use static spectrum policies, the dynamic adjustment of transmission parameters, power levels, and frequency allocations by means of RL-based resource management aims at increasing efficiency while minimizing energy consumption. For example, in a multi-RAT IoT deployment, RL can:

- Predict network traffic patterns and provision bandwidth before congestion occurs.
- Modify IoT transmission power in response to proximity to other devices and interference from the environment.
- Choose the best RAT in terms of energy efficiency (e.g., NB-IoT for low power consumption, 5G for very high-speed data) in accordance with the demand of the network.
- Using RL-based SDR virtualization may allow IoT networks to self-optimize this process in real time, minimizing the need for human intervention and reducing energy losses and operational costs.

Federated Learning (FL) for distributed AI-based IoT networking

FL is a decentralized AI training in which multiple IoT devices and base stations can collaboratively train AI models without exchanging sensitive data. FL is thus a determinant in preserving privacy, energy efficiency, and AI-based resource management when applied in the context of SDR-based virtualized IoT networks.

FL permits limited distribution learning on all the IoT edge devices, such that SDR networks learn using localized data without relying on cloud-based computation that incurs high latency and energy costs [29]. Some of the advantages of FL in SDR virtualization include:

- Decentralized training for artificial intelligence models, which diminishes the level of congestion in the network and energy usage.
- Spectrum allocation while remaining private, with IoT devices optimizing radio parameters locally without open exposure of sensitive data.
- Modification of higher priority PLMN selection to include shared Mobile Country Code (MCC).
- Increased the accuracy of AI models through collaboration with many IoT nodes.

With the implementation of FL-sustained SDR networks, IoT operators are able to achieve scalable, adaptive, and extremely energy-efficient virtualized IoT connectivity, especially in smart and city, industrial automation, and remote IoT deployments.

6.5.2 Optimizing IoT network slices with AI

Energy-efficient scheduling for IoT edge and core networks

AI-enabled scheduling algorithms will allow for efficient, dynamic task allocation in energy-efficient modes between edge and core network layers in SDR-based virtualized IoT networks [30]. Instead of processing all IoT-generated data on a centralized cloud server, AI-based scheduling will ensure that only high-priority tasks are relayed to the core, while routine, low-latency tasks are executed at the edge.

For example:

- IoT sensors in smart cities can process local temperature readings themselves instead of clouds receiving raw data.
- Industrial IoT (I-IoT) applications can delegate real-time control tasks to SDR-based edge networks to relieve processing delays.
- V2X networks allow for intelligent switching between depending on low-latency applications using edge processing or cloud AI inference through an intelligent system.

AI-enabled performing based processing distributions optimize energy usage and ensure low latency and reduced unnecessary data transmission between SDR-enabled IoT edge devices and centralized cloud networks [31].

AI-based QoS-aware dynamic RAT switching

Quality-of-Service (QoS) needs from various applications in the context of 6G IoT networks vary widely [32]. Smart agriculture sensors, autonomous vehicles, industrial automation, and AR/VR IoT applications require different levels of data rates, latency, and reliability. Dynamic RAT switching using AI ensures that:

- Low-power IoT devices maximize energy savings through NB-IoT/LTE-M.
- Ultra-low latency applications (for example, V2X, AR/VR) can switch to 5G or 6G when needed.
- Tasks that require high bandwidth demands (for example, video streaming, AI inference at the edge) can leverage the higher frequency mmWave/Terahertz bands.

The AI-based RAT switching makes real-time traffic analysis, predictive modeling, and reinforcement learning to connect IoT devices with the most energy-efficient and QoS-compliant RAT in real time, which leads to optimized spectral efficiency, minimal energy waste, and smooth connectivity for various IoT applications [33].

6.5.3 Security and privacy in virtualized IoT SDR networks

AI-driven anomaly detection for energy-efficient security

With the virtualization of SDRs into the IoT, security threats have become more complex, such as signal jamming, unauthorized spectrum access, and cyber-attack. Traditional signature-based Intrusion Detection Systems (IDS) are ineffective in handling the large volume and diverse data generated by SDRs [34]. AI-based anomaly detection overcomes this, employing:

- Machine learning models trained on network traffic behavior to flag suspicious patterns.
- An energy-efficient security mechanism to automatically mitigate malicious activities with light computational loads.
- A self-adaptive security algorithm that changes over time, dynamically discovering new attack.

Through AI-based security monitoring, virtualized SDRs can keep detecting and mitigating threats continuously while consuming less power and a small computational load.

Blockchain-based secure network slicing for IoT and 6G

Network slicing in SDR-based virtualized IoT networks allows the creation of isolated logical networks for different applications [35]. Maintaining slices with security and privacy turns into a difficult task, mainly due to multi-tenancy and the dynamic nature of resource allocation. Blockchain technology offers the decentralized and immutable integrity framework for enhancing SDR-based network slicing by:

- Ensuring the resource allocation records are transparent.
- Preventing unauthorized access to the network slices through cryptographic authentication.
- Making use of smart contracts for automatic policy-based execution in network configuration.

Therefore, blockchain and SDR integration safeguard IoT operators in ensuring secured virtualized networks by preventing them from cyber-attacks.

6.6 Challenges and future research directions

Since SDR-based virtualization are being evolved, some challenges need to be tackled to achieve scalable, energy-efficient, and ideally secure IoT networks. While SDR

virtualization does provide multi-RAT flexibility, spectrum efficiency, and adaptive resource management, issues related to interference, hardware efficiency, URLLC, and integration with 6G NTN remain key areas for future research.

This section discusses the major technology-related challenges in deploying SDR-based virtualized IoT networks and discusses possible research directions that can help overcome these limitations.

6.6.1 Interference management in virtualized multi-RAT SDR

The prime challenge in SDR-based virtualized networks is interference management, especially when multiple RATs are operating simultaneously. Unlike in traditional networks, each RAT operates over pre-defined frequency bands [36]. However, multi-RAT SDR virtualization allows dynamic spectrum sharing, thereby increasing the probability of co-channel interference, internal RAT collision, and adjacent channel leakage.

Challenges

- The coexistence of varied radio access technologies results in interference, lowering performance on the SDR platform.
- Adaptive waveform switching for SDRs can generate unwanted harmonics and intermodulation distortion and lower spectral efficiency.
- Advanced detection and mitigation of noise sources, such as IoT devices, legacy wireless systems, and NTN communications, need to be developed.

Future research directions

- AI-Powered Interference Prediction: Machine learning models analyze spectrum utilization patterns and proactively devise allocations to non-overlapping resources to different access technologies [37].
- Dynamic Spectrum Access (DSA) Strategies: Cognitive software-defined radio using artificial intelligence is capable of performing real-time frequency hopping and adaptive power control to mitigate interference [38].
- Multi-Agent Reinforcement Learning (MARL) for Spectrum Coordination: AI-based multi-agent frameworks can enable collaborative interference management, allowing SDR nodes to autonomously negotiate spectrum access in dense IoT environments.

6.6.2 Energy-efficient SDR hardware for IoT and V2X

Although SDR virtualization reduces hardware dependence, power consumption is one of the major challenges for IoT edge devices and vehicular networks (V2X). SDRs for real-time waveform processing require highly accurate Digital Signal Processing (DSPs) and Field-programmable Gate Arrays (FPGAs), which in many cases results in excessive power consumption and thermal dissipation [39].

Challenges

- Computational overhead increases power consumption on SDR-based IoT devices and reduces battery life.
- The high-energy requirements results in setbacks for deployment in low-power IoT scenarios.
- Vehicular networks (V2X) need ultra-fast SDR-based signal processing techniques to maintain low latency with energy efficiency.

Future research directions

- AI-Optimized SDR Hardware Acceleration: Machine learning algorithms can optimize signal processing pipelines, thus reducing computational redundancy and wastage of energy.
- Building Ultra-Low-Power SDR Chips: Building specialized SDR hardware with built-in AI acceleration (e.g., neuromorphic computing, AI-driven DSP) can significantly reduce energy consumption in IoT applications.
- Green SDR Hardware Architectures: Energy-harvesting SDRs that use solar, RF, or kinetic energy can improve sustainability in remote IoT deployments [40].

6.6.3 AI-driven RAT selection for ultra-reliable low-latency IoT (URLLC IoT)

With URLLC connectivity for communications, such as that between connected cars, industrial automation, and mission-critical IoT, requires delays as low as 1 ms and reliability levels of more than 99.999% [41]. It is essential to apply AI to the selection of RATs to ensure that communication for URLLC IoT applications occurs through the most reliable and low-latency service standards at any point in time. However, achieving real-time AI-based RAT switching while maintaining reliability and energy efficiency remains a challenge.

Challenges

- Real-time decision-making for RAT selection requires ultra-fast AI inference, which increases the computational demands.
- Switching between RATs introduces transient latency, which could affect time-sensitive applications such as autonomous driving and remote surgery.
- Ensuring network reliability in high-mobility environments (such as V2X, UAVs, and industrial IoT) provides a great challenge when trying to achieve seamless integration among multiple RATs.

Future research directions

- Deep Reinforcement Learning (DRL) for Real-Time RAT Selection: AI models trained on large IoT traffic datasets can predict network conditions, allowing for proactive RAT switching before link degradation occurs.
- AI-Based Proactive Handover Mechanisms: Applying predictive handover techniques based on AI-driven policy (for vehicles, drones, and mobile robots) allows to further improve URLLC reliability.

- AI-enabled Network Slicing for URLLC Applications: AI-based dynamic network slicing allows prioritization of URLLC traffic above other IoT services to secure ultra-low-latency connectivity [42].

6.6.4 SDR virtualization for 6G NTN & space communications

NTN, including Low Earth Orbit (LEO) satellites, High Altitude Platforms (HAPs), and Unmanned Aerial Vehicles (UAV) based relay networks, are becoming integral components of 6G IoT architectures. SDR virtualization will enable seamless integration between terrestrial and space-based IoT networks, but still has enormous challenges to overcome.

Challenges

- Dynamic radio environment in NTN makes SDR-based waveform adaptation complex, whereas Doppler shifts, propagation delays, and signal blockages vary for satellite and aerial platforms.
- Limited energy resources in space-based IoT platforms make power-efficient SDR virtualization critical for extending the lifetime of satellites.
- Interference and spectrum coordination of terrestrial and NTN IoT networks require AI-aided spectrum-sharing techniques and advanced strategies.

Future research directions

- AI-Driven SDR Virtualization for NTN Spectrum Management: Cognitive SDR systems driven by AI can adapt to the modulation and coding scheme according to dynamic factors like satellite trajectory, weather conditions, and spectrum availability.
- SDR-Enabled Multi-RAT NTN Connectivity: Virtualized SDRs implemented on LEO satellites and UAVs can extend cross-domain connectivity by dynamically switching between NTN 5G, THz communications, and terrestrial IoT networks.
- Energy Efficient SDR Platforms for NTN: Energy-saving techniques include AI-powered sleep scheduling, dynamic beamforming, and adaptive power control [43].

6.7 Conclusions

The evolution to 6G-based IoT networks demands scalable, energy-efficient, and intelligent solutions to cater to the increasing complexity of heterogeneous IoT applications. SDR-based virtualization and AI-powered resource allocation provide a breakthrough solution to achieve sustainability demands, enabling dynamic spectrum utilization, hardware dependency minimization, and power efficiency optimization. This chapter covers how SDR virtualization is used to develop Multi-RAT interoperability for enabling an NB-IoT, LTE, 5G, V2X, and NTN capability using a single piece of hardware.

AI-optimized dynamic resource allocation, one of the key enablers of SDR-based sustainable IoT, dynamically optimizes network slicing, RAT selection, and energy-aware scheduling. RL-FL integrated solution supports real-time adaptation to network conditions, ensuring low-latency, high-reliability connectivity for autonomous vehicle, industrial automation, and smart city infrastructure use cases. AI-aided interference management and waveform adaptation also optimize spectrum efficiency, ensuring seamless communication in IoT-rich environments. Though it has benefits, some challenges still exist, such as handling interference in virtualized multi-RAT SDRs, enhancing energy efficiency in hardware implementations, providing ultra-reliable low-latency communication (URLLC) for mission-critical use cases, and incorporating SDR virtualization into 6G NTN-based IoT deployments.

Future work should concentrate on the design of ultra-low-power SDR chips, AI-driven proactive RAT switching, and blockchain-secured network slicing for improved network security, power efficiency, and decentralized trust management. Through evolving 6G networks, SDR virtualization, AI automation, and NTN-based connectivity will shape the future of green IoT ecosystems. Self-optimizing, intelligent, and energy-efficient SDR architectures, when incorporated into future IoT infrastructures, have the potential to achieve seamless global connectivity, carbon footprint reduction, and enhanced network resilience to establish a greener, smarter, and adaptive future IoT.

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References

- [1] J.S. Yalli, M.H. Hasan, A. Badawi, Internet of Things (IoT): origin, embedded technologies, smart applications and its growth in the last decade, *IEEE Access* (2024).
- [2] R. Kumar, S.K. Gupta, H.-C. Wang, C.S. Kumari, S.S.V.P. Korlam, From efficiency to sustainability: exploring the potential of 6g for a greener future, *Sustainability* 15 (23) (2023) 16387.
- [3] M.A. Altafrawi, N.F. Abdullah, R. Nordin, M. Ismail, Multi-radio access software-defined vehicular network, *IEEE Transactions on Intelligent Transportation Systems* 23 (8) (2021) 10030–10048.
- [4] R.M. Sandoval, S. Canovas-Carrasco, A.-J. Garcia-Sanchez, J. Garcia-Haro, A reinforcement learning-based framework for the exploitation of multiple rats in the IoT, *IEEE Access* 7 (2019) 123341–123354.

- [5] Y. Ye, C. Pan, C. Zhang, A performance evaluation method based on virtualization architecture, in: 2024 Fifteenth International Conference on Ubiquitous and Future Networks (ICUFN), IEEE, 2024, pp. 390–394.
- [6] M.M. Saad, F.A. Bhatti, A. Zafar, S. Jangsher, D. Kim, M. Maqsood, Air-interface virtualization using filter bank multicarrier and orthogonal frequency division multiplexing configurations, *Transactions on Emerging Telecommunications Technologies* 32 (2) (2021) 4154.
- [7] M. Polese, M. Dohler, F. Dressler, M. Erol-Kantarci, R. Jana, R. Knopp, T. Melodia, Empowering the 6g cellular architecture with open ran, *IEEE Journal on Selected Areas in Communications* 42 (2) (2023) 245–262.
- [8] M.R. Maheshwarappa, Software Defined Radio (SDR) Architecture for Concurrent Multi-Satellite Communications, University of Surrey, United Kingdom, 2016.
- [9] B. Rana, Y. Singh, P.K. Singh, A systematic survey on Internet of Things: energy efficiency and interoperability perspective, *Transactions on Emerging Telecommunications Technologies* 32 (8) (2021) e4166.
- [10] R. Ferrús, H. Koumaras, O. Sallent, G. Agapiou, T. Rasheed, M.-A. Kourtis, C. Boustie, P. Gélard, T. Ahmed, Sdn/nfv-enabled satellite communications networks: opportunities, scenarios and challenges, *Physical Communication* 18 (2016) 95–112.
- [11] C. Tsirakis, P. Matzoros, G. Agapiou, State-of-the-Art on Virtualization and Software Defined Networking for Efficient Resource Allocation on Multi-Tenant 5g Networks, *MATEC Web of Conferences*, vol. 125, EDP Sciences, 2017, p. 03009.
- [12] D. Robu, T. Balan, A. Stanciu, F. Sandu, Sdr-assisted device-to-device communication in radio-congested environments, in: 2017 IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB), IEEE, 2017, pp. 1–7.
- [13] M.A. Albreem, A.M. Sheikh, M.H. Alsharif, M. Jusoh, M.N.M. Yasin, Green Internet of Things (GloT): applications, practices, awareness, and challenges, *IEEE Access* 9 (2021) 38833–38858.
- [14] K. Zia, A. Chiumento, P.J. Havinga, AI-enabled reliable qos in multi-rat wireless IoT networks: prospects, challenges, and future directions, *IEEE Open Journal of the Communications Society* 3 (2022) 1906–1929.
- [15] J.M.C.S.d. Bastos, Energy efficient radio resource management for heterogeneous networks, 2019.
- [16] M. Kist, Radio and baseband unit virtualization: pushing the boundaries of future mobile networks, 2020.
- [17] M. Kist, J.F. Santos, D. Collins, J. Rochol, L.A. DaSilva, C.B. Both, Airtime: end-to-end virtualization layer for ran-as-a-service in future multi-service mobile networks, *IEEE Transactions on Mobile Computing* 21 (8) (2020) 2701–2717.
- [18] N.H. Mahmood, H. Alves, O.A. López, M. Shehab, D.P.M. Osorio, M. Latva-Aho, Six key features of machine type communication in 6g, in: 2020 2nd 6G Wireless Summit (6G SUMMIT), IEEE, 2020, pp. 1–5.
- [19] A. Vlahov, D. Ekova, V. Poulkov, T. Cooklev, Virtualized, open and intelligent: the evolution of the radio access network, in: 6G Enabling Technologies, Publishers, River, 2023, pp. 181–214.
- [20] L.B. Le, V. Lau, E. Jorswieck, N.-D. Dao, A. Haghighat, D.I. Kim, T. Le-Ngoc, Enabling 5g Mobile Wireless Technologies, 2015.
- [21] F.A. de Figueiredo, R. Mennes, I. Jabandžić, X. Jiao, I. Moerman, A baseband wireless spectrum hypervisor for multiplexing concurrent ofdm signals, *Sensors* 20 (4) (2020) 1101.

- [22] S.A. Gbadamosi, G.P. Hancke, A.M. Abu-Mahfouz, Building upon nb-IoT networks: a roadmap towards 5g new radio networks, *IEEE Access* 8 (2020) 188641–188672.
- [23] K. Boz, Integration of a cellular Internet-of-Things transceiver into 6g test network and evaluation of its performance, Master's thesis, 2023.
- [24] R. Jacob, N. Franchi, G. Fettweis, Hybrid v2x communications: multi-rat as enabler for connected autonomous driving, in: 2018 IEEE 29th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), IEEE, 2018, pp. 1370–1376.
- [25] S. Plastras, D. Tsoumatidis, D.N. Skoutas, A. Rouskas, G. Kormentzas, C. Skianis, Non-terrestrial networks for energy-efficient connectivity of remote IoT devices in the 6g era: a survey, *Sensors* 24 (4) (2024) 1227.
- [26] J. Cunha, P. Ferreira, E.M. Castro, P.C. Oliveira, M.J. Nicolau, I. Núñez, X.R. Sousa, C. Serôdio, Enhancing network slicing security: machine learning, software-defined networking, and network functions virtualization-driven strategies, *Future Internet* 16 (7) (2024) 226.
- [27] N.M. Yungaicela-Naula, V. Sharma, S. Scott-Hayward, Misconfiguration in o-ran: analysis of the impact of ai/ml, *Computer Networks* (2024) 110455.
- [28] A. Mudvari, N. Makris, L. Tassiulas, Exploring ml methods for dynamic scaling of beyond 5g cloud-native rans, in: ICC 2022-IEEE International Conference on Communications, IEEE, 2022, pp. 2284–2289.
- [29] D.C. Nguyen, M. Ding, P.N. Pathirana, A. Seneviratne, J. Li, H.V. Poor, Federated learning for Internet of Things: a comprehensive survey, *IEEE Communications Surveys and Tutorials* 23 (3) (2021) 1622–1658.
- [30] H. Gu, L. Zhao, Z. Han, G. Zheng, S. Song, Ai-enhanced cloud-edge-terminal collaborative network: survey, applications, and future directions, *IEEE Communications Surveys and Tutorials* 26 (2) (2023) 1322–1385.
- [31] D. Kafetzis, S. Vassilaras, G. Vardoulas, I. Koutsopoulos, Software-defined networking meets software-defined radio in mobile ad hoc networks: state of the art and future directions, *IEEE Access* 10 (2022) 9989–10014.
- [32] R. Ahmed, M.R. Mahmood, M.A. Matin, Challenges in meeting qos requirements toward 6g wireless networks: a state of the art survey, *Transactions on Emerging Telecommunications Technologies* 34 (2) (2023) e4693.
- [33] A. Nauman, Y.A. Qadri, M. Amjad, Y.B. Zikria, M.K. Afzal, S.W. Kim, Multimedia Internet of Things: a comprehensive survey, *IEEE Access* 8 (2020) 8202–8250.
- [34] C. Gavrilă, V. Popescu, M. Alexandru, M. Murroni, C. Sacchi, An sdr-based satellite gateway for Internet of Remote Things (IoRT) applications, *IEEE Access* 8 (2020) 115423–115436.
- [35] T. Ahmed, A. Alleg, N. Marie-Magdelaine, An architecture framework for virtualization of IoT network, in: 2019 IEEE Conference on Network Softwarization (NetSoft), IEEE, 2019, pp. 183–187.
- [36] E.T. Michailidis, K. Maliatsos, D. Vouyioukas, Software-defined radio deployments in UAV-driven applications: a comprehensive review, *IEEE Open Journal of Vehicular Technology* (2024).
- [37] A.J. Morgado, F.B. Saghezchi, S. Mumtaz, V. Frascolla, J. Rodriguez, I. Otung, A novel machine learning-based scheme for spectrum sharing in virtualized 5g networks, *IEEE Transactions on Intelligent Transportation Systems* 23 (10) (2022) 19691–19703.
- [38] A. Kaur, K. Kumar, A comprehensive survey on machine learning approaches for dynamic spectrum access in cognitive radio networks, *Journal of Experimental and Theoretical Artificial Intelligence* 34 (1) (2022) 1–40.

- [39] G.N. Nurkahfi, A. Triwinarko, B. Prawara, N. Armi, T. Juhana, N.R. Syambas, E. Mulyana, E. Dogheche, I. Dayoub, On sdn to support the IEEE 802.11 and C-v2x-based vehicular communications use-cases and performance: a comprehensive survey, *IEEE Access* 12 (2023) 95926–95958.
- [40] D. Das, M. Nasrollahpour, Z. Xu, M. Zaeimbashi, I. Martos-Repath, A. Mittal, A. Khalifa, S.S. Cash, A. Shrivastava, N.X. Sun, et al., A radio frequency magnetoelectric antenna prototyping platform for neural activity monitoring devices with sensing and energy harvesting capabilities, *Electronics* 9 (12) (2020) 2123.
- [41] O.N. Yilmaz, Y.-P.E. Wang, N.A. Johansson, N. Brahmi, S.A. Ashraf, J. Sachs, Analysis of ultra-reliable and low-latency 5g communication for a factory automation use case, in: 2015 IEEE International Conference on Communication Workshop (ICCW), IEEE, 2015, pp. 1190–1195.
- [42] M. Dubey, A.K. Singh, R. Mishra, Ai based resource management for 5g network slicing: history, use cases, and research directions, *Concurrency and Computation: Practice and Experience* 37 (2) (2025) e8327.
- [43] S. Mahboob, L. Liu, Revolutionizing future connectivity: a contemporary survey on AI-empowered satellite-based non-terrestrial networks in 6g, *IEEE Communications Surveys and Tutorials* 26 (2) (2024) 1279–1321.

Energy and spectrum efficient DRL-based algorithms to support sustainable IoT devices

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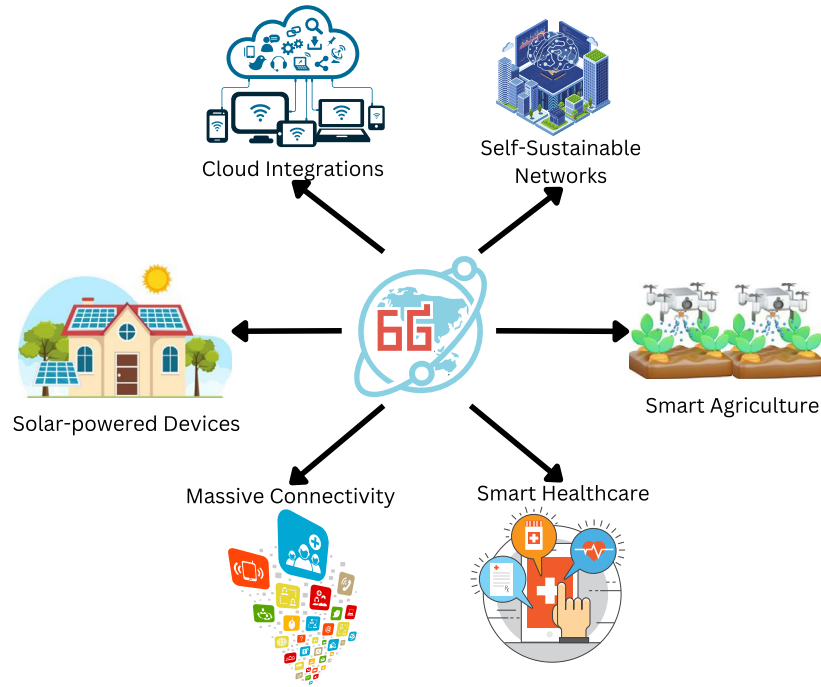
7.1 Introduction

In the past years, there has been an increasing demand of IoT devices in various areas such as smart applications and industrial automation. With this increase brings a challenge to produce energy and spectral efficient solutions for long-term sustainability. This section explores and identifies, deep reinforcement learning (DRL) based solutions to identify optimized solutions in terms of energy and spectrum efficiency.

7.1.1 Background and motivation

The paradigm shift from 5G to 6G era enabled concepts such as self-organizing networks (SONs) and self-sustainable networks (SSNs). Applications like smart cities, ultra-massive machine-type communication (umMTC), and ubiquitous instant connectivity are now building on these advancements being brought up by the 6G regime. In this context, the Internet of things (IoT) [1] enables intelligent communication with multiple objects interacting with each other seamlessly. This has interconnected ranging of areas from healthcare to agriculture, by enhancing decision making accuracy and increasing efficiencies. With the growth of IoT devices, there is an increasing demand of higher data rates, connectivity and reliability. The arrival of 6G networks is set to revolutionize IoT while supporting countless devices and applications.

In earlier generations, orthogonal frequency division multiple access (OFDMA) [2] has been widely used in various IoT and 6G models and applications. In OFDMA, bandwidth is divided into orthogonal subcarriers. Each subcarrier is assigned to a single user at any given time, minimizing inter user interference and providing flexibility in resource management. However, a major drawback of OFDMA is the strict orthogonality of the limited number of subcarriers that can be used simultaneously.

**FIGURE 7.1**

6G-enabled IoT ecosystems.

To overcome these limitations, non-orthogonal multiple access (NOMA) [3] has emerged as a promising solution. It offers superior spectral and energy efficiency, particularly in environments with diverse user requirements. NOMA uses power domain multiplexing and successive interference cancellation (SIC) at the receiver. This allows multiple users to share the same spectrum resources efficiently. This approach not only increases the number of supported users, but also improves spectrum utilization. A comparative analysis in [4] demonstrates that NOMA outperforms OFDMA in both spectral efficiency (SE) and energy efficiency (EE) under various network configurations (Fig. 7.1).

Recent studies have explored the integration of NOMA with cognitive radio (CR) to improve SE and EE. In [5], a framework integrating CR-NOMA with simultaneous wireless information and power transfer (SWIPT) is proposed, focusing on improving SE by optimizing the sensing sub slot. Similarly, [6] examines downlink multiple input multiple output (MIMO) NOMA systems, leveraging different linear beamforming strategies to enhance power allocation across user clusters, thereby achieving maximum sum of SE. Moreover, [7] proposes an energy harvesting (EH) incremental relaying NOMA protocol (IR-EH-NOMA) and analyzes its throughput. It derives analytical expressions for throughput under delay-limited transmission, considering

imperfect SIC and optimal power splitting at the relay. In addition, the authors in [8] focused on optimizing throughput in IoT networks by introducing a power allocation strategy tailored for NOMA systems. They used Lagrange multipliers and Karush–Kuhn–Tucker (KKT) to optimize channel capacity while catering constraints like Nakagami-m fading channels. Though efficient, these methods face significant challenges, including high complexity and increased power consumption by users. Therefore, with growing advancements in intelligent machine learning solutions, it is important to integrate existing transmission models into these solutions. In this context, DRL [9] has proven to be a game changer, helping IoT systems manage the dynamic and complex demands of modern networks effectively.

7.1.2 Challenges in supporting sustainable IoT devices

The rise of IoT devices has changed industries, making communication and automation smoother. But keeping these devices sustainable is tough due to energy limits, limited spectrum, and environmental concerns. As the demand for connected devices grows, solving these problems is key for future IoT networks. Many IoT devices in remote areas rely on batteries, making energy efficiency a top concern. It's hard to recharge or replace batteries regularly.

While techniques like energy harvesting and power efficient protocols have been tried, their use is tricky because of different environmental factors and device limitations. The rapid growth of IoT devices adds to the problem of spectrum shortage. Traditional methods can not keep up with the increased data demands, causing congestion and lower service quality.

Implementing previous solutions means dealing with issues like interference and meeting regulations. As IoT networks expand to billions of devices, ensuring devices from different manufacturers work together gets harder. Efforts to standardize are ongoing, but differences in protocols and technologies make it hard to integrate smoothly. To solve these challenges, researchers are exploring new solutions like energy-efficient protocols, adaptive spectrum sharing, and machine learning-based optimization. One promising approach in this area is DRL, which can handle the dynamic and complex challenges in IoT networks.

7.1.3 Role of energy and spectrum efficiency in IoT

Despite many advancements, the rapid growth of IoT devices and the rising demand for high data rates and energy-efficient communication create big challenges. The combination of spectrum shortage and energy limits requires new solutions to improve EE and SE. In this regard, both EE and SE are key issues in the growing IoT landscape. SE, which measures how well bandwidth is used, is important for meeting the increasing data demands of IoT systems. At the same time, EE ensures that devices can operate sustainably by maximizing data transfer while using less energy. Balancing these two factors is essential for building the future communication networks.

7.1.4 Relevance of DRL based algorithms

Integrating DRL into wireless communication networks offers a new way to solve key challenges like energy efficiency, spectrum optimization, and smart resource allocation. DRL uses neural networks and reinforcement learning to model complex decisions without relying on preset assumptions or fixed optimization models.

This adaptability is crucial in the fast-changing environment of IoT networks, where the number of devices is growing rapidly, causing dynamic network conditions. Unlike traditional methods that may lose efficiency as networks change, DRL learns from real-time data and makes decisions that improve network performance.

DRL algorithms are also great for managing different quality of service (QoS) needs in mixed networks. They help distribute resources fairly across devices with varying data, latency, and energy needs, improving efficiency and user experience.

In cases with EH and spectrum sharing, DRL helps with task scheduling, channel selection, and power allocation. It adjusts to external interference and traffic changes, keeping communication strong and secure. DRL is key to next-generation wireless networks, enabling smart automation and efficient resource management for large-scale IoT deployments.

7.2 Overview of sustainable IoT devices

Sustainable IoT devices are key to modern technology, designed for low power use and efficient resource management. They aim to reduce environmental impact while supporting the growing need for connected services. This section highlights the main features, challenges, and trends shaping sustainable IoT networks.

7.2.1 Characteristics of sustainable IoT

Sustainable IoT systems are designed for efficiency and minimal environmental impact. One key feature is EE. As noted in [10], the growth of IoT demands low power sensors that can operate reliably and sustainably. Traditional battery-powered sensors face limitations in lifespan and performance, but EH technology offers a more eco-friendly option by extending sensor life and lowering maintenance costs.

Another important aspect is resource optimization. This includes lightweight communication, data compression, and edge computing to reduce energy use and improve response times. [11] presents an edge computing model for IoT applications like precision agriculture, e-health, and smart homes. It introduces a task offloading mechanism that distributes tasks among devices, helping reduce resource use while meeting QoS needs. Evaluations show its effectiveness in optimizing resource usage.

Scalability and interoperability are also essential for various IoT applications. [12] looks at the balance between interoperability and performance in IoT platforms by analyzing FIWARE, ThingsBoard, and Konker. It assesses their scalability, response times, and resource usage in smart city and smart health contexts. The study finds that interoperability does not significantly impact platform performance.

7.2.2 Energy and spectrum constraints in IoT networks

The rapid growth of IoT devices has created major challenges in energy management and spectrum use. IoT devices run on small batteries that are hard to replace or recharge, especially in remote areas like factories, farms, or monitoring sites. At the same time, more devices are competing for limited bandwidth, making it harder to maintain efficient communication.

7.2.2.1 Energy constraints in IoT networks

Unlike traditional systems with constant power, IoT devices need smart energy management to last longer and reduce maintenance. Efficient communication protocols help save battery by cutting down unnecessary data transmissions and idle time. Techniques like data aggregation, adaptive compression, and optimized packet sizes reduce communication overhead. Sleep scheduling lets devices switch between active and low-power states. EH uses ambient sources like solar, thermal, vibration, or RF signals to recharge batteries, extending device life and improving sustainability.

7.2.2.2 Spectrum utilization challenges

Effective spectrum use is key to maintaining IoT network performance as device density grows. The varied data rate and latency needs of IoT applications make spectrum allocation difficult. Interference, poor spectrum sharing, and underused frequencies worsen the problem. To tackle these challenges, strategies like cognitive radio, dynamic spectrum allocation, and cooperative communication are used. These help IoT systems adapt to changing spectrum conditions, improve sharing, and reduce interference.

7.2.2.3 Balancing energy and spectrum efficiency

Balancing energy and spectrum efficiency requires smart resource management that adapts to network conditions and demands. Machine learning and optimization algorithms are increasingly used to improve decision-making in energy and spectrum management. These methods optimize transmission schedules, choose the right communication channels, and balance power use with reliability. In many algorithms one of the major drawback is the inverse proportional relation between energy and spectrum efficient solutions. Optimizing one often degrades the other. Therefore, there is a need of solutions which aims to optimize both the solutions.

To ensure scalability, reliability, and sustainability, addressing energy and spectrum challenges is key for IoT networks. With innovative designs and adaptive strategies, IoT systems can be more efficient and resilient, meeting the growing needs of a connected world.

7.3 Fundamentals of Deep Reinforcement Learning (DRL)

This section explores the fundamental concepts of DRL.

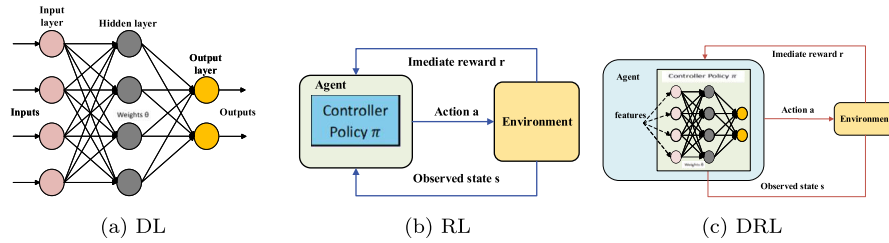
**FIGURE 7.2**

Illustration of (a) DL, (b) RL, and (c) DRL.

7.3.1 Basics of Deep Learning (DL)

Deep learning (DL) is a branch of machine learning (ML) that uses multi layered neural networks (NNs) to automatically extract complex features from raw data. This ability has led to DL's success in areas such as image recognition, natural language processing (NLP), autonomous systems, and strategic game playing.

Inspired by the human brain, neural networks consist of layers of connected artificial neurons. These neurons exchange information through weighted connections, which are adjusted during training using methods like backpropagation and gradient descent optimization.

This iterative refinement helps DL models learn and represent data at different levels of abstraction, capturing complex patterns and relationships that traditional algorithms often miss. These hierarchical feature representations make DL effective at solving challenging AI problems. Fig. 7.2 (a) shows a schematic of a DL framework, illustrating the flow of data through hidden layers to output generation.

7.3.2 Basics of Reinforcement Learning (RL)

Reinforcement learning (RL) [13] is a type of machine learning where an agent learns to make decisions by interacting with an environment. The agent takes actions, receives feedback in the form of rewards or penalties, and learns to optimize its behavior to maximize cumulative rewards over time. Key components of RL include:

- **Agent:** The decision maker that takes actions in the environment.
- **Environment:** The external system with which the agent interacts, providing observations and rewards.
- **State:** The current situation or configuration of the environment that the agent observes.
- **Action:** The decision made by the agent to interact with the environment.
- **Reward:** Feedback given to the agent after an action is performed, guiding learning towards better outcomes.
- **Policy:** The strategy or mapping from states to actions, aiming to maximize cumulative rewards.

- **Value Function:** A function estimating the long-term rewards of states or actions, guiding the agent's decisions.

The goal of RL is to learn an optimal policy that maximizes cumulative rewards through trial and error. The agent updates its knowledge from experiences to adapt its actions. In RL, also known as an experience-driven approach, no prior data is given for learning. Instead, the agent gains knowledge by interacting with the environment. Through a series of actions, the agent receives rewards or penalties based on the outcomes of its decisions [14], generating data in real time through these interactions. The environment in an RL framework is typically modeled mathematically, with them Markov decision process (MDP) [15], [16] being the most commonly employed model. The primary objective is to derive an optimal policy that maximizes cumulative rewards (or minimizes cumulative penalties) over a specified future time horizon, taking into account the agent's current state. Fig. 7.2 (b) illustrates the fundamental components of an RL setup.

7.3.3 Introduction to DRL

Deep RL (DRL), first introduced in [17], integrates DL with RL, forming the basis of its nomenclature. Traditional RL methods are effective for problems involving limited state and action spaces. However, real-world scenarios often encompass high-dimensional and continuous state and action spaces, posing significant challenges for traditional RL approaches as determining an optimal policy becomes increasingly complex. DRL was developed to overcome these limitations by efficiently addressing high-dimensional applications and enabling learning in continuous spaces. In DRL, the RL component involves a self-learning agent that aims to maximize long-term rewards without requiring prior knowledge of the underlying system model. Meanwhile, inspired by biological NNs, DL has advanced significantly in managing the complexities of high-dimensional environments. By combining these approaches, DRL effectively mitigates the curse of dimensionality through efficient feature extraction.

DRL methods are predominantly applied to sequential decision-making tasks [18], where an agent must make a series of decisions to solve a given problem effectively. The objective in such tasks is to identify a sequence of decisions that maximizes the expected cumulative future reward. Sequential decision-making problems are well-modeled using MDPs, which satisfy the Markov property, implying that the next state depends solely on the current state, with outcomes being partially random and partially under the agent's control. The following discussion delves into the fundamental concept of MDPs and their role in shaping and facilitating the DRL framework.

7.3.3.1 Markov Decision Processes (MDPs)

An MDP is a discrete-time stochastic control process commonly represented as a tuple, (S, A, T_a, R_a) , where:

- S represents the finite set of states in the environment,

- A denotes the action space,
- T_a represents the probability that action a taken at time t in state s leads to a transition to state s' at time $t + 1$, and
- R_a denotes the immediate reward obtained after action a , facilitating the transition from state s to s' .

The agent's goal in an MDP is to interact with the environment across different time steps to find an optimal policy, π^* , which maps states to actions to maximize the cumulative reward over the long term. The policy π can be deterministic, providing a single state-to-action mapping, or stochastic, offering a probability distribution over all possible actions.

An MDP may operate under a finite or infinite time horizon. In a finite time horizon MDP, the optimal policy π^* maximizes the expected total reward, represented as:

$$\max_{\pi} \mathbb{E} \left\{ \sum_{t=0}^T r_t(s_t, \pi(s_t)) \right\}. \quad (7.1)$$

For an infinite time horizon MDP, the objective is to maximize the expected discounted total reward:

$$\max_{\pi} \mathbb{E} \left\{ \sum_{t=0}^{\infty} \gamma r_t(s_t, \pi(s_t)) \right\}, \quad (7.2)$$

where $\gamma \in [0, 1]$ is the discount factor, determining the relative importance of future rewards compared to immediate rewards. A discount factor of $\gamma = 0$ results in a “myopic agent” that prioritizes instant rewards, whereas $\gamma \approx 1$ incentivizes long-term reward maximization.

Depending on the application, MDPs can be classified as fully observable (FOMDP) or partially observable (POMDP) [19]. In an FOMDP, the agent has full access to the environment's states. Conversely, in a POMDP, the agent only has partial access to the states, introducing additional complexity. A POMDP is typically represented as $(S, A, T_a, R_a, \Omega, O)$, where:

- Ω denotes the set of partial observations accessible to the agent, and
- O represents the transition probabilities of partially observable states from s to s' .

A *belief set*, consisting of probability distributions over states, is maintained in a POMDP. The agent selects an action a based on its belief $b(s)$, transitions to the next state s' , and receives the reward $r \in R_a$ along with the current observation $o \in O$. The agent then updates its belief about the new state s' using the following equation [19, 20]:

$$b_a^o(s') = \frac{p(o|s, a, s') \sum_s p(s'|s, a) b(s)}{\sum_{s, s'} p(o|s, a, s') p(s'|s, a) b(s)}, \quad (7.3)$$

where $p(o|s, a, s')$ denotes the probability of receiving observation o given that the agent takes action a in state s and transitions to state s' , and $p(s'|s, a)$ represents

the probability of transitioning to state s' from state s upon taking action a . The corresponding reward R_a is provided through the immediate reward function. Similar to MDPs (or FOMDPs), agents in POMDPs seek an optimal policy π^* to maximize the expected long-term cumulative reward:

$$\max_{\pi} \mathbb{E} \left\{ \sum_{t=0}^{\infty} \gamma r_t(s_t, \pi^*(s_t)) \right\}. \quad (7.4)$$

7.3.4 Classification of DRL models

Given the wide array of applications of DRL, various DRL algorithms have been developed, categorized based on their reliance on predefined models or their ability to function without them. Accordingly, DRL techniques can be broadly classified into the following.

7.3.4.1 Model-based methods

Model-based DRL methods begin by constructing a model of the environment using feedback from the agent's interactions. This model is then employed to predict the outcomes of actions on states and rewards, thereby enabling the derivation of an optimal policy. Examples of model-based methods include AlphaZero [21], model-based RL with model-free fine-tuning (MBMF) [22], imagination-augmented agents (I2A) [23], and Monte Carlo tree search (MCTS) [24]. These methods offer lower sample complexity by reducing the need for extensive interaction with the environment. However, their reliance on potentially inaccurate models can lead to suboptimal policies and reduced accuracy.

7.3.4.2 Model-free methods

In contrast, model-free DRL methods directly interact with the environment to learn optimal policies or value functions, eliminating the need for explicitly modeling the environment's dynamics. These methods are further classified into the following sub-categories:

7.3.4.3 Value-based methods

Value-based DRL methods focus on learning a value function, such as the state-value function $V^{\pi}(s)$, rather than directly storing a policy $\pi(s)$. The state-value function represents the expected cumulative reward for each state under a given policy π and is defined as $V^{\pi}(s) : S \Rightarrow R_a$. Its mathematical expression is:

$$V^{\pi}(s) = \sum P(\tau|\pi, s)G(\tau), \quad (7.5)$$

where $P(\tau|\pi, s)$ represents the probability of trajectories given the initial state s and policy π , and $G(\tau) = \sum_{t=0}^T \gamma r_t(s_t, \pi(s_t))$. The optimal state-value function is given by:

$$V^*(s) = \max_{\pi} V^{\pi}(s), \forall s \in S. \quad (7.6)$$

The action-value function $Q^\pi(s, a)$ maps a state-action pair to its long-term expected reward:

$$Q^\pi(s, a) : S \times A \Rightarrow R_a, \quad (7.7)$$

and is mathematically expressed as:

$$Q^\pi(s, a) = \sum_{\tau} P(\tau|\pi, s, a)G(\tau). \quad (7.8)$$

The optimal action-value function is:

$$Q^*(s, a) = \max_{\pi} Q^\pi(s, a), \forall s \in S, \forall a \in A. \quad (7.9)$$

The agent's objective in value-based DRL is to derive an optimal policy π^* that maximizes expected cumulative rewards:

$$\pi^*(s) = \max_{\pi} V^\pi(s), \forall s \in S. \quad (7.10)$$

For an optimal Q-value function, the corresponding optimal policy is:

$$\pi^* = \max_{a \in A} Q^*(s, a), \forall s \in S. \quad (7.11)$$

In practice, finding an optimal policy involves approximating the optimal action-value function using methods like temporal difference (TD) learning or Monte Carlo (MC) estimation. MC methods, while yielding lower bias, require full episodes for updates and are suitable for episodic MDPs. TD methods, which leverage the Markov property, allow online updates after every decision epoch and are more flexible, making them widely used in contemporary DRL algorithms. Examples of value-based methods include Q-Learning (QL) [25], Deep Q-Learning (DQL) [26], and Rainbow [27].

7.3.4.4 Policy-based methods

Policy-based DRL methods directly optimize policies without relying on value functions. These methods refine policy parameters iteratively using gradient-based optimization. The objective is to maximize the long-term reward:

$$J(\theta) = \sum_{\tau} P(\tau|\pi_{\theta})G(\tau), \quad (7.12)$$

where $P(\tau|\pi_{\theta})$ represents the trajectory probabilities under policy π_{θ} . The policy gradient is:

$$\nabla_{\theta} J(\theta) = P_{\pi_{\theta}} \left[G(\tau|s, a) \nabla_{\theta} \ln \pi_{\theta}(a|s) \right], \quad (7.13)$$

and the updates are performed as:

$$\theta_{t+1} = \theta_t + \beta \gamma^t \left[G(\tau|s_t, a_t) \nabla_{\theta} \ln \pi_{\theta}(a_t|s_t) \right]. \quad (7.14)$$

The examples of policy-based methods include REINFORCE [28], trust region policy optimization (TRPO) [29], and proximal policy optimization (PPO) [30].

7.3.4.5 Actor-critic methods

Actor-critic methods integrate value-based and policy-based approaches. The actor network selects actions, while the critic network evaluates them. The actor updates policies based on feedback from the critic, which estimates value functions. Examples include asynchronous advantage actor-critic (A3C) [31], deep deterministic policy gradient (DDPG) [32], and soft actor-critic (SAC) [33]. Table 7.1 summarizes the different categories of the DRL models.

7.3.5 Advantages of DRL for IoT applications

Deep RL has emerged as a transformative approach for optimizing complex, dynamic systems, making it particularly advantageous for IoT applications. By leveraging the power of neural networks to approximate policies and value functions, DRL facilitates efficient decision-making in environments with significant uncertainty and variability.

One of the primary strengths of DRL lies in its capability to handle high-dimensional state and action spaces. Traditional optimization techniques, such as linear programming or heuristic-based methods, struggle with scalability and heterogeneity in IoT networks. These networks consist of many devices operating under different protocols and standards. DRL algorithms address these challenges by learning directly from the environment, without needing predefined models. This model-free approach allows DRL to handle complex interactions between IoT devices, ensuring stable performance even in dynamic situations.

IoT networks often face unpredictable changes, such as fluctuating traffic, varying latency, and energy constraints. In this context, DRL adapts well to real world conditions. Unlike traditional methods, which require re-optimization under changing conditions, DRL continuously updates its policies based on rewards and state transitions. This allows IoT systems to adjust to the evolving conditions, such as shifting communication schedules, balancing loads, or redistributing resources, etc.

Another advantage of DRL in IoT is its support for multi objective optimization. It can balance competing goals like energy efficiency, latency, throughput, and QoS. By adjusting rewards, DRL can prioritize specific objectives while maintaining overall system performance. For example, in energy-limited IoT networks, DRL can optimize data throughput while minimizing power consumption, ensuring sustainable operation.

Additionally, DRL can be improved with techniques like transfer learning and meta-learning. These methods speed up training and improve generalization across different IoT scenarios by using pre-trained models or knowledge from similar tasks. This is useful in IoT applications with changing topologies or dynamic environments, where retraining from scratch would be too costly.

Table 7.1 Summary of DRL algorithms.

Algo.	Key Characteristics	Applications
Value-Based DRL Algorithms		
QL	A TD learning algorithm tailored for discrete state and action spaces, which iteratively refines action-value estimates to converge toward the optimal policy.	Applied in robotics, industrial automation, gaming, and finance.
DQL	Employs DNNs to approximate the Q-function, enabling efficient learning in high-dimensional state spaces.	Appropriate for MDPs that involve discrete state and action spaces.
PDQL	Prioritizes experiences with significant TD errors, assigning them higher replay priority to improve sample efficiency and speed up learning.	Appropriate for MDPs prioritizing experiences.
DDQL	Mitigates Q-value overestimation by using two distinct networks to independently estimate target and current Q-values, enhancing stability and performance.	Used in gaming, robotics, and finance, with effective DQ-value estimation for decision-making.
ADQL	A parallelized DQL approach where multiple agents interact with separate environment instances, accelerating learning through asynchronous Q-network updates.	Effective for managing asynchronous updates in distributed environments.
Dis-DQL	Distributes the training process across multiple machines, enabling faster training and better scalability for larger environments and datasets.	Excels at capturing uncertainty and enhancing performance in stochastic environments.
Due-DQL	Breaks the Q-value into an advantage function and a state value function, improving learning efficiency and yielding more precise Q-value approximations.	Effective for MDPs with large action spaces.
DQLNN	Introduces noisy layers into the neural network, dynamically adjusting exploration strategies to enhance learning efficiency.	Appropriate for MDPs with large action, and state spaces.
Rainbow	Combines advanced techniques like PER, DQL, dueling networks, and noisy layers to achieve cutting-edge performance in DQL.	Ideal for complex problems with high-dimensional state and action spaces and uncertainty.
SARSA	An on-policy TD learning algorithm that updates action values using outcomes from its own actions, factoring in the next action and its corresponding reward.	Used in discrete state-action spaces for on-policy learning and optimal policy convergence.
Policy-Based DRL Algorithms		
REIN-FORCE	Leverages deep neural networks to train the policy function, optimizing it by directly estimating gradients based on received rewards.	Appropriate for problems with discrete action spaces.
TRPO	Imposes constraints on policy updates to maintain stability and prevent large, destabilizing changes, thereby ensuring reliable optimization.	Effective for large-scale continuous control problems.

continued on next page

Table 7.1 (continued)

Algo.	Key Characteristics	Applications
PPO	Utilizes a clipped surrogate objective function to regulate policy updates, avoiding large, disruptive changes and fostering stable improvement.	Effective for high-dimensional or continuous action spaces, like robotics and games.
Actor-Critic DRL Algorithms		
A2C	Merges policy gradient and value-based approaches by concurrently learning action selection and value estimation, boosting efficiency and training stability.	Appropriate for problems with continuous action spaces.
A3C	Combines policy gradient and value-based methods with multiple parallel agents, enhancing sample efficiency and stability via asynchronous updates.	Ideal for problems needing asynchronous training for efficient exploration.
SAC	Incorporates entropy regularization into stochastic policies and value function learning, fostering exploration and robustness in continuous action spaces.	Appropriate for problems requiring stable learning and robust exploration.
DDPG	Designed for continuous action spaces, using deterministic policy gradients and experience replay for stable and efficient learning.	Used for continuous action spaces needing stable learning and efficient exploration.
CER-DDPG	Builds on DDPG by prioritizing recent experience tuples in batch selection, improving sample efficiency and learning stability.	Used where sample efficiency and fast convergence are crucial.
PER-DDPG	Combines prioritized experience replay with DDPG, assigning higher replay priority to experiences with larger TD errors.	Beneficial for problems requiring improved sample efficiency and faster convergence.
MADDPG	Adapts DDPG for multi agent scenarios, enabling centralized training and decentralized execution to support cooperation in complex environments.	Appropriate multi agent problems in complex environments.
TD3	Utilizes twin critics and delayed policy updates to stabilize training and enhance policy robustness.	Ideal for continuous action spaces where stability and robustness in learning are key for efficient exploration and decision-making.
RDPG	Incorporates RNNs into the policy network to learn deterministic policies in sequential or time-sensitive observation settings.	Effective for sequential decision-making with crucial temporal dependencies in time-sensitive scenarios.
D4PG	Enhances DDPG by integrating distributional RL techniques and parallelized training across multiple actors, enabling efficient exploration in expansive continuous action spaces.	Used in continuous action spaces where stability and robustness in learning are crucial for efficient exploration and decision-making.

DRL also supports cooperative and distributed decision-making in IoT systems. In multi-agent networks, DRL can coordinate actions among devices, leading to collaborative strategies that improve overall system efficiency. Algorithms like multi agent DDPG (MADDPG) are used to optimize tasks such as spectrum allocation, resource sharing, and task offloading.

Finally, advancements in DRL frameworks, such as model-based DRL and actor-critic methods, enhance its effectiveness in IoT. Model-based approaches simulate IoT environments to predict outcomes and optimize actions, reducing trial-and-error. Actor-critic methods combine policy-based and value-based learning to speed up training and improve stability.

7.4 DRL-based algorithms for energy and spectrum efficiency

Energy and spectral efficiency are key to sustainable IoT systems, with EH and power management being important factors. DRL based algorithms have shown great potential in optimizing these areas by learning strategies in real time. This section looks into how DRL can improve EE in IoT networks, with supporting case studies.

7.4.1 DRL in EH systems

Recent advances in machine learning, especially DRL, have shown great potential. Smart solutions with optimised resource allocation, high spectrum management, and great security protocols can be build using DRL-based algorithms in IoT systems. With billions of devices expected to be interconnected, this capability is essential to ensure sustainable operation, efficient resource utilization, and meet the stringent QoS requirements of modern IoT applications. By leveraging DRL, IoT networks can adapt to the dynamic and complex nature of wireless communication environments, paving the way for more efficient and sustainable future networks. Example, [34] presented a DRL-based framework to enhance the throughput of a stationary secondary user within a CR-NOMA communication system, where the secondary user performs EH and data transmission during the primary user's time slot. Expanding on this foundation, [35,36] investigated self-sustaining IoT networks powered by wireless communication, utilizing EH and RF-EH diversity-combining techniques. Their approach incorporated a QoS-aware NOMA scheme for uplink transmissions, optimizing both linear and non-linear EH models, duration and transmission power through DRL to maximize the sum rate of a stationary secondary node. Similarly, [37,38] proposed an energy-efficient communication protocol tailored for resource-constrained IoT networks. By employing DRL, specifically the CER-DDPG algorithm, they achieved throughput maximization for the secondary sensor. Building on this model, [39] further optimized the network's SE using DRL to manage EH and data transmission in a CR-NOMA framework. [40] further improved the model by incorporating mobility for the secondary user using a random waypoint model, making it more applicable to real-world scenarios.

7.4.2 Spectrum and energy allocation via DRL

Spectrum scarcity is a critical challenge in IoT networks, especially with the proliferation of ultra-massive machine-type communication (umMTC). DRL-based frameworks provide innovative solutions for spectrum efficiency by:

- Enabling dynamic spectrum access in cognitive radio (CR) systems, where devices opportunistically utilize underused spectrum bands.
- Optimizing NOMA schemes by dynamically adjusting power allocation and user clustering strategies.
- Enhancing spectral reuse through intelligent channel assignment and interference management.
- Optimizing power allocation and scheduling to minimize energy consumption without compromising performance.
- Determining the optimal time allocation for EH and data transmission in energy-constrained scenarios.
- Dynamically redistributing traffic loads among IoT devices to avoid overburdening specific nodes, reducing overall energy consumption.

7.4.3 Case studies

In this section, we present two case studies related to EE and SE of IoT systems.

7.4.3.1 Background and motivation

As the demand for low-power sensing grows, modern wireless networks face significant challenges in accommodating additional devices while simultaneously maximizing SE and EE. Traditional wireless infrastructures struggle to meet these dual demands due to the constrained energy resources of low-power devices and the inefficient utilization of available spectrum. To overcome these challenges, EH-enabled symbiotic radio has emerged as a promising approach, enabling secondary devices to coexist with primary wireless systems. By leveraging RF-EH and opportunistic spectrum sharing, EH-enabled symbiotic radio provides a sustainable and efficient solution, addressing both SE and EE requirements, and aligning with the vision of future wireless networks.

In this case study, we explore an innovative framework that tackles the complexities of optimizing EH-enabled symbiotic radio in dynamic environments characterized by nonlinear EH circuitry and pre-scheduled operations of primary devices. The proposed framework employs advanced techniques to achieve a balanced enhancement of SE and EE, ensuring sustainable operation while maintaining the commensalistic relationship between secondary and primary systems.

7.4.3.2 System model: overview of EE optimization

As illustrated in Fig. 7.3, we analyze a wireless IoT network configuration consisting of a central base station (BS) and J pre-scheduled primary IoT devices, denoted as M_j , where $1 \leq j \leq J$. The primary devices communicate using a time division multiple access (TDMA) mechanism, where each device is assigned a dedicated time

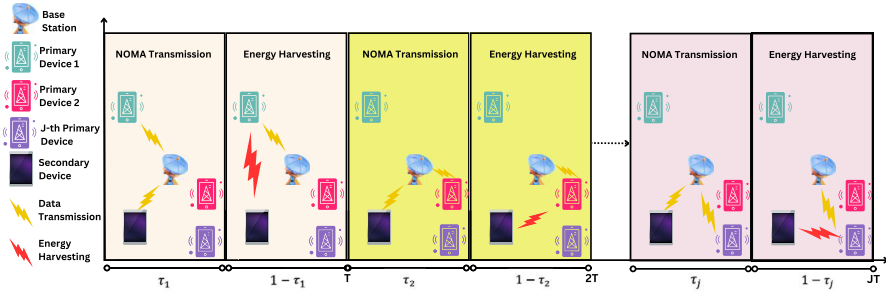
**FIGURE 7.3**

Illustration of the considered IoT network.

slot of T seconds within a frame duration of NT , given that $N \geq J$. The scheduling of these devices operates such that during the k -th time slot, labeled t_k and satisfying $1 \leq k \leq N$, the j -th primary device is active. Here, j is determined by the relation $((k - 1) \oplus J) + 1$, with $\oplus$ representing the modulo operation.

In this configuration, an energy-constrained device, referred to as the EH-enabled symbiotic radio, transmits sensor data to the BS during the time slots allocated to primary devices. The EH-enabled symbiotic radio employs the CR-NOMA method, which enables its transmissions to coexist with those of the primary devices while ensuring that their QoS requirements are met. This QoS guarantee is achieved through a QoS-driven SIC decoding order, ensuring that the EH-enabled symbiotic radio's signal is decoded first in the SIC process [41].

A unique feature of the EH-enabled symbiotic radio is its ability to harvest energy from the uplink RF transmissions of primary devices. For example, in the k -th time slot, where t_k is identical for all k , the EH-enabled symbiotic radio dedicates the initial $\tau_k T$ seconds to data transmission and the remaining $(1 - \tau_k)T$ seconds to EH, where $\tau_k \in [0, 1]$ is the time-sharing coefficient. To simplify notation, let the primary device scheduled at time t_k be represented as M_k , where $M_k = M_j$ and $j = ((k - 1) \oplus J) + 1$. Henceforth, k will denote both the time slot and the corresponding primary device. The channel gain between the EH-enabled symbiotic radio and the BS during the k -th time slot is denoted as $\tilde{g}_k$. Additionally, for the k -th primary device, its channel gains to the BS and EH-enabled symbiotic radio during the k -th time slot are denoted as g_k and $g_{k,0}$, respectively.

We assume that the EH-enabled symbiotic radio starts communication with a fully charged battery and has prior knowledge of the channel state information (CSI) of each primary device transmitting at time t_k . Let Γ_k denote the energy stored in the EH-enabled symbiotic radio's battery at time t_k . The total transmission energy of the EH-enabled symbiotic radio is constrained by Γ_k , expressed as:

$$\tau_k T (\tilde{S}_k + \lambda) \leq \Gamma_k, \quad (7.15)$$

where λ represents the fixed RF circuit power and signal processing power of the EH-enabled symbiotic radio, accounting for the constant energy consumption of RF

operations, and $\tilde{\Omega}_k$ denotes the EH-enabled symbiotic radio's transmit power at time t_k .

The total energy available in the EH-enabled symbiotic radio's battery at time t_{k+1} is given by:

$$\Gamma_{k+1} = \min \left\{ \Gamma_k + (1 - \tau_k) T [\Phi_{\text{Prac}}(\Omega_k)] |g_{k,0}|^2 - \tau_k T (\tilde{\Omega}_k + \lambda), \Gamma_{\max} \right\}, \quad (7.16)$$

where $\Phi_{\text{Prac}}(\Omega_k)$ represents the practical nonlinear EH model of the EH-enabled symbiotic radio, Ω_k is the transmit power of the k -th primary device, and $\Gamma_{\max}$ denotes the maximum battery capacity of the EH-enabled symbiotic radio.

The system's nonlinear EH model is expressed as:

$$\mathcal{P}_{\text{EH}}(\tilde{\Omega}_k) = \frac{\beta_3 (e^{\beta_1 \tilde{\Omega}_k} - 1)}{e^{\beta_1 \tilde{\Omega}_k} + e^{\beta_1 \beta_2}}, \quad (7.17)$$

where β_1 , β_2 , and β_3 are parameters defining the EH circuit characteristics. The time-sharing coefficient τ_k determines the portion of a time slot allocated to transmission, with the remainder dedicated to EH.

7.4.3.3 Problem formulation

This section formulates the mathematical model for maximizing the EE and frames it within a DRL context.

The data rate achieved by the EH-enabled symbiotic radio during time t_k is defined as:

$$\tilde{R}_k = \tau_k \log_2 \left(1 + \frac{\tilde{\Omega}_k |\tilde{g}_k|^2}{1 + \Omega_k |g_k|^2} \right). \quad (7.18)$$

The order of SIC decoding follows the definition in (7.18), where the EH-enabled symbiotic radio's signal is decoded first, and the scheduled primary device's signal is decoded subsequently. This ensures the QoS requirements for primary devices. To achieve the objective of maximizing the EE of the EH-enabled symbiotic radio, the EE at the k -th time slot is expressed as:

$$\Pi_k(\tau_k, \tilde{\Omega}_k) = \frac{\tau_k \log_2 \left(1 + \frac{\tilde{\Omega}_k |\tilde{g}_k|^2}{1 + \Omega_k |g_k|^2} \right)}{\bar{\lambda}}, \quad (7.19)$$

where the numerator represents the instantaneous data rate of the EH-enabled symbiotic radio, and the denominator is the total power consumed, with $\bar{\lambda}$ denoting the total average power consumed for transmission. This formulation ensures that the QoS of the scheduled primary device is satisfied as the EH-enabled symbiotic radio's signal is decoded without interference. The optimization parameters in (7.3) are τ_k and $\tilde{\Omega}_k$.

The EE maximization problem is then formulated as:

$$\underset{\tau_k, \tilde{\Omega}_k}{\text{maximize}} \quad \mathbb{E} \left\{ \sum_{k=1}^N \alpha^{k-1} \Pi_k(\tau_k, \tilde{\Omega}_k) \right\} \quad (\text{P1})$$

$$\begin{aligned} \Gamma_{k+1} = \min & \left\{ (1 - \tau_k) T \left[\frac{\beta_3 [e^{\beta_1 \Omega_k} - 1]}{e^{\beta_1 \Omega_k} + e^{\beta_1 \beta_2}} \right] |h_{k,o}|^2 \right. \\ \text{s.t.} & \left. -\tau_k T (\tilde{\Omega}_k + \lambda) + \Gamma_k, \Gamma_{\max} \right\}, \end{aligned} \quad (7.20)$$

$$R_k \geq \gamma_k, \quad (7.21)$$

$$\tau_k T (\tilde{\Omega}_k + \lambda) \leq \Gamma_k, \quad (7.22)$$

$$0 \leq \tilde{\Omega}_k \leq \Omega_{\max}, \quad (7.23)$$

$$0 \leq \tau_k \leq 1. \quad (7.24)$$

In Problem (P1), $\mathbb{E}\{\cdot\}$ represents the expected sum of discounted energy efficiencies of the EH-enabled symbiotic radio, where α is the discount factor prioritizing long-term rewards. The term $R_k = \log(1 + \Omega_k |h_k|^2)$ denotes the data rate of the k -th primary device, and γ_k represents its minimum required rate. Constraint (7.20) defines the total energy in the EH-enabled symbiotic radio's battery at time t_{k+1} , while Constraint (7.21) ensures QoS for the primary devices. Constraint (7.22) limits the total energy consumed by the EH-enabled symbiotic radio to its available energy at time t_k , and Constraints (7.23) and (7.24) restrict the EH-enabled symbiotic radio's transmit power and time-sharing coefficient, respectively.

Problem (P1) is non-convex due to: (i) the non-convex nature of the long-term EE function in the objective, (ii) the non-affine structure of Constraint (7.20), and (iii) the bilinear term in Constraint (7.22) involving optimization variables. The need for timely EH and transmission decisions under resource constraints motivates the use of RL, while the continuous action space makes the problem suitable for the modified DDPG (MDDPG) algorithm. However, the varying ranges of optimization variables in Constraints (7.23) and (7.24) necessitate additional processing.

To address these challenges, we employ a primal decomposition approach, splitting Problem (P1) into a two-layer optimization problem:

Introducing the energy fluctuation parameter $\bar{\Gamma}_k$, defined as the difference between harvested and consumed energy:

$$\bar{\Gamma}_k = (1 - \tau_k) T \left[\frac{\beta_3 [e^{\beta_1 \Omega_k} - 1]}{e^{\beta_1 \Omega_k} + e^{\beta_1 \beta_2}} \right] |h_{k,o}|^2 - \tau_k T (\tilde{\Omega}_k + \lambda). \quad (7.25)$$

This parameter indicates an energy deficit ($\bar{\Gamma}_k < 0$) or surplus ($\bar{\Gamma}_k > 0$) at time t_k . Accordingly, for a given $\bar{\Gamma}_k$, maximize instantaneous EE:

$$\begin{aligned} \text{maximize} \quad & \Pi_k(\tau_k, \tilde{\Omega}_k) \\ \text{s.t.} \quad & \tau_k, \tilde{\Omega}_k \end{aligned} \quad (P2) \quad (7.26)$$

$$\begin{aligned} \bar{\Gamma}_k = (1 - \tau_k) T & \left[\frac{\beta_3 [e^{\beta_1 \Omega_k} - 1]}{e^{\beta_1 \Omega_k} + e^{\beta_1 \beta_2}} \right] |h_{k,o}|^2 \\ & - \tau_k T (\tilde{\Omega}_k + \lambda), \end{aligned}$$

$$(7.21), (7.22), (7.23), (7.24), \quad (7.27)$$

and the second layer optimization problem is given by:

$$\underset{\bar{\Gamma}_k}{\text{maximize}} \quad \mathbb{E} \left\{ \sum_{k=1}^N \beta^{k-1} \Pi_k(\tau_k, \tilde{\Omega}_k) \right\} \quad (\text{P3})$$

$$\text{s.t.} \quad \Gamma_{k+1} = \min \left\{ \Gamma_{\max}, \bar{\Gamma}_k + \Gamma_k \right\}, \quad (7.28)$$

which has been formulate following [42].

The solution approach to this problem is divided into two phases. In the first phase, convex optimization is employed to derive closed-form expressions for the optimization variables for a given $\bar{\Gamma}_k$ in Problem (P2). Consequently, the optimal solution is expressed as functions of $\bar{\Gamma}_k$ in Problem (P2), i.e., $\tau_k^*(\bar{\Gamma}_k)$ and $\Omega_k^*(\bar{\Gamma}_k)$. In the second phase, the MDDPG algorithm is utilized to solve Problem (P3), while incorporating the optimal solutions derived in the first phase. Using these closed-form expressions, Problem (P3) can be reformulated as follows:

$$\underset{\bar{\Gamma}_k}{\text{maximize}} \quad \mathbb{E} \left\{ \sum_{k=1}^N \beta^{k-1} \Pi_k(\tau_k^*(\bar{\Gamma}_k), \Omega_k^*(\bar{\Gamma}_k)) \right\} \quad (\text{P4})$$

$$\text{s.t.} \quad \Gamma_{k+1} = \min \left\{ \Gamma_{\max}, \bar{\Gamma}_k + \Gamma_k \right\}. \quad (7.29)$$

This reformulation highlights that the EH-enabled symbiotic radio's action is to select $\bar{\Gamma}_k$. Problem (P4) is a single-variable function, and the continuous nature of the parameter of interest, $\bar{\Gamma}_k$, makes this one-dimensional, continuous action space optimization problem particularly suited for a DRL algorithm such as the MDDPG algorithm.

The closed-form solutions are given as:

$$\Omega_k^*(\bar{\Gamma}_k) = \left[\frac{(1 - \tau_k^*(\bar{\Gamma}_k)) T \alpha_3 [e^{\beta_1 \Omega_k} - 1] |g_{k,o}|^2}{(e^{\beta_1 \Omega_k} + e^{\beta_1 \beta_2}) \tau_k^*(\bar{\Gamma}_k) T} \right] - \frac{\bar{\Gamma}_k}{\tau_k^*(\bar{\Gamma}_k) T} - \lambda, \quad (7.30)$$

and

$$\tau_k^*(\bar{\Gamma}_k) = \begin{cases} \min \{ \Theta, 1 \} & \text{if } R_k \geq \gamma_k \\ 0 & \text{otherwise,} \end{cases} \quad (7.31)$$

where $\Theta = \max \{ \hat{\tau}_k, \Psi \}$, for $\hat{\tau}_k = \frac{x_1 - x_2}{e^{U_0(e^{-1}(1-x_1-x_3))^{+1} + x_1 + x_3 - 1}}$, and

$$\Psi = \max \left\{ \frac{X - (e^{\beta_1 \Omega_k} + e^{\beta_1 \beta_2}) \bar{\Gamma}_k}{X + T[\lambda + \Omega_{\max}](e^{\beta_1 \Omega_k} + e^{\beta_1 \beta_2})}, 1 - \frac{[\bar{\Gamma}_k + \Gamma_k](e^{\beta_1 \Omega_k} + e^{\beta_1 \beta_2})}{X} \right\},$$

with $X = T\alpha_3[e^{\beta_1\Omega_k} - 1]|g_{k,o}|^2$. The expressions for x_1 , x_2 , and x_3 are given by

$$x_1 = \frac{|\tilde{g}_k|^2 T \beta_3 [e^{\beta_1\Omega_k} - 1] |g_{k,o}|^2}{YT(1 + \Omega_k |g_k|^2)}, \quad (7.32)$$

where $Y = e^{\beta_1\Omega_k} + e^{\beta_1\beta_2}$

$$x_2 = \frac{\bar{\tau}_k |\tilde{g}_k|^2}{T(1 + \Omega_k |g_k|^2)}, \quad (7.33)$$

and

$$x_3 = \frac{\lambda |\tilde{g}_k|^2}{(1 + \Omega_k |g_k|^2)}. \quad (7.34)$$

Using the above closed-form expressions, the reward parameter is defined as

$$\Pi_k(\tau_k^*(\bar{\Gamma}_k), \tilde{\Omega}_k^*(\bar{\Gamma}_k)) = \frac{\tau_k^*(\bar{\Gamma}_k) \log_2 \left(1 + \frac{\tilde{\Omega}_k^*(\bar{\Gamma}_k) |\tilde{g}_k|^2}{1 + \Omega_k |g_k|^2} \right)}{\bar{\lambda}}. \quad (7.35)$$

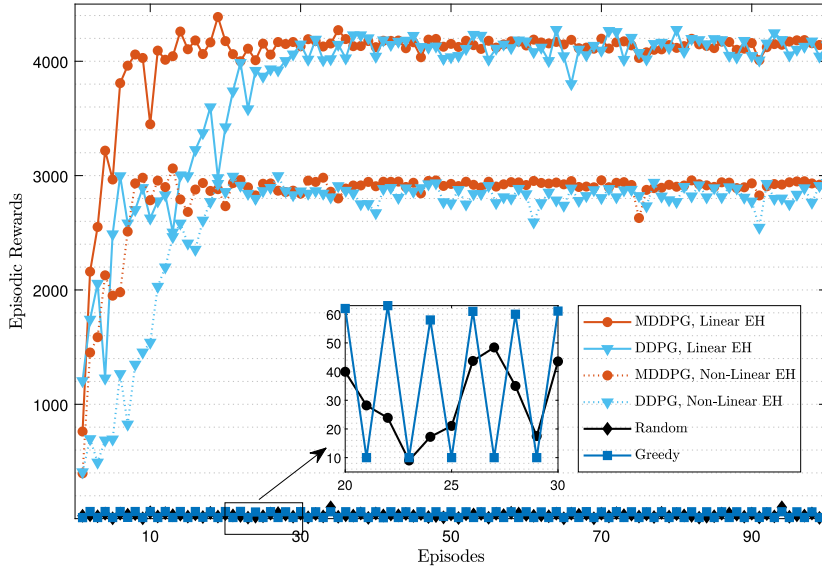
7.4.3.4 Performance evaluation

The effectiveness of the proposed strategy was validated through extensive simulations. The learning efficiency analysis evaluates the performance of the proposed MDDPG algorithm in comparison to the baseline DDPG algorithm and non-DRL methods, including the random and greedy approaches, focusing on episodic reward (or EE) and sum rate. The greedy method prioritizes data transmission by using all available energy before initiating EH, setting the transmission power to $\Omega_{\max}$ and computing τ_k as $\tau_k = \min\{1, \frac{T_k}{T\Omega_{\max}}\}$. In contrast, the random method fixes the transmit power at $\Gamma_{\max}$ and selects τ_k randomly from a uniform distribution within a predefined range. The analysis highlights the convergence performance of these algorithms under both non-linear and linear EH dynamics. As shown in Fig. 7.4, episodic reward decreases by approximately 30% for the non-linear EH model across all learning methods, reflecting the complexity of practical EH scenarios with inherent non-linearities. Nevertheless, the proposed MDDPG algorithm outperforms both DDPG and non-DRL methods for the non-linear EH model, achieving a higher episodic reward upon convergence. Moreover, the MDDPG algorithm exhibits faster convergence than the DDPG, particularly in the case of the linear EH model.

7.4.3.5 System model: overview of SE optimization

This system operates similarly to the model described above, where the primary IoT devices, M_j , transmit data in a cyclic TDMA scheme. In each time slot, a secondary device employs the CR-NOMA technique to transmit its data while ensuring co-existence with the primary devices. However, unlike the EH-enabled symbiotic radio, which uses a nonlinear EH model, the secondary IoT device, denoted as $\tilde{M}$ in this model operates under a linear EH model. This change simplifies the energy harvesting process while maintaining the overall network functionality and QoS requirements.

The following assumptions are made at the beginning of each transmission:

**FIGURE 7.4**

Comparison of episodic rewards (or EE) for EH-enabled symbiotic radio using the proposed MDDPG algorithm and baseline methods under both linear and non-linear EH models, with parameters $J = 2$, $\lambda = 0$ dBm, and $\Omega_k = 30$ dBm.

- The secondary IoT device has full knowledge of the CSI.
- The secondary IoT device's battery is fully charged at the start of the communication.

Taking these assumptions into account, the energy available at the beginning of the next time slot is calculated as follows:

$$\Gamma_{k+1} = \min \left\{ (1 - \tau_k) T \eta \Omega_k |g_{k,0}|^2 - \tau_k T \tilde{\Omega}_k + \Gamma_k, \Gamma_{\max} \right\}, \quad (7.36)$$

where $\Gamma_{\max}$ represents the upper limit of the secondary device, η is the EH coefficient, and Ω_k and $\tilde{\Omega}_k$ represents transmit power of M_k and $\tilde{M}$ respectively. Under the energy constraint, the secondary device transmit power is restricted to the energy stored in its battery, as

$$\tau_k T \tilde{\Omega}_k \leq \Gamma_k. \quad (7.37)$$

Therefore, the SE of the network at the k -th time slot is given by [43],

$$\xi_k = \frac{R_k + \tilde{R}_k}{B}, \quad (7.38)$$

In Eq. (7.38), R_k and $\tilde{R}_k$ denote the data rates of M and $\tilde{M}$, at the k -th time slot, respectively. As in [52], they are given by

$$\tilde{R}_k = \tau_k B \log_2 \left(1 + \frac{\tilde{\Omega}_k |\tilde{g}_k|^2}{\Omega_k |g_k|^2 + \sigma} \right), \quad (7.39)$$

and

$$R_k = B \log_2 \left(1 + \frac{\Omega_k |g_k|^2}{\sigma} \right), \quad (7.40)$$

respectively, where σ represents the noise power.

7.4.3.6 Problem formulation

Our primary objective here is to optimize the system's overall SE, therefore, the SE maximization problem is defined as

$$\begin{aligned} & \underset{\tau_k, \tilde{\Omega}_k}{\text{maximize}} && \left[\frac{\tau_k B \log_2 \left(1 + \frac{\tilde{\Omega}_k |\tilde{g}_k|^2}{\Omega_k |g_k|^2 + \sigma} \right) + R_k}{B} \right], \\ & \text{s.t.} && \text{C1: } \Gamma_{k+1} = \min\{\Gamma_{\max}, \tilde{Q}\}, \\ & && \text{C2: } \beta_k T \tilde{\Omega}_k - \Gamma_k \leq 0, \\ & && \text{C3: } 0 \leq \tau_k \leq 1, \\ & && \text{C4: } 0 \leq \tilde{\Omega}_k \leq \tilde{\Omega}_{sm}, \end{aligned} \quad (7.41)$$

where $\tilde{\Omega}_{sm}$ denotes the maximum transmit power of the secondary device, and $\tilde{Q} = (1 - \tau_k) T \eta \Omega_k |\tilde{g}_k|^2 - \tau_k T \tilde{\Omega}_k + \Gamma_k$. Constraint C1 ensures that the energy level of the secondary device's battery at time slot $k + 1$ does not exceed its maximum capacity while considering harvested energy. Constraint C2 guarantees that energy consumption during the k -th time slot does not surpass the available battery energy, thereby maintaining a non-negative battery level per C1. Constraint C3 ensures that the time-sharing coefficient τ_k remains within the valid range of 0 to 1. Lastly, constraint C4 limits the secondary device's transmit power to be within the range of 0 to $\tilde{\Omega}_{sm}$, representing its maximum allowable transmit power.

The optimization problem in (7.41) is non-convex due to the non-affine nature of C1 and the presence of variable multiplications in C2. Since the optimization variables take continuous values, solving Problem (7.41) is possible using the DDPG algorithm. However, applying DDPG directly presents significant challenges due to the wide range of optimization variable values. To address this, Problem (7.41) is decomposed into two subproblems for effective handling.

The first subproblem introduces an energy fluctuation parameter $\hat{\Gamma}_k$. This parameter signifies the variance between the energy utilized and the energy gathered at the

k -th time slot.

$$\begin{aligned} & \underset{\tau_k, \tilde{\Omega}_k}{\text{maximize}} \quad \left[\frac{\tau_k B \log_2 \left(1 + \frac{\tilde{\Omega}_k |\tilde{g}_k|^2}{\Omega_k |g_k|^2 + \sigma} \right) + R_k}{B} \right], \\ & \text{s.t.} \quad \text{C1: } \hat{f} = 0, \\ & \quad \quad \text{C2, C3, C4 in (7.41)}, \end{aligned} \quad (7.42)$$

where $\hat{f} = (1 - \tau_k)T\eta\Omega_k|\tilde{g}_k|^2 - \tau_k T\tilde{\Omega}_k - \hat{\Gamma}_k$, and $\hat{\Gamma}_k = (1 - \tau_k)T\eta\Omega_k|\tilde{g}_k|^2 - \tau_k T\tilde{\Omega}_k$. In (7.42), $\hat{\Gamma}_k$ represents the energy surplus during the k -th time slot. As a result, Problem (7.42) is solved using convex optimization techniques, allowing explicit formulas to be derived for a given $\hat{\Gamma}_k$. These formulations, as discussed in [34], yield closed-form solutions for the problem, expressed as follows:

$$\tilde{\Omega}_k^*(\hat{\Gamma}_k) = \frac{(1 - \tau_k^*)T\eta\Omega_k|\tilde{g}_k|^2}{\tau_k^*} - \frac{\hat{\Gamma}_k}{\tau_k^* T}, \quad (7.43)$$

and

$$\tau_k^*(\hat{\Gamma}_k) = \min \{1, \max \{f_1, f_2\}\}, \quad (7.44)$$

where $f_1 = \frac{x_1 - x_2}{e^{w_0(e^{-1}(x_1 - 1)) + 1} - 1 + x_1}$, while $w_0(\cdot)$ represents the Lambert- W -function, $x_1 = \frac{\eta\Omega_k|\tilde{g}_k|^2|\tilde{g}_0|^2}{\Omega_k|g_k|^2 + 1}$, $x_2 = \frac{\hat{\Gamma}_k|\tilde{g}_0|^2}{T(\Omega_k|g_k|^2 + 1)}$ and $f_2 = \max \left\{ 1 - \frac{\Gamma_k + \hat{\Gamma}_k}{T\eta\Omega_k|\tilde{g}_k|^2}, \frac{T\eta\Omega_k|\tilde{g}_k|^2 - \hat{\Gamma}_k}{T\eta\Omega_k|\tilde{g}_k|^2 + T\tilde{\Omega}_{sm}} \right\}$.

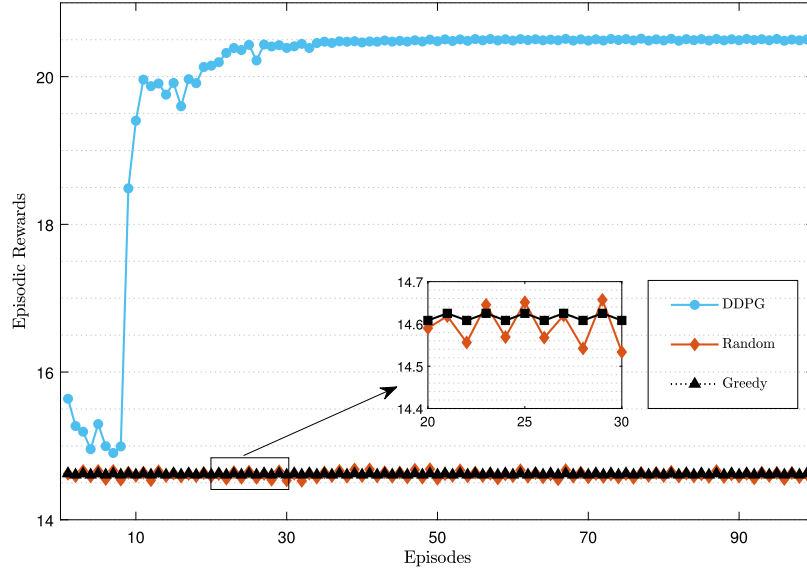
As our goal is to maximize the SE of the system, the second subproblem is given by

$$\begin{aligned} & \underset{\hat{\Gamma}_k}{\text{maximize}} \quad \sum_{i=1}^X \gamma^{i-1} \left[\frac{\tau_k^*(\hat{\Gamma}_k) B \log_2 \left(1 + \frac{\tilde{\Omega}_k^*(\hat{\Gamma}_k) |\tilde{g}_k|^2}{\Omega_k |g_k|^2 + \sigma} \right) + R_k}{B} \right], \\ & \text{s.t.} \quad \Gamma_{k+1} = \min \left\{ \Gamma_{\max}, \Gamma_k + \hat{\Gamma}_k \right\}, \end{aligned} \quad (7.45)$$

where γ denotes the discount factor, which ranges between 0 and 1. We can observe that Problem (7.45) is a univariate, continuous-valued function, suitable for solution using the DDPG algorithm.

7.4.3.7 Performance evaluation

To integrate the DDPG algorithm into our system model, the state comprises the channel gains and the current battery level of the secondary device, while the action corresponds to Γ_k , and the reward is defined by the SE. We evaluate the DDPG algorithm's performance by benchmarking it against traditional greedy and random strategies. In these baseline approaches, the transmit power of $\tilde{M}$ is kept constant at $\tilde{\Omega}_k$, while the time-sharing coefficient τ_k is determined differently:

**FIGURE 7.5**

Comparison of episodic rewards (or SE) for secondary IoT device using the proposed DDPG algorithm and baseline methods under linear EH models, with parameters $J = 2$, $\lambda = 0$ dBm, and $\Omega_k = 30$ dBm.

This comparison allows us to assess the efficiency and adaptability of DDPG in optimizing system performance over conventional methods. Fig. 7.5 presents a comparison of episodic rewards in terms of SE for the DDPG algorithm and benchmark methods, namely the greedy and random approaches, over multiple episodes. The figure clearly demonstrates that the DDPG algorithm consistently achieves superior rewards compared to the benchmark strategies. Notably, the DDPG approach exhibits signs of convergence after approximately 20 episodes, indicating that any further gains in episodic rewards become marginal. This observation highlights the DDPG algorithm's ability to learn and stabilize its performance efficiently, surpassing the other methods in effectiveness.

7.5 Implementation and practical considerations

While DRL based solutions have clear benefits, implementing them in practice comes with challenges like high computational demands, scalability issues, and real-time adaptability. This section focuses on practical factors such as tuning parameters, training methods, and deployment strategies to make DRL work effectively in real-world IoT networks.

7.5.1 Computational complexity and scalability

Implementing DRL in real world IoT networks faces significant challenges, with computational complexity being a primary concern. DRL algorithms rely on deep neural networks for policy optimization, which requires processing large datasets and demands high computational resources. Training these models can be both time consuming and resource-intensive.

Scalability is another major issue. As IoT networks grow, the number of devices and sensors increases, making the problem more complex. DRL models trained in small scale environments often struggle to adapt to larger, dynamic networks, limiting their effectiveness in real-world applications.

To tackle these challenges, techniques like model pruning, parallel training, and the use of specialized hardware like GPUs and TPUs can help reduce computational demands. Research into algorithm optimization and distributed learning is also advancing to improve the scalability of DRL for IoT systems.

7.5.2 Training and convergence challenges

DRL model training has many convergence issues. A drawback of RL is that the learning can vary from hundreds to millions episodes. The traditional DRL approached require millions of interactions with the environment for the agent to learn the optimized action. Applying this to real-time applications can be highly impractical. Furthermore, the highly dynamic real-world environment, causes the agent to take time to learn the correct actions and bring stability in its processes.

Other than this, exploration and exploitation trade off is also a major concern. Too much exploration leads to inefficiency in training. On the other hand, excessive exploitation of known policies can prevent the model from adapting to changes in the environment. Balancing these two aspects is crucial for the model's success.

To mitigate these challenges, techniques such as reward shaping, curriculum learning, and experience replay are used to improve the stability and speed of convergence. Additionally, adaptive learning rates and multi-agent systems are being explored to handle complex, multi device environments.

7.5.3 Deployment in real-world IoT scenarios

Implementing DRL in real-world scenarios involves more than just achieving good algorithmic performance. As the environment keeps changing, adapting to it comes difficulty and requires more time to train. With frequent changes in terms of devices, behaviors and network condition, IoT network usually become extremely dynamic. DRL models must continuously adjust to maintain optimal performance.

Secondly, real-time deployment also faces latency challenges. Many IoT applications require quick decision making, but the computational demands of DRL can cause delays. These delays can be unacceptable in time-sensitive scenarios. Ensuring that DRL policies run efficiently in real time is essential for such applications.

Another challenge is integrating DRL solutions into existing IoT setups. This requires hardware upgrades and software modifications to support deployment. Edge

computing and federated learning offer practical solutions. They enable DRL algorithms to operate on distributed devices with low latency, improving efficiency and adaptability.

7.6 Future directions

DRL has great potential to improve IoT systems, but several challenges still need to be addressed. Technologies like reconfigurable intelligent surfaces (RIS) [44], federated learning, and edge computing offer new possibilities for advancing DRL-based solutions. This section highlights key areas for future research to support the development of more sustainable IoT networks.

7.6.1 Integration with emerging technologies (e.g., RIS, backscatter, MEC)

As IoT continues to grow, technologies like RIS, backscatter communications [45], and MEC are emerging as key components of next-generation IoT networks. These technologies offer new ways to improve the performance of DRL based solutions.

Reconfigurable Intelligent Surfaces (RIS): by modifying radio waves propagation RIS, can adjust the wireless environment. This way, if combined with DRL algorithms, RIS can help optimize signal strength, reduce interference, and improve energy efficiency. RIS and DRL together can enhance the reliability and efficiency of communication in large IoT networks, by controlling the environment in real time based on network conditions. For example, [46] highlights a RIS-assisted aerial NTN integrate UAVs and HAPs with RIS to enhance wireless communication by optimizing signal propagation for better coverage and reliability. This study highlights how DRL, specifically H-PPO, can optimize these networks in a CoMP-NOMA scenario.

Backscatter Communications: By reflecting existing signals instead of generating new ones this technique allows devices to transmit data. Combining backscatter communications with DRL can help save energy, especially in battery-powered IoT devices. Similarly, DRL models can also adjust communication strategies to optimize backscatter performance under different environmental conditions. For example, [47] explores optimizing the sum rate for energy-harvesting IoT devices in a CR-NOMA-assisted backscatter network using the DDPG algorithm. This approach improves reflection coefficient management, ensuring QoS for primary devices and efficient performance for passive IoT nodes.

Mobile Edge Computing (MEC): MEC enables data processing closer to the edge of the network, reducing reliance on cloud computing. Integrating DRL with MEC can lead to faster decision-making in IoT applications. For instance, [48] explains how MEC enhances IoT performance by offloading tasks closer to User Equipment (UE), while DRL aids decision making in dynamic environments. By using edge servers, DRL models can process data locally, reducing delays and improving system performance. This is especially important for time-sensitive applications like autonomous vehicles and real-time healthcare monitoring.

7.6.2 Federated and distributed DRL for IoT

Federated learning (FL) and distributed DRL (DDRL) allow training models without centralizing data, making them suitable for IoT networks spread across large areas. This approach avoids the need to send all data to a central server.

In federated DRL, IoT devices work together to train a shared model while keeping their data local. This reduces communication requirements and protects privacy since sensitive data is not transmitted. Future efforts can focus on improving how updates are aggregated and addressing challenges from non-uniform data distributions. Example [49], a DRL-based management mechanism is proposed to select trustworthy devices, improving FL model accuracy by 20 percent with fewer training iterations. This model aims to improve the security challenges from malicious or resource-limited devices.

DDRL involves multiple agents learning from different parts of the environment. This approach enables scaling in IoT networks by allowing devices to explore and share insights independently. It helps reduce training times and improves model reliability, making it useful for real-time applications requiring quick adjustments. In [50], a DDRL-based computation offloading scheme is proposed to improve QoE in edge computing. Simulations show it outperforms existing methods with higher rewards and lower variability.

7.6.3 Security and privacy considerations

When using DRL algorithms that depend on large datasets, security and privacy are essential for IoT systems. However, protecting data and ensuring DRL model integrity are key challenges.

Data Privacy: IoT devices gather large amounts of sensitive data, raising privacy concerns. Methods like differential privacy, homomorphic encryption, and secure multiparty computation can help protect data during DRL training and use.

Adversarial Attacks: DRL systems can be targeted by attacks that disrupt learning with false information or environment manipulation. Research should focus on making DRL more resistant to these attacks using techniques like adversarial training and anomaly detection.

Secure Communication: IoT devices face threats like data interception and unauthorized access. Secure communication between devices and DRL models is vital, especially in distributed learning setups. Tools like TLS and blockchain [51] can help ensure data security and integrity.

7.6.4 Towards fully sustainable IoT networks

The long-term sustainability of IoT networks relies on reducing resource use, lowering environmental impact, and ensuring long-lasting systems. DRL can help achieve these goals by improving energy use, resource management, and overall performance.

Energy Efficiency: DRL can optimize energy use in IoT devices by adjusting transmission power, scheduling tasks, and managing network resources. This is crucial for battery-powered devices, as better energy management extends their lifetimes and reduces battery replacements.

Environmentally Friendly IoT: Future IoT systems need to be energy efficient and eco-friendly. DRL can help create power-saving communication protocols, efficient network designs, and energy-aware hardware. It can also optimize the use of renewable energy sources like solar power, ensuring sustainable operation of IoT devices.

Circular Economy: Sustainability also involves managing the lifecycle of IoT devices. DRL can support smart recycling systems where devices decide when to upgrade or replace parts. This helps promote a circular economy by focusing on reuse, recycling, and reducing waste.

7.7 Conclusion

This chapter explored the integration of DRL algorithms for optimization of energy and spectrum efficiency for IoT networks. The chapter focused on DRL ability to address the complex and evolving challenges of modern IoT deployments. We examined the characteristics and constraints of IoT devices. Beside this we emphasized on the importance of energy and spectrum management to ensure the long-term viability of these networks. DRL-based algorithms, with their ability to learn from dynamic environments, offer promising solutions to many challenges. By leveraging algorithms like DDPG, TD3, PPO, and SAC, these approaches optimize energy consumption and spectrum utilization in real time, driving greater network performance and sustainability.

However, as highlighted in the practical considerations, there remains several challenges. These challenges include computational complexity and scalability. Moreover, we discussed how the integration of DRL algorithms with technologies such as RIS, MEC, and FL has the potential to further enhance the capabilities of DRL for IoT. DRL-based algorithms addresses the evolving needs of diverse applications while ensuring that the underlying infrastructure remains secure and efficient. The future of IoT networks lies in the continued development of intelligent, sustainable, and efficient solutions. DRL-based algorithms, pave their way for greener and efficient future, with their ability to optimize both energy and spectrum use. Ultimately, these efforts will contribute to the realization of fully sustainable IoT networks that are capable of meeting the growing demands of the digital world while minimizing their environmental impact.

References

- [1] Y. Liu, Z. Qin, M. El Kashlan, Z. Ding, A. Nallanathan, L. Hanzo, Non-orthogonal multiple access for 5G and beyond, *Proceedings of the IEEE* 105 (12) (2017) 2347–2381.
- [2] H. Yin, S. Alamouti, OFDMA: a broadband wireless access technology, in: 2006 IEEE Sarnoff Symposium, 2006, pp. 1–4.
- [3] B. Makki, K. Chitti, A. Behravan, M.-S. Alouini, A survey of NOMA: current status and open research challenges, *IEEE Open Journal of the Communications Society* 1 (2020) 179–189.

- [4] K. Selvam, K. Kumar, Energy and spectrum efficiency trade-off of non-orthogonal multiple access (NOMA) over OFDMA for machine-to-machine communication, in: 2019 Fifth International Conference on Science Technology Engineering and Mathematics (ICONSTEM), vol. 1, 2019, pp. 523–528.
- [5] Z. Song, X. Wang, Y. Liu, Z. Zhang, Joint spectrum resource allocation in NOMA-based cognitive radio network with SWIPT, *IEEE Access* 7 (2019) 89594–89603.
- [6] S. Park, A.Q. Truong, T.H. Nguyen, Power control for sum spectral efficiency optimization in MIMO-NOMA systems with linear beamforming, *IEEE Access* 7 (2019) 10593–10605.
- [7] K. Reshma, A.V. Babu, Throughput analysis of energy harvesting enabled incremental relaying NOMA system, *IEEE Communications Letters* 24 (7) (2020) 1419–1423.
- [8] R. Sirait, W. Hardjawana, G. Wibisono, Performance of downlink NOMA for a massive IoT network over a Nakagami-m fading channel with optimized power allocation, *IEEE Access* 11 (2023) 67779–67790.
- [9] K. Arulkumaran, M.P. Deisenroth, M. Brundage, A.A. Bharath, Deep reinforcement learning: a brief survey, *IEEE Signal Processing Magazine* 34 (6) (2017) 26–38.
- [10] T. Sanislav, G.D. Mois, S. Zeadally, S.C. Folea, Energy harvesting techniques for Internet of Things (IoT), *IEEE Access* 9 (2021) 39530–39549.
- [11] X. Chen, Q. Shi, L. Yang, J. Xu, Thriftyedge: resource-efficient edge computing for intelligent IoT applications, *IEEE Network* 32 (1) (2018) 61–65.
- [12] D. Ottolini, I. Zyrianoff, C. Kamienski, Interoperability and scalability trade-offs in open IoT platforms, in: 2022 IEEE 19th Annual Consumer Communications & Networking Conference (CCNC), 2022, pp. 1–6.
- [13] R.S. Sutton, A.G. Barto, Reinforcement Learning: An Introduction, 2nd ed, MIT Press, 2018 [Online]. Available <http://incompleteideas.net/book/the-book-2nd.html>.
- [14] L.P. Kaelbling, M.L. Littman, A.W. Moore, Reinforcement learning: a survey, *Journal of Artificial Intelligence Research* 4 (1996) 237–285.
- [15] M.L. Puterman, Markov decision processes, in: *Handbooks in Operations Research and Management Science*, vol. 2, 1990, pp. 331–434.
- [16] M.L. Puterman, *Markov Decision Processes: Discrete Stochastic Dynamic Programming*, John Wiley & Sons, 2014.
- [17] V. Mnih, K. Kavukcuoglu, D. Silver, A.A. Rusu, J. Veness, M.G. Bellemare, A. Graves, M. Riedmiller, A.K. Fidjeland, G. Ostrovski, et al., Human-level control through deep reinforcement learning, *Nature* 518 (7540) (2015) 529–533.
- [18] A.G. Barto, R.S. Sutton, C. Watkins, *Learning and Sequential Decision Making*, vol. 89, University of Massachusetts, Amherst, MA, 1989.
- [19] G.E. Monahan, State of the art—a survey of partially observable Markov decision processes: theory, models, and algorithms, *Management Science* 28 (1) (1982) 1–16.
- [20] M.T. Spaan, *Partially observable Markov decision processes*, in: *Reinforcement Learning: State-of-the-Art*, Springer, 2012, pp. 387–414.
- [21] D. Silver, T. Hubert, J. Schrittwieser, I. Antonoglou, M. Lai, A. Guez, M. Lanctot, L. Sifre, D. Kumaran, T. Graepel, et al., A general reinforcement learning algorithm that masters chess, shogi, and go through self-play, *Science* 362 (6419) (2018) 1140–1144.
- [22] A. Nagabandi, G. Kahn, R.S. Fearing, S. Levine, Neural network dynamics for model-based deep reinforcement learning with model-free fine-tuning, in: 2018 IEEE International Conference on Robotics and Automation (ICRA), IEEE, 2018, pp. 7559–7566.
- [23] S. Racanière, T. Weber, D. Reichert, L. Buesing, A. Guez, D. Jimenez Rezende, A. Puigdomènech Badia, O. Vinyals, N. Heess, Y. Li, et al., Imagination-augmented agents for

- deep reinforcement learning, *Advances in Neural Information Processing Systems* 30 (2017).
- [24] C.B. Browne, E. Powley, D. Whitehouse, S.M. Lucas, P.I. Cowling, P. Rohlfshagen, S. Tavener, D. Perez, S. Samothrakis, S. Colton, A survey of Monte Carlo tree search methods, *IEEE Transactions on Computational Intelligence and AI in Games* 4 (1) (2012) 1–43.
 - [25] C.J. Watkins, P. Dayan, Q-learning, *Machine Learning* 8 (1992) 279–292.
 - [26] V. Mnih, K. Kavukcuoglu, D. Silver, A.A. Rusu, J. Veness, M.G. Bellemare, A. Graves, M. Riedmiller, A.K. Fidjeland, G. Ostrovski, et al., Human-level control through deep reinforcement learning, *Nature* 518 (7540) (2015) 529–533.
 - [27] M. Hessel, J. Modayil, H. Van Hasselt, T. Schaul, G. Ostrovski, W. Dabney, D. Horgan, B. Piot, M. Azar, D. Silver, Rainbow: combining improvements in deep reinforcement learning, in: *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 32, 2018.
 - [28] R.J. Williams, Simple statistical gradient-following algorithms for connectionist reinforcement learning, *Machine Learning* 8 (1992) 229–256.
 - [29] J. Schulman, S. Levine, P. Abbeel, M. Jordan, P. Moritz, Trust region policy optimization, in: *International Conference on Machine Learning*, PMLR, 2015, pp. 1889–1897.
 - [30] J. Schulman, F. Wolski, P. Dhariwal, A. Radford, O. Klimov, Proximal policy optimization algorithms, *arXiv preprint*, arXiv:1707.06347, 2017.
 - [31] V. Mnih, A.P. Badia, M. Mirza, A. Graves, T. Lillicrap, T. Harley, D. Silver, K. Kavukcuoglu, Asynchronous methods for deep reinforcement learning, in: *International Conference on Machine Learning*, PMLR, 2016, pp. 1928–1937.
 - [32] T.P. Lillicrap, J.J. Hunt, A. Pritzel, N. Heess, T. Erez, Y. Tassa, D. Silver, D. Wierstra, Continuous control with deep reinforcement learning, *arXiv preprint*, arXiv:1509.02971, 2015.
 - [33] T. Haarnoja, A. Zhou, K. Hartikainen, G. Tucker, S. Ha, J. Tan, V. Kumar, H. Zhu, A. Gupta, P. Abbeel, et al., Soft actor-critic algorithms and applications, *arXiv preprint*, arXiv:1812.05905, 2018.
 - [34] Z. Ding, R. Schober, H.V. Poor, No-pain no-gain: DRL assisted optimization in energy-constrained CR-NOMA networks, *IEEE Transactions on Communications* 69 (9) (2021) 5917–5932.
 - [35] S. Asad Ullah, M. Abdullah Sohail, H. Jung, M. Omer, Bin Saeed, S. Ali Hassan, Sum rate maximization in IoT networks with diversity-enhanced energy harvesting: a DRL-guided approach, *IEEE Internet of Things Journal* 11 (18) (2024) 30 309–30 322.
 - [36] A.A. Mohammed, M.W. Baig, M.A. Sohail, S.A. Ullah, H. Jung, S.A. Hassan, Navigating boundaries in quantifying robustness: a DRL expedition for non-linear energy harvesting IoT networks, *IEEE Communications Letters* (2024) 1.
 - [37] S.A. Ullah, S. Muhammad Khalid, U.A. Korai, A. Ullah, An energy-efficient communication protocol for power-constrained IoT networks: a deep reinforcement learning approach, in: *2023 Global Conference on Wireless and Optical Technologies (GCWOT)*, 2023, pp. 1–6.
 - [38] S.A. Ullah, S. Zeb, A. Mahmood, S.A. Hassan, M. Gidlund, Deep RL-assisted energy harvesting in CR-NOMA communications for next-G IoT networks, in: *IEEE Globecom Wkshps*, IEEE, 2022, pp. 74–79.
 - [39] N. Mazhar, S.A. Ullah, H. Jung, Q.-U.-A. Nadeem, S.A. Hassan, Enhancing spectral efficiency in IoT networks using deep deterministic policy gradient and opportunistic NOMA, in: *2024 IEEE 100th Vehicular Technology Conference (VTC2024-Fall)*, 2024, pp. 1–6.

- [40] N. Mazhar, S.A. Ullah, H. Jung, Q.-U.-A. Nadeem, S.A. Hassan, Mobility-aware DRL strategy for throughput optimization in QoS-driven opportunistic NOMA IoT networks, in: GLOBECOM 2024–2024 IEEE Global Communications Conference, 2024, pp. 1–6.
- [41] Z. Ding, R. Schober, H.V. Poor, A new QoS-guarantee strategy for NOMA assisted semi-grant-free transmission, *IEEE Transactions on Communications* 69 (11) (2021) 7489–7503.
- [42] S. Boyd, et al., *Convex Optimization*, Cambridge University Press, 2004.
- [43] Q. Liu, F. Tan, T. Lv, H. Gao, Energy efficiency and spectral-efficiency tradeoff in downlink NOMA systems, in: 2017 IEEE International Conference on Communications Workshops (ICC Workshops), 2017, pp. 247–252.
- [44] C. Huang, A. Zappone, G.C. Alexandropoulos, M. Debbah, C. Yuen, Reconfigurable intelligent surfaces for energy efficiency in wireless communication, *IEEE Transactions on Wireless Communications* 18 (8) (2019) 4157–4170.
- [45] B. Ji, B. Xing, K. Song, C. Li, H. Wen, L. Yang, The efficient backfi transmission design in ambient backscatter communication systems for IoT, *IEEE Access* 7 (2019) 31 397–31 408.
- [46] M. Umer, M.A. Mohsin, A. Kaushik, Q.-U.-A. Nadeem, A.A. Nasir, S.A. Hassan, Reconfigurable intelligent surface-assisted aerial nonterrestrial networks: an intelligent synergy with deep reinforcement learning, *IEEE Vehicular Technology Magazine* (2025) 2–11.
- [47] H.M. Ali Zeeshan, S.A. Ullah, S.A. Hassan, Z. Ding, H. Jung, DDPG-based sum rate optimization for opportunistic backscatter NOMA networks, in: GLOBECOM 2023–2023 IEEE Global Communications Conference, 2023, pp. 3312–3317.
- [48] Y. Wang, H. Wu, R. Li, Deep graph reinforcement learning for mobile edge computing: challenges and solutions, *IEEE Network* 38 (5) (2024) 314–323.
- [49] N. Al-Maslamani, M. Abdallah, B.S. Ciftler, Secure federated learning for IoT using drl-based trust mechanism, in: 2022 International Wireless Communications and Mobile Computing (IWCMC), 2022, pp. 1101–1106.
- [50] J. Park, K. Chung, Distributed drl-based computation offloading scheme for improving qoe in edge computing environments, *Sensors* 23 (8) (2023) [Online]. Available, <https://www.mdpi.com/1424-8220/23/8/4166>.
- [51] E. Beckwith, G. Thamilarasu, Ba-tls: blockchain authentication for transport layer security in Internet of Things, in: 2020 7th International Conference on Internet of Things: Systems, Management and Security (IOTSMS), 2020, pp. 1–8.
- [52] P. Thakur, G. Singh, Performance analysis of MIMO-based CR-NOMA communication systems, *IET Communications* 14 (16) (2020) 2677–2686.

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Optimizing techniques to support the development of Green IoT

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8.1 Introduction

An interconnected network of physical devices embedded with sensors, connectivity, and processing power capable of collaboratively exchanging data through the Internet forms the basis of the Internet-of-things (IoT). The idea of densely connected small devices has garnered significant attention since its inception in 1999 [1]. This growing interest is further indicated by the 934.2 billion dollar expected worldwide total annual revenue from the IoT industry [2]. According to some estimates, 127 IoT devices are added to the Internet every second, and 125 billion IoT devices are expected to be connected to the Internet by the end of 2030 [3]. These projections indicate a massive increase in the connection load on the existing communication infrastructure. In addition to the communication overhead, the power consumption of such a large number of devices in dense deployments is a major concern in academia and industries in the design of next-generation systems [4].

In addition to the exponential increase in the number of IoT devices that are expected to be operational in the coming years, the support of the growing IoT landscape in its entirety requires the assimilation of sensing functionality inside the IoT devices. As these IoT devices must be able to sense the environment around them, the concept of integrated sensing and communication (ISAC) has been put forward as the way to enable the functional feasibility of IoT systems [5]. ISAC is expected to enable the sensing of the surrounding environment using either a monostatic or bistatic configuration. In both these configurations, the communication signals can be used for information transmission and environmental sensing. Environmental sensing from information-bearing signals is a complicated procedure involving more processing, complex interference cancellation, and waveform optimization, etc. Due to these reasons, energy-efficient designs are starting to be explored in the literature to make the adoption of ISAC-enabled systems more practically feasible, especially in the context of IoT [5].

As wireless communication infrastructure becomes more ubiquitous and reliable, and machines and processes become more complex, intelligent automation of these processes not only becomes more feasible but also necessary. The optimal use of resources in production, logistics, and many other industrial processes increases efficiency and reduces workload on human workers who may have otherwise been overworked in the management of menial tasks. Owing to the advances enabled through automation, machine-to-machine (MTM) communication has become one of the main design focuses of modern communication systems [6]. The nature of communication between machines varies significantly from human-to-human (HTH) communications owing to their focus on short but frequent messages with an enhanced focus on reliability rather than bandwidth. As the scale of deployment and latency sensitivity of IoT in the industry is much different from typical HTH communications, the optimization of these systems plays an important role in their feasibility within such industrial environments. In addition to the aforementioned challenges, the move towards green IoT demands the efficient use of resources in order to maximize utility, limit power consumption, and reduce CO₂ emissions [7].

To fulfill the objectives required for the optimal functioning of IoT networks in the presence of energy constraints, every aspect of IoT systems, from design to implementation and operation, has to be optimized. This objective can only be fulfilled after a comprehensive understanding of the mindset, designs, and algorithms involved throughout the process. Understanding the bottlenecks and optimization variables involved in the problem can have a significant impact on the quality of the optimization performed for the desired functioning of the system. Therefore, in this chapter, we highlight the techniques and steps typically involved in the optimization of a system, including a primer on optimization, the structure of an optimization problem, and types of optimization paradigms. We then move towards the introduction of optimization in green IoT and the opportunities typically exploitable in the design and optimization of green IoT networks in terms of typical wireless communication technologies. We then finally move towards communication protocols that can be employed for the optimal functioning of a green IoT architecture. Finally, the chapter is concluded by providing insights learned from the comprehensive treatment of the techniques and protocols mentioned in the chapter. Possible future directions are also mentioned that may be undertaken to explore feasible optimization opportunities.

8.2 Optimization

Optimization is the process of determining the most favorable solution to a given problem from a set of feasible alternatives, based on a defined objective and subject to constraints. The objective of optimization may be to maximize or minimize a particular quantity in order to obtain the best performance. The process is central to many disciplines, providing a systematic framework for decision making and

operational improvement in complex systems. By systematically exploring solution spaces within the defined constraints, the best solution that satisfies the objective can be identified. Constraints typically represent limitations or requirements, such as resource availability, physical boundaries, or operational rules that must be satisfied for the solution to be feasible.

Optimization algorithms are employed when explicit solutions cannot be directly computed due to the complexity of the problem or time constraints. These algorithms iteratively refine candidate solutions and converge toward the optimal outcome by evaluating and improving upon intermediate results. The field of optimization encompasses a wide range of methodologies and techniques that are best suited to specific types of problems.

Optimization is integral to various applications ranging from engineering design and supply chain management to financial planning and medicine. By ensuring optimal decisions, system operations can be enhanced and made more efficient across diverse domains.

8.2.1 Types of optimization problems

Optimization problems can be broadly classified into either constrained or unconstrained optimization problems based on the presence or absence of constraints. These classifications provide a foundational structure for formulating and solving optimization problems in various applications.

Unconstrained optimization problems

In unconstrained optimization, the objective is to find the optimal solution without any constraints on the decision variables. The domain of a decision variable is defined as the set of all of the values a variable can take, and this set can be either finite or infinite. The formulation of an unconstrained optimization involves minimizing or maximizing an objective function $f(x)$ over the entire domain of the decision variables. These problems are simpler to solve as there are no additional constraints to consider while searching for the solution. Common methods for solving unconstrained problems include gradient-based techniques such as gradient descent, Newton's method, and quasi-Newton methods. These approaches rely on the smoothness and differentiability of the objective function and therefore struggle with problems not possessing these properties.

Constrained optimization problems

Constrained optimization problems involve additional restrictions, expressed as mathematical equalities or inequalities, that the solution must satisfy. Mathematically, these problems are formulated as:

$$\begin{aligned} &\text{minimize} && f(x) \\ &\text{subject to} && g_i(x) \leq 0, \quad i = 1, \dots, m, \\ & && h_j(x) = 0, \quad j = 1, \dots, p, \end{aligned}$$

where $g_i(x)$ and $h_j(x)$ represent the inequality and equality constraints, respectively. Constraints define a feasible domain within which the decision variables can exist. Constrained problems are inherently more complex than their unconstrained counterparts, as the constraints may introduce non-linearities or limit the feasible decision space.

Constrained optimization techniques include methods that transform the problem into an unconstrained form, such as penalty methods, barrier methods, etc., which prevent exploration of the space outside the constraints, or those that deal directly with constraints, such as interior-point or augmented Lagrangian methods. These approaches ensure that the solution satisfies all imposed constraints while optimizing the objective function.

The distinction between constrained and unconstrained problems is fundamental in optimization, influencing the selection of solution techniques and the complexity of the problem. While unconstrained optimization focuses purely on the properties of the objective function due to the absence of constraints, constrained optimization problems require a balance between objective optimization and constraint satisfaction, making them crucial in real-world applications where restrictions are inevitable.

8.2.2 Structure of an optimization problem

An optimization problem is mathematically represented by an objective function, decision variables, and constraints. A general form of an optimization problem is given by

$$\begin{aligned} &\text{minimize} && f_0(x) \\ &\text{subject to} && f_i(x) \leq b_i, \quad i = \{1, \dots, m\}, \end{aligned}$$

where $x \in \mathbb{R}^n$ denotes the decision variables, $f_0(x) : \mathbb{R}^n \rightarrow \mathbb{R}$ is the objective function, and $f_i(x) : \mathbb{R}^n \rightarrow \mathbb{R}$ are the functions defining the constraints. The constraints restrict the original domain of the decision variables to specify a smaller domain, often denoted as $\mathcal{F}$, which represents all x that satisfy the constraints. A solution x^* is said to be optimal if it lies within the feasible domain and minimizes (or maximizes) the objective function compared to all other values in that domain. It is important to note that in the case of constrained optimization problems, the global optimum over the entire domain may be different from the optimum in the constrained domain of the decision variables. A mathematical structure is crucial for classifying optimization problems, such as linear, quadratic, or nonlinear, and for determining appropriate solution methods.

Objective

The objective of an optimization problem is the function $f_0(x)$ that numerically quantifies the goal to be achieved. For a minimization problem, the objective of the algorithm is to find a decision vector x^* such that $f_0(x^*) \leq f_0(x)$ for all $x \in \mathcal{F}$, where $\mathcal{F}$ represents the feasible region. The cases involving function maximization can be handled by minimizing the negative of the function, i.e., $-f_0(x)$. The properties of the objective function, such as linearity, convexity, differentiability, and smoothness, significantly affect the complexity of the problem and the algorithms required to solve it.

Metrics

Metrics are quantitative measures that evaluate the quality of solutions to optimization problems. The most commonly used metric is the value of the objective function at the optimal point, $f_0(x^*)$, which indicates how well the solution satisfies the problem's goal. However, in some use cases, the constraints involved in the optimization problem must be strictly met, e.g., power constraints on transmit antennas, load balancing in network traffic, etc., to keep the system stable and operational. Constraint satisfaction metrics, employing residuals of $f_i(x) - b_i$ for inequality constraints or $h_j(x)$ for equality constraints can also be used to measure the performance of an optimization algorithm. In multi-objective optimization, metrics such as Pareto dominance, Pareto front distance, or hypervolume are used to assess trade-offs among competing objectives. Metrics are also used to define stopping criteria, convergence rates, and computational efficiency.

Constraints

Real-world systems are inherently subject to constraints that must be taken into account to ensure reliability and stability. These limitations are effectively modeled in constrained optimization problems, where constraints explicitly define the allowable values of decision variables. Mathematical optimization provides a rigorous framework for incorporating these limitations as constraints, ensuring that solutions remain feasible within the defined operational bounds.

Constraints delineate the feasible region in which decision variables can exist, and the optimal solution must be obtained within this region. Formally, constraints can be categorized into:

- **Equality Constraints:** Requiring decision variables to satisfy specific exact relationships, represented by equalities.
- **Inequality Constraints:** Restricting decision variables to meet upper or lower bounds or other limiting conditions, represented by inequalities.

Constraints can be linear or nonlinear, and their interaction determines the geometry of the region formed by the feasible set. For instance, linear constraints form polyhedra, while nonlinear constraints often result in curved boundaries. Proper handling of constraints is crucial for problem formulation and solution, as setting loose constraints may affect the stability of complex systems and overly restrictive constraints might exclude the optimal solution.

Decision variables

Decision variables $x = (x_1, x_2, \dots, x_n) \in \mathbb{R}^n$ are the variables that need to be determined to solve the optimization problem. They serve as parameters for both the objective function and the constraints, with their values influencing the value of the metrics as well. Decision variables can belong to either continuous spaces or discrete spaces, each possessing different properties.

Discrete Spaces: A discrete space consists of elements that are distinct, and countable. They correspond to decision variables that can only take specific values,

e.g., integers or categorical values. These spaces are encountered in scheduling, or routing problems where the solutions involve selecting from a finite or countable set of possibilities. The set of integers $\{1, 2, 3, \dots\}$ or the set of antennas to select for transmission are problems with discrete decision variables.

Continuous Spaces: In contrast, a continuous space is characterized by values within a specified range or domain of real numbers. Decision variables in continuous spaces are not restricted to discrete levels. These spaces are frequently used in problems involving real-valued functions, such as beamforming optimization and power allocation, etc. The interval $[0, 1]$ or the entire Euclidean space $\mathbb{R}^n$ are continuous in nature.

Mixed-integer optimization problems involve both types of variables and are generally more complex. The domain boundaries of the decision variables are often explicitly specified by constraints, such as bounds $l \leq x \leq u$, where $l, u \in \mathbb{R}^n$.

8.2.3 Complexity of optimization problems

The complexity of an optimization problem is determined by the nature of its objective function, constraints, and metrics. Problems with linear objectives and constraints, called linear programming (LP) problems, are efficiently solvable in polynomial time using algorithms such as the simplex method or interior-point methods. For example, we have

$$\begin{aligned} &\text{minimize} && c^\top x \\ &\text{subject to} && Ax \leq b, \\ &&& x \geq 0, \end{aligned}$$

where the variables $c \in \mathbb{R}^n$, $A \in \mathbb{R}^{m \times n}$, and $b \in \mathbb{R}^m$ form a linear programming problem with a linear objective and linear constraints.

Quadratic programming (QP), where the objective function is quadratic and constraints are linear, also allows polynomial-time solutions if the objective function is convex. For instance,

$$\text{minimize } \frac{1}{2}x^\top Qx + c^\top x \quad \text{subject to } Ax \leq b$$

is a quadratic programming problem, where Q is a positive semidefinite matrix. The term $x^\top Qx$ makes the objective function quadratic.

In contrast, nonconvex optimization problems, such as those with multiple local minima or combinatorial structures, are often NP-hard. These problems require heuristic or approximate methods, such as genetic algorithms or simulated annealing, for practical solutions. Combinatorial optimization problems, like the traveling salesman problem (TSP), are also non-convex and NP-hard. The dimensionality of the problem and the sparsity of constraints further influence computational complexity. Examples of these constraints can be found in the literature on user association and resource allocation optimization [8].

8.2.4 Types of optimization solutions

An optimum is determined by identifying the minimum or maximum value of an objective function within the domain of the decision variables. Since the optimum must represent the extremum value achievable within the feasible region, optimization algorithms can be categorized into two classes based on the nature of the optimal solution they identify. These classes are:

- Global Optimization
- Local Optimization

Global optimization

Global optimization focuses on identifying the best solution across the entire search space. Unlike local optimization, it avoids being confined to local optima and is particularly important for problems with multi-modal or highly complex response curves, where multiple local optima exist.

Techniques for global optimization, including simulated annealing and genetic algorithms, emphasize the exploration of the decision space. These methods utilize random, population-based, or probabilistic approaches to ensure broad coverage of the solution space. Global optimization is essential for problems where finding the true global optimum is critical, even at the cost of high computation.

Local optimization

Local optimization seeks the best solution within a restricted neighborhood of a random starting point. It assumes that the objective function behaves consistently and allows for iterative refinement of the solution using information such as gradients and curvatures. Typical gradient-based optimization techniques such as Newton's method and quasi-Newton methods are widely used to solve problems with these assumptions.

Local optimization is computationally efficient as compared to global optimization, and effective when applied to smooth and convex problems where any local minimum is guaranteed to be a global minimum. However, it may fail in non-convex or multi-modal landscapes, where solutions may converge to a local optimum that may not be globally optimal.

8.3 Types of optimization frameworks

Optimization techniques can be broadly classified based on various criteria, such as the nature of the problem, the structure of the optimization space, and the methodology.

8.3.1 Mathematical optimization

Mathematical optimization focuses on systematically identifying the best solution to a problem by maximizing or minimizing an objective function within defined

constraints. Unlike other techniques that may rely on approximate and often problem-specific strategies or on learning patterns from data to make predictions or decisions, mathematical optimization provides exact or provably optimal solutions when the problem structure allows and models objectives and constraints for decision making.

Convex optimization

Convex optimization addresses problems where the objective function is convex, and the feasible region forms a convex set. A convex function is defined as a function in which the intermediate values between two function values are always lower than or equal to the line connecting the two function values. This property guarantees that every local minimum is also a global minimum. The mathematical structure of convex optimization problems allows for the development of efficient algorithms, such as gradient descent and interior-point methods.

- **Examples:** Linear programming (LP), Quadratic programming (QP), Semidefinite programming (SDP), etc.
- **Advantages:** Global optimum is guaranteed due to convexity.
- **Techniques:** Gradient descent, interior-point methods, etc.
- **Applications:** Beamforming, power allocation, etc.

Non-convex optimization

Non-convex optimization deals with problems where the objective function or constraints lack convexity, leading to multiple local optima. Unlike convex optimization, there is no guarantee that a local minimum is a global minimum. Non-convex problems rely on effective methods to explore the solution space and escape local optima. To address the problem of premature convergence, techniques such as simulated annealing allow for probabilistic “jumps” that explore regions beyond the current local solution, mimicking the physical process of cooling metals. Similarly, Genetic algorithms leverage evolutionary principles, such as selection and mutation, to explore diverse regions of the solution space. These methods, aim to balance optimal search and solution refinement to achieve robust results.

- **Examples:** Non-linear programming, combinatorial optimization, etc.
- **Challenges:** Fine-tuning to find the global optimum, computationally expensive, etc.
- **Techniques:** Simulated annealing, genetic algorithms, branch and bound, etc.
- **Applications:** Antenna selection, cell user association, etc.

Stochastic optimization

Stochastic optimization incorporates randomness into the optimization process or directly into the problem formulation, enabling the handling of uncertainties, and incomplete or noisy information. Instead of relying on precise function evaluations, these methods work with noisy or sampled data to iteratively improve solutions. A method called stochastic gradient descent (SGD) updates the solution using small random subsets of data (mini-batches), reducing the computational cost while maintaining significant convergence properties. These methods are particularly effective

for large-scale problems where deterministic approaches are computationally prohibitive. Stochastic optimization techniques are often sensitive to optimization parameters like learning rate and stopping criteria therefore appropriate parameter selection is one of the challenges involved in stochastic modeling and optimization.

- **Examples:** Stochastic gradient descent (SGD), particle swarm optimization (PSO), Monte Carlo methods, Bayesian optimization, etc.
- **Challenges:** Convergence issues in complex scenarios, sensitivity to hyperparameters (e.g., learning rates), and computational overhead in large-scale systems.
- **Techniques:** Mini-batch stochastic gradient descent, Markov Chain Monte Carlo (MCMC), Gaussian process-based Bayesian optimization, etc.
- **Applications:**
 - Dynamic spectrum allocation in cognitive radio networks.
 - Power control in massive MIMO systems.
 - User scheduling and beamforming optimization.
 - Resource allocation in ultra-dense networks.
 - Channel estimation in IoT-enabled networks.

Combinatorial optimization

Combinatorial optimization focuses on problems where the objective is to find the best solution from a finite or countably infinite set of feasible solutions, often characterized by discrete decision variables and complex constraints. The large solution spaces of combinatorial problems make exhaustive search impossible, and special optimization techniques have to be developed to efficiently explore the solution space. Techniques including integer dynamic programming and dynamic programming might be able to tackle smaller problems, but for large solution spaces, meta-heuristic algorithms have to be employed to find a feasible solution within reasonable time bounds.

Combinatorial optimization is well suited for problems with a structure consisting of discrete elements, such as graphs. These methods are sensitive to problem-specific factors such as the structure of the feasible region, the behavior of the cost function, and the complexity of the constraints, which influence the choice of algorithm and its effectiveness.

- **Examples:** Scheduling problems, resource allocation, routing optimization, etc.
- **Challenges:** Large solution spaces, NP-hard complexity, difficulty in finding globally optimal solutions, and computational infeasibility for real-time applications.
- **Techniques:** Integer programming, branch and bound, dynamic programming, genetic algorithms, greedy algorithms, etc.
- **Applications:**
 - Frequency assignment in wireless networks.
 - User association in heterogeneous networks.
 - Beam selection in millimeter-wave MIMO systems.
 - Optimal routing in ad-hoc and sensor networks.
 - Subcarrier and power allocation in OFDMA systems.

8.3.2 Heuristic and metaheuristic techniques

Heuristic and metaheuristic techniques focus on efficiently finding near-optimal solutions to complex optimization problems, particularly where exact methods are computationally infeasible due to the size or structure of the problem. Unlike mathematical optimization, which relies on rigorous modeling of objectives and constraints, heuristic and metaheuristic methods use approximate, problem-independent strategies (in the case of metaheuristics) inspired by nature, physics, or random processes to optimize complex systems.

Heuristic methods

Heuristic methods are approximate strategies designed to produce good solutions within reasonable timeframes, especially for complex problems where exact solutions are infeasible. These methods rely on intuitive rules or insights about the problem structure rather than rigorous mathematical formulations. Hill climbing is one notable example of heuristic methods, in which the algorithm iteratively adjusts the current solution by evaluating neighboring solutions and moving toward the one with the highest improvement. While heuristic methods are not guaranteed to find the optimal solution, they are highly desirable for quickly obtaining optimized results that may prove to be much better than random selection. They often form the foundation for more advanced optimization frameworks by providing initial solutions or guidance.

- **Examples:** Hill climbing, greedy algorithms, random search, etc.
- **Challenges:** Prone to getting stuck in local optima, lack of scalability for complex problems, and no guarantee of global optimality.
- **Techniques:** Constructive heuristics, neighborhood-based search, iterative improvement, etc.
- **Applications:**
 - Channel allocation in wireless networks.
 - Beamforming vector selection in MIMO systems.
 - Resource scheduling in edge computing environments.
 - Frequency planning in cellular networks.
 - Pathfinding in ad-hoc and sensor networks.

Metaheuristic methods

Metaheuristic methods are generalized frameworks that enhance heuristic approaches by introducing mechanisms to explore the solution space more systematically. For instance, genetic algorithms simulate natural selection by evolving a population of candidate solutions utilizing crossover and mutation. Simulated annealing, inspired by the cooling process of metals, probabilistically accepts worse solutions to escape local optima early in the process. Other methods, such as particle swarm optimization, model collective behaviors to guide search efforts. Metaheuristics provide a versatile toolkit for tackling diverse and complex optimization problems while being adaptable to a wider class of problems than heuristic algorithms at the cost of added complexity.

- **Examples:** Genetic algorithms (GA), simulated annealing (SA), particle swarm optimization (PSO), ant colony optimization (ACO), differential evolution (DE), etc.
- **Challenges:** High computational cost for large-scale problems, risk of premature convergence, difficulty in parameter tuning, and lack of problem-specific guarantees.
- **Techniques:**
 - Population-based techniques (e.g., GA, PSO, DE).
 - Trajectory-based techniques (e.g., SA, ACO).
 - Hybrid metaheuristics that combine elements of multiple algorithms.
- **Applications:**
 - Power allocation in heterogeneous networks.
 - Beamforming optimization in massive MIMO systems.
 - Resource allocation in multi-access edge computing (MEC).
 - Spectrum sharing in cognitive radio networks.
 - Clustering in wireless sensor networks.

8.3.3 Machine learning-based optimization

Machine learning-based optimization leverages the predictive and adaptive capabilities of machine learning models to guide the search for optimal solutions. Unlike traditional mathematical optimization, which relies on explicit models of objectives and constraints, machine learning-based approaches learn patterns and relationships directly from data. These techniques are particularly effective when the problem structure is not fully known or the problem is too complex to model using classical approaches. By integrating data-driven insights into the optimization process, machine learning can significantly reduce the effort required in classical modeling while also providing comparable or better optimization results.

- **Examples:** Supervised learning for optimization, deep learning-based optimization, Bayesian optimization, etc.
- **Challenges:** High computational complexity, requirement for large datasets, susceptibility to overfitting, lack of interpretability, and difficulty in convergence for complex wireless environments.
- **Techniques:**
 - Deep reinforcement learning (e.g., DDPG, PPO).
 - Bayesian optimization for hyperparameter tuning.
 - Supervised learning for predictive optimization.
 - Transfer learning for dynamic network adaptation.
 - Federated learning for distributed optimization.
- **Applications:**
 - Dynamic spectrum allocation in cognitive radio networks.
 - Power control in energy-efficient communication systems.
 - User scheduling in multi-user MIMO systems.
 - Resource allocation in ultra-dense networks.
 - Beamforming optimization in millimeter-wave systems.

Gradient-based optimization

Gradient-based optimization uses derivatives to guide the search for optimal solutions in continuous spaces. For convex problems, gradient-based methods like gradient descent or Newton's method are highly efficient, converging to the global minimum. Differential objective functions are necessary for the proper functioning of these techniques, therefore the design of smooth and differentiable objective functions is of significant interest in this domain of optimization. Proper tuning of parameters, such as learning rates or step sizes, is critical for achieving a balance between convergence speed and stability. Advanced variants, such as adaptive moment estimation (Adam), incorporate momentum and adaptive learning rates to enhance performance in complex problems.

- **Examples:** Gradient descent, stochastic gradient descent (SGD), conjugate gradient method, Newton's method, quasi-Newton methods, etc.
- **Challenges:** Dependence on the differentiability of objective functions, sensitivity to initial conditions, risk of convergence to local optima in non-convex problems, and computational inefficiency for high-dimensional systems.
- **Techniques:**
 - Adaptive gradient methods (e.g., Adam, RMSprop).
 - Momentum-based optimization techniques.
 - Line search and trust-region methods for step size optimization.
- **Applications:**
 - Beamforming optimization in massive MIMO systems.
 - Power allocation in multi-user communication networks.
 - Resource allocation in OFDMA-based networks.

Gradient-free optimization

Gradient-free optimization methods are designed for situations where gradients are unavailable, unreliable, or expensive to compute. These methods rely on sampling and evaluating the objective function directly, making them suitable for black-box problems where the internal structure of the function is unknown. Techniques like Bayesian optimization model the objective function probabilistically, using prior evaluations to guide exploration and exploitation. While these methods are computationally intensive, they are robust to noisy, non-differentiable, or multi-modal functions, making them effective for a broad range of optimization challenges, even in fields employing machine learning algorithms.

- **Examples:** Bayesian optimization, random search, genetic algorithms (GA), particle swarm optimization (PSO), evolutionary strategies, etc.
- **Challenges:** High computational complexity for large solution spaces, slower convergence compared to gradient-based methods, sensitivity to algorithmic parameters.
- **Techniques:**
 - Bayesian optimization with Gaussian processes for black-box functions.
 - Evolutionary algorithms (e.g., genetic algorithms, differential evolution).

- Metaheuristics (e.g., simulated annealing, particle swarm optimization).
- Direct search methods (e.g., Nelder-Mead, pattern search).
- **Applications:**
 - Beamforming optimization in multi-user MIMO systems without analytical gradients.
 - Resource allocation in non-differentiable energy-efficient communication systems.
 - UAV placement and trajectory optimization in IoT-enabled wireless systems.

Reinforcement Learning (RL)

Reinforcement learning is an optimization framework where an agent learns to make sequential decisions by interacting with its environment. Unlike other optimization methods, RL focuses on maximizing long-term cumulative rewards rather than a single objective. The agent explores actions, observes outcomes, and adjusts its strategy based on the feedback from the environment. Techniques like Q-learning use value functions to estimate the expected rewards of actions in discrete spaces, while policy gradient methods directly optimize the policy governing action selection and are more suitable for continuous space problems. RL is particularly effective in complex and dynamic environments with stochastic feedback.

- **Techniques:** Q-learning, policy gradient methods.
- **Applications:** sum-rate maximization, path planning, resource allocation, etc.

8.3.4 Multi-objective optimization

Multi-objective optimization addresses problems involving multiple conflicting objectives that must be optimized simultaneously. Rather than seeking a single optimal solution, these problems yield a set of Pareto-optimal solutions, where improving one objective requires compromising another. The Pareto frontier represents these trade-offs, allowing decision-makers to evaluate and select solutions based on their priorities.

- **Techniques:** Pareto optimization, NSGA-II (Non-dominated Sorting Genetic Algorithm).
- **Applications:** Quality of service (QoS) vs Resource Utilization, Throughput vs Interference, etc.

8.4 Optimization in Green IoT

In this section, we will introduce optimization in the context of green IoT. In particular, the allocation of network resources is an important aspect of effective network management, especially in wireless networks where resources such as frequency, bandwidth, and channel access are scarce. The reuse and optimal distribution of these

Table 8.1 Technical differences.

Aspect	Convex Optimization	Reinforcement Learning	Heuristic Methods	Metaheuristic Methods
Nature	Deterministic, analytical	Stochastic, environment-based	Problem-specific, heuristic-driven	General-purpose, framework-driven
Objective Function	Convex	Reward maximization	Any	Any
Search Space	Continuous, convex	Sequential, dynamic	Discrete/continuous	Discrete/continuous
Optimality Guarantee	Global optimum	No guarantees	No guarantees	Near-optimal solutions
Computational Cost	Moderate	High (training over time)	Low to moderate	Moderate to high
Scalability	High	Problem-dependent	High	High
Applications	Engineering, economics	Robotics, AI	Scheduling, basic optimizations	Complex and global optimizations

resources are necessary for enhancing network operation. For this reason, designing efficient resource allocation mechanism is crucial in multiple access systems, as it governs the management of both radio resources and interference, ensuring high-speed and reliable communication. In this context, next-generation multiple access (NGMA) has gained significant attention. From 1G to 5G, multiple access technologies have evolved with the goal of allocating orthogonal radio resources to users, thereby preventing multi-user interference. However, in conventional orthogonal multiple access (OMA) methods such as time division multiple access (TDMA), frequency division multiple access (FDMA), code division multiple access (CDMA), and orthogonal frequency-division multiple access (OFDMA), each user is assigned an individual orthogonal resource, which limits the number of users supported and reduces spectral efficiency (Table 8.1).

The next generation of communication systems aims to enhance user experience by supporting advanced applications and services like industrial automation, smart cities, virtual and augmented reality, remote medical surgery, autonomous vehicles, and unmanned aerial vehicles (UAVs). These emerging services introduce demanding requirements, including low latency, high data rates, massive connectivity, high reliability, and varied quality of service support. The massive connectivity needs in 5G and beyond are largely driven by the rapid expansion of IoT devices. Notably, 6G networks are expected to support a connection density of 10^7 devices/km², 1000 times higher than 4G and 10 times higher than 5G. However, traditional OMA schemes, which allocate distinct resource blocks (e.g., time and frequency) to individual users, face challenges in accommodating a larger number of devices. Specifically, since each orthogonal resource in OMA is assigned to one user, the maximum simultaneous user capacity is limited by the number of available resources, restricting spectral

efficiency. Additionally, low-rate IoT users requiring minimal resources may occupy an entire resource block, leading to further inefficiency in spectrum utilization.

In contrast, non-orthogonal multiple access (NOMA) and rate-splitting multiple access (RSMA), using superimposed coding and successive interference cancellation (SIC), allow the same radio resource to be shared by multiple users, increasing spectral efficiency compared to OMA. Specifically, NOMA leverages superposition coding (SC) at the transmitter to layer user signals by power levels and applies SIC at the receivers, effectively managing multi-user interference by decoding other users' signals. On the other hand, RSMA is based on the rate-splitting concept, where user messages are divided into common and private parts, enabling partial interference decoding, while treating some interference as noise. With their strong interference management capabilities, NOMA and RSMA are promising next-generation multiple access (NGMA) technologies for supporting massive IoT connectivity.

In addition, because of their remarkable compatibility with other technologies, NOMA and RSMA have been combined with techniques such as mobile edge computing (MEC) and simultaneous wireless information and power transfer (SWIPT) for IoT networks. Additionally, the flexibility of NOMA and RSMA is ready to support emerging applications such as cell-free massive multiple-input multiple-output (CF-mMIMO), reconfigurable intelligent surfaces (RIS), and backscatter communications (BackCom). Thus, NOMA and RSMA represent a promising approach for resource allocation in 6G that will transform the physical (PHY) and lower medium access control (MAC) layers in wireless communication network design. In this context, we have comprehensively investigated studies on NOMA- and RSMA-enabled resource allocation algorithms for green IoT networks. Further, we also describe the functional layers where optimization algorithms can be employed to enhance the operational feasibility of NOMA- and RSMA-assisted green IoT, followed by sections that focus on different technologies and paradigms where optimization would help in the development of feasible architectures supporting green IoT.

8.4.1 Network architectures

The rapid expansion of IoT brings significant concerns related to energy consumption and sustainability [9]. This challenge has driven the development of green IoT — a paradigm focused on minimizing the energy footprint of IoT systems while maintaining their efficiency and performance. In order to achieve green IoT, it is essential to explore network architectures that prioritize energy efficiency and implement various optimization techniques aimed at reducing the carbon footprint of IoT ecosystems.

Green IoT network architectures prioritize energy efficiency and sustainability by adopting solutions such as fog computing, edge computing, and Low-Power Wide-Area Networks (LPWANs). These architectures optimize data processing, transmission, and storage to significantly reduce energy consumption while maintaining performance. This is essential for sustainably scaling IoT systems, minimizing their carbon footprint, and meeting environmental goals [10]. Additionally, optimizing network architectures to reduce energy consumption lowers operational costs.

Energy-efficient networks reduce the need for frequent battery replacement, and by processing data locally, they minimize data transmission costs, which can otherwise be significant due to high bandwidth requirements, data center usage fees, and energy consumed during transmission. This helps organizations reduce maintenance costs and improve the financial feasibility of large-scale IoT deployments.

Green IoT architectures, such as fog and edge computing, enable efficient management of large-scale IoT deployments by distributing processing power closer to the devices [11]. This reduces the need for centralized cloud data centers, thereby reducing bandwidth consumption, latency, and power consumption. Additionally, LPWANs and other low-power communication protocols enhance the scalability of IoT networks, allowing them to accommodate billions of devices [12] with minimal environmental impact. By leveraging these architectures, IoT systems can handle massive data traffic and ensure high performance without excessive energy use. As IoT expands globally, these solutions enable networks to grow sustainably, ensuring both environmental and operational efficiency.

Green IoT network architectures improve reliability and performance, particularly in time-sensitive applications such as autonomous vehicles or industrial automation. Edge and fog computing reduces data transfer distances, lowering latency and enhancing response times, resulting in faster, more responsive networks. Moreover, energy-efficient architectures such as Software-Defined Networking (SDN) and Network Function Virtualization (NFV) allow for real-time adaptation to dynamic network conditions, adjusting resources, rerouting traffic, and modifying device operations based on energy availability or traffic changes [13]. This adaptability ensures efficient energy use and optimal performance, enhancing network resilience and versatility in fluctuating environments.

As IoT networks grow, the demand for efficient, scalable, and sustainable architectures becomes critical. Green IoT systems future-proof ecosystems by ensuring that network expansion does not result in unsustainable energy consumption. By investing in energy-efficient architectures today, organizations can prepare for future performance requirements while meeting stricter environmental and regulatory standards. These architectures help reduce carbon footprints, ensure compliance with regulations on energy use and e-waste regulations, and support long-term sustainability goals. Proactively adopting green IoT solutions ensures that IoT ecosystems remain viable and adaptable to future environmental and technological challenges.

Network architectures in Green IoT

Several network architectures are being developed and researched with the goal of creating a more energy-efficient IoT. These architectures typically focus on the following key areas: data processing, communication protocols, and resource management.

- **Fog Computing and Edge Computing Architectures:** Traditional cloud-based IoT architectures often suffer from high latency and increased energy consumption due to the need to transfer large volumes of data to centralized cloud servers [14]. To address this issue, fog computing and edge computing architectures have

gained prominence. In these architectures, data processing occurs closer to the source of the data, such as IoT devices or local edge servers, reducing the need for long-distance data transfers and thereby reducing energy consumption [15].

Fog computing involves the deployment of intermediate layers between IoT devices and cloud data centers, enabling localized data processing [16]. This architecture is critical to reduce the bandwidth load on central servers and minimizing the power required for long-range data transmissions. By processing data locally, fog computing can offload energy-intensive tasks from both the IoT devices and the cloud, thus reducing the overall energy consumption.

Similar to fog computing, edge computing brings the processing power even closer to IoT devices, typically at the device or gateway level [17]. This enables real-time data processing and analytics, significantly reducing the latency and energy costs associated with cloud-based architectures. Edge computing also reduces the energy consumed by data transmission, as only relevant data is sent to cloud servers when necessary.

Both fog and edge computing architectures offer substantial energy-saving potential by minimizing the reliance on centralized data centers. They also improve the scalability of IoT networks by distributing computational workloads, making these architectures central to the development of Green IoT systems.

- **Software-Defined Networking (SDN) and Network Function Virtualization (NFV):** Software-Defined Networking (SDN) and Network Function Virtualization (NFV) have emerged as transformative approaches to network management, enabling greater flexibility, efficiency, and energy savings in IoT networks [18]. They can help IoT networks achieve significant energy savings through more efficient resource management, dynamic routing, and the reduction of idle network functions.

In SDN, the control plane is separated from the data plane, allowing for centralized network management and more efficient routing of data. This is particularly important for Green IoT, as SDN can dynamically optimize network resources and routes based on real-time traffic patterns, reducing unnecessary energy consumption [19]. SDN also allows for the intelligent allocation of resources to different devices, which can help ensure that energy is used efficiently across the network. NFV complements SDN by virtualizing network functions (such as firewalls, load balancers, and routers) and running them on general-purpose hardware instead of dedicated, energy-hungry devices. NFV reduces the hardware footprint of IoT networks, thereby lowering both capital and operational energy costs. The ability to virtualize and scale network functions dynamically also improves energy efficiency, as resources can be provisioned on demand rather than kept running continuously.

- **Low-Power Wide-Area Networks (LPWANs):** Low-Power Wide-Area Networks (LPWANs) are a category of wireless IoT communication standards that aim to reduce architectural requirements, specifically for energy-constrained IoT applications [15,16]. These networks, which include technologies such as LoRaWAN, Sigfox, and Narrowband IoT (NB-IoT), are optimized for long-range communication with minimal energy consumption [20].

LoRaWAN is a popular LPWAN technology that supports low data rates and long-range communication. It is widely used in smart agriculture, environmental monitoring, and smart cities [21] due to its ability to connect a large number of low-power devices over long distances. The architecture of LoRaWAN is optimized to minimize power consumption, making it ideal for battery-powered IoT devices that require infrequent communication with the network [22].

Sigfox is another LPWAN technology that focuses on ultra-narrowband communication, enabling energy-efficient transmission over long distances. Sigfox is designed for applications where small packets of data are sent intermittently, making it well-suited for remote sensing and monitoring applications. NB-IoT is a cellular-based LPWAN technology that leverages existing LTE infrastructure to provide wide coverage and low power consumption. It is highly energy-efficient and is optimized for IoT applications that require reliable, low-cost communications with limited data throughput.

LPWANs are essential for Green IoT because they enable large-scale IoT deployments without the high energy consumption typically associated with wireless communication technologies such as Wi-Fi or cellular networks. By optimizing communication protocols and focusing on low-power transmissions, LPWANs offer a promising solution for sustainable IoT networks.

Optimization Green IoT network architectures

While the aforementioned network architectures are inherently designed to improve energy efficiency, further optimization is needed to maximize their sustainability. Following are some of the optimization techniques critical to enhancing the energy efficiency of these architectures.

- **Energy-Aware Routing Protocols:** One of the most significant sources of energy consumption in IoT networks is the data transmission process. Traditional routing protocols are not optimized for energy efficiency, often leading to unnecessary transmissions and energy wastage. To address this, energy-aware routing protocols have been developed. Energy-aware routing protocols optimize the path that data takes through the network by considering the energy levels of devices and nodes. These protocols aim to minimize the energy consumed during data transmission and ensure that no single node is overburdened, which could lead to premature battery depletion [23]. Techniques such as multi-hop routing, where data is transmitted through multiple intermediate nodes rather than directly to a central hub, can further reduce transmission power requirements.
- **Sleep Scheduling and Duty Cycling:** For battery-powered IoT devices, sleep scheduling and duty cycling are crucial for reducing energy consumption. These techniques involve periodically putting devices into low-power sleep modes when they are not actively transmitting or receiving data. By reducing the active time of IoT devices, significant energy savings can be achieved. In duty cycling, devices alternate between active and inactive states based on pre-defined schedules or triggers. Optimization algorithms can be applied to determine the ideal duty cycles for different devices, balancing energy savings with the need for timely data collection and transmission.

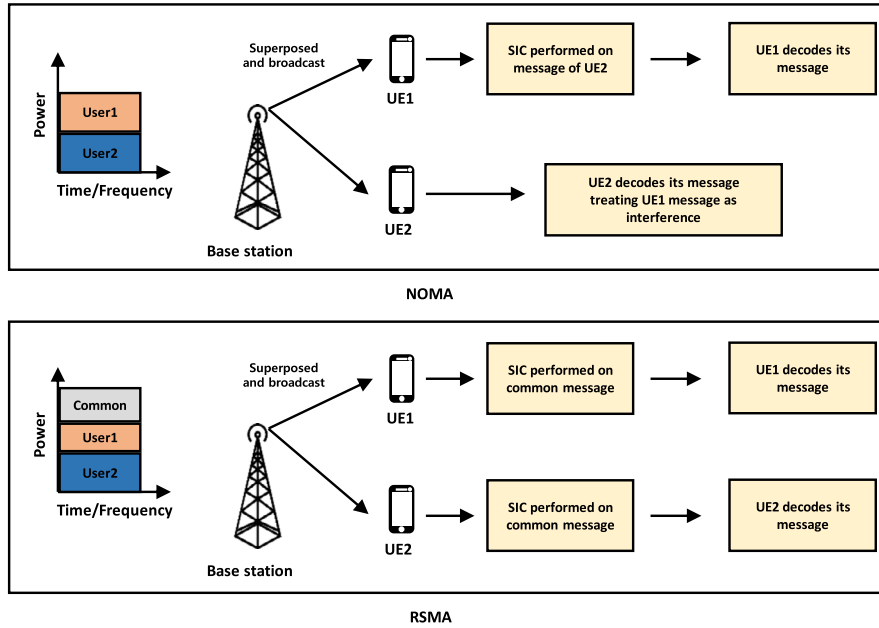
- **Data Aggregation and Compression:** Data transmission is one of the most energy-intensive operations in IoT networks. To reduce the energy consumed by communication, data aggregation, and compression techniques can be employed. In data aggregation, multiple data packets from different sensors are combined into a single packet before being transmitted, reducing the total number of transmissions required. Similarly, data compression algorithms can be used to minimize the size of the transmitted data, further reducing energy consumption [24]. Fog and edge computing architectures are particularly well suited to implement these optimization techniques, as they have the computational power to perform data aggregation and compression close to the data source, thus reducing the energy overhead associated with long-distance transmissions to the cloud.
- **Machine Learning for Energy Optimization:** Machine learning (ML) techniques have emerged as powerful tools for optimizing energy efficiency in Green IoT architectures. ML algorithms can analyze data on network traffic, device energy consumption, and environmental factors to predict future energy needs and optimize resource allocation dynamically. By leveraging historical data, ML models can intelligently adjust communication protocols, routing paths, and device duty cycles to minimize energy consumption without compromising performance. For example, reinforcement learning algorithms can be used to dynamically adjust the configuration of IoT networks based on real-time feedback, ensuring that energy is used efficiently in response to changing network conditions.

8.4.2 Resource allocation

SIC decoding order

In NOMA and RSMA systems, the SIC decoding process is crucial for allowing multiple users to share the same radio resource by eliminating interference from other users' signals [25]. The order of SIC decoding plays a significant role in resource allocation performance. For single-cell NOMA, the decoding order is determined by the channel-to-noise ratio (CNR) [26], whereas in multi-cell NOMA, it is based on the signal-to-interference-plus-noise ratio (SINR), making the optimal solution more complex. To address this, a joint approach for SIC decoding and resource allocation using deep neural networks (DNN) is proposed for multi-cell NOMA [27]. However, even with an optimal order, decoding errors may still occur, requiring strategies to mitigate them.

RSMA, on the other hand, reduces the SIC decoding errors seen in NOMA, particularly as the number of users increases. In the basic RSMA model, known as 1-layer RSMA, only one round of SIC is required, which helps reduce errors while offering comparable or superior resource allocation performance to NOMA. Despite this, RSMA still faces challenges related to high complexity and error propagation during the SIC process. To tackle these issues, new receiver designs are being proposed for RSMA, that provide more options in terms of complexity and performance beyond the conventional SIC receiver [28]. While the 1-layer RSMA scheme shows advantages over traditional schemes such as OMA and NOMA, in high-throughput

**FIGURE 8.1**

SIC decoding procedure for two-user cases of NOMA and RSMA.

scenarios, schemes like rate splitting and common message decoding (RS-CMD), which perform multiple SIC processes, should be explored. This enhanced flexibility and message splitting capability lead to improved bit error rates [29]. Future studies will focus on optimizing the SIC decoding order in RS-CMD systems.

Power allocation

Power allocation is considered a critical aspect of resource allocation, as it is closely tied to the dynamically changing, time-varying nature of wireless channels. For this reason, it mostly considers MEC, SWIPT, and UAV scenarios, where efficient power management is critical. Similarly, in IoT networks, the large number of users increases the need for efficient power allocation, even with the advantages of NOMA and RSMA. Specifically, various power allocation algorithms are developed to optimize key performance metrics such as spectral and energy efficiency, which are essential in NOMA- and RSMA-enabled IoT network systems. As a result, recent studies have analyzed the optimal conditions for power allocation coefficients in these systems [26,30]. However, applying traditional iterative algorithms for power allocation in dense IoT networks can lead to high complexity. To address this issue, deep learning-based power allocation algorithms have been introduced, significantly reducing complexity while maintaining performance close to the optimal solution [31].

This approach improves system metrics and enables rapid decision-making, resulting in more efficient resource allocation for a sustainable and seamless green IoT network.

Beamforming

In the SIC decoding process, IoT devices are typically grouped into clusters to reduce error probability and signal processing load, a technique known as user clustering. SIC is then applied only within each cluster. However, inter-cluster interference persists between clusters, negatively impacting system performance. To address this problem, spatial beamforming is commonly employed at multi-antenna base station scenarios such as CF-mMIMO systems. Beamforming works by adjusting the signals from antenna array elements to create constructive interference at specific angles and destructive interference at others. As a result, beamforming in NOMA and RSMA-enabled IoT networks proves to be highly effective and robust in maximizing energy efficiency for large-scale IoT systems [32,33].

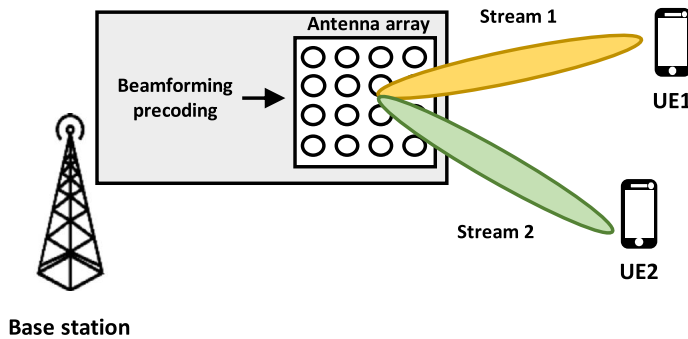


FIGURE 8.2

Beamforming system model for the multiuser MIMO beamforming.

Channel access (MAC)

Medium Access Control (MAC) protocols are fundamental to the efficient operation of wireless networks. In wireless networks, MAC protocols manage access to the shared communication medium, ensuring that data transmission between nodes occurs without collision and with minimal interference. Techniques like time-division multiple access (TDMA), code-division multiple access (CDMA), and contention-based protocols such as IEEE 802.11 have been developed for managing medium access in voice and data networks. A key challenge in these networks is ensuring fairness, reducing latency, and maximizing throughput, while maintaining efficient use of bandwidth.

For the Internet of Things (IoT) network, however, the focus shifts toward energy efficiency due to the limited power resources of IoT nodes, which are often battery-operated. In many IoT applications, replacing or recharging batteries is either impractical or impossible, making energy conservation the primary concern. As

a result, the design of MAC protocols for IoT networks must prioritize prolonging network lifetime. To meet this challenge, protocols are designed with mechanisms that address key sources of energy waste: collisions, overhearing, and idle listening.

Collisions, which occur when two nodes transmit simultaneously, result in packet corruption and retransmission, thereby wasting energy and increasing latency. Overhearing happens when a node listens to packets intended for other nodes, consuming energy needlessly. Finally, idle listening, in which nodes remain in a listening state to detect possible transmissions even when there is no traffic, is particularly detrimental in sensor networks. Idle listening consumes more energy than the other factors of energy waste.

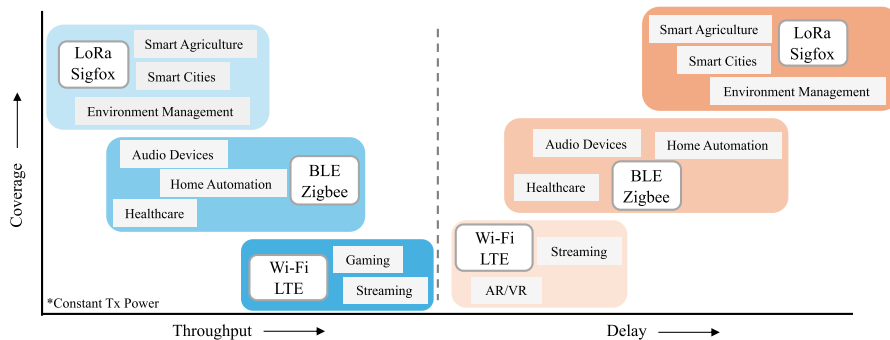
At the same time, IoT applications introduce new requirements, not only for energy efficiency, but also for the evolution of the MAC protocol. The wide variety of IoT devices—ranging from wearable sensors and home automation systems to large-scale industrial applications—means that IoT networks must be flexible and scalable. Moreover, IoT networks often have unique demands such as long-range communication, low power consumption, and robust performance in dynamic environments. For example, forest fire monitoring applications demand very large deployments, high reliability, and high density of sensors. In contrast, a body sensor network should have a maximum latency of 125 ms for medical applications and 250 ms for non-medical applications such as healthcare [34–36]. It should also be low power consumption, low overhead, and adaptable to various topologies.

Moreover, especially in dense environments like smart cities or industrial IoT (IIoT) systems, the MAC layer must ensure efficient communication without excessive delays or collisions. In such scenarios, MAC protocols can employ techniques such as duty cycling, where nodes switch between active and sleep states to conserve energy, while maintaining network connectivity. Additionally, collision avoidance mechanisms are critical in IoT networks to prevent interference and ensure reliable data transmission across multiple devices.

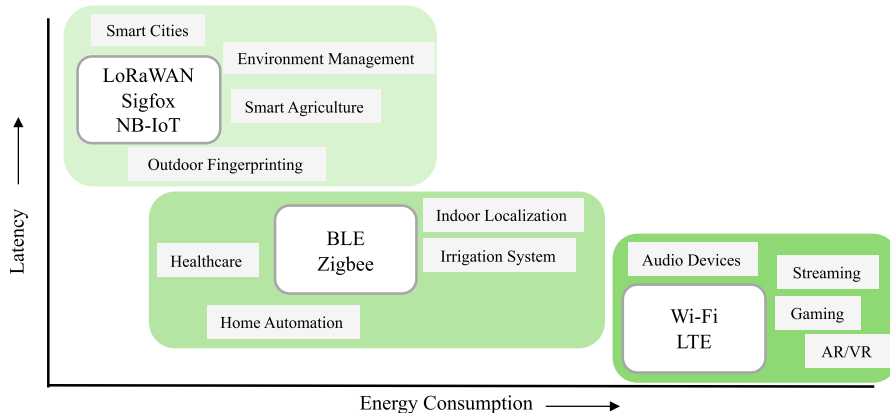
In conclusion, the evolution of MAC protocols for IoT networks highlights the need for specialized designs that cater to the unique challenges of each application, whereas traditional MAC protocols focus on optimizing throughput, latency, and bandwidth utilization. In the IoT domain, MAC protocols must be flexible, scalable, and adaptable to diverse application requirements, balancing power consumption, transmission range, and data rate needs. As IoT continues to expand into new areas like smart cities, healthcare, and industrial automation, MAC protocols will remain at the forefront of ensuring efficient, reliable, and energy-conscious communication.

MAC protocol and optimization method

One of the primary challenges in IoT network design is balancing the trade-offs between transmission range, delay, and data rates, as shown in Fig. 8.3 and Fig. 8.4, low power wide area network (LPWAN), such as LoRa and Sigfox, are optimized for long-range communication with minimal power usage, but they offer lower data rates compared to short-range networks. In contrast, wireless personal area networks (WPANs) such as IEEE 802.15.4, which underpins Zigbee, prioritize short-range

**FIGURE 8.3**

Effect of data rate and delay on coverage area.

**FIGURE 8.4**

Relationship between energy consumption and latency.

communication with higher data rates and energy efficiency, making them suitable for home automation and industrial control systems.

To efficiently address various requirements such as data rate, delay, latency, network efficiency, and connectivity, different MAC protocols tailored to network characteristics are required. This section briefly describes the MAC protocols used in BLE, NB-IoT, Zigbee, LoRa, and Sigfox. Additionally, optimization techniques based on the characteristics of these MAC protocols are discussed.

- **ALOHA:** As shown in Fig. 8.5, Aloha is a random access protocol, which means that devices decide autonomously when to transmit over the shared channel. An important feature of this method is that a device does not check if the channel is free before transmitting. Devices transmit data as soon as they are ready, without checking whether other devices are transmitting.

The protocol operates as follows: Devices transmit data as soon as they are ready. If two devices transmit simultaneously, a collision occurs. In such cases, the receiver fails to send an acknowledgment (ACK), signaling a collision. The sender, upon not receiving an ACK, realizes a collision has occurred and waits for a random backoff time before retransmitting. This strategy reduces the likelihood of repeated collisions [37]. This slotted version of ALOHA is called S-ALOHA [38].

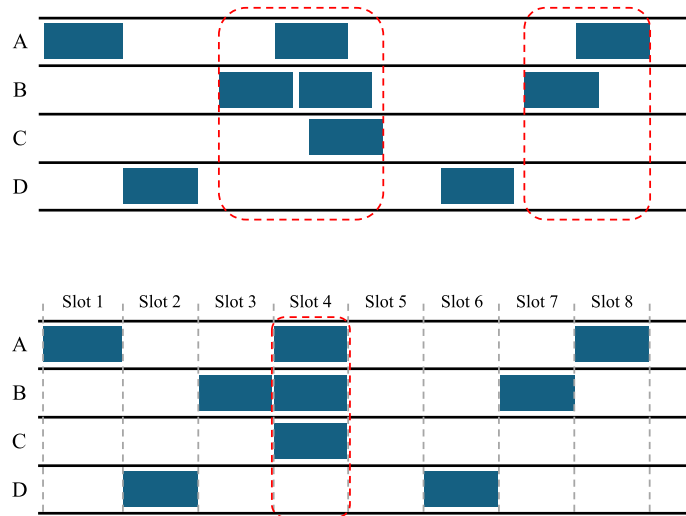


FIGURE 8.5

Example of ALOHA and S-ALOHA.

Pure Aloha has a maximum throughput efficiency of approximately 18.4%, primarily due to frequent collisions and retransmissions. Slotted Aloha improves upon Pure Aloha by introducing time slots. Devices can only transmit at the start of a time slot, reducing the chance of collisions. Slotted Aloha achieves up to 36.8% efficiency, nearly double that of Pure Aloha. Aloha's design is straightforward, making it easy to implement. Due to their simple structure and low cost, LoRa and Sigfox use a MAC protocol based on ALOHA. However, the downside is that as the number of devices in the network increases, the number of collisions and retransmissions also increases, making the network less scalable.

In [39], Metzner et al. analyzed a system with two transmit power groups: high and low. Packets transmitted with high power can be successfully decoded even when low-power packets are present. However, if multiple packets from the same power group are transmitted simultaneously, none can be decoded. As a result, packets sent with high transmit power gain higher priority and achieve greater throughput compared to those transmitted with low power.

Lee et al. introduced an algorithm designed to enhance the scalability of LoRaWAN by efficiently scheduling spreading factors (SFs), frequency channels, and time slots for wireless links between end nodes and gateways in [40]. This

algorithm is activated upon receiving a scheduling request message from a device. Initially, the algorithm allocates an appropriate SF based on the device's received signal strength. Subsequently, it assigns a frequency channel and a time slot. Compared to the ALOHA protocol used for LoRaWAN uplink transmissions, the proposed method demonstrated significant improvements, with simulation results indicating over a 60% increase in the number of end devices that can be connected to a single gateway.

In addition, in [41], Polonelli et al. optimized LoRaWAN communication by implementing a S-ALOHA variant over the standard pure-ALOHA protocol. To ensure slot alignment across all end nodes, a lightweight synchronization method specifically designed for LoRaWAN devices was employed. This approach had minimal impact on the devices' power consumption, while theoretically doubling network throughput and reducing packet collisions by 26% in a real-world deployment with 24 nodes.

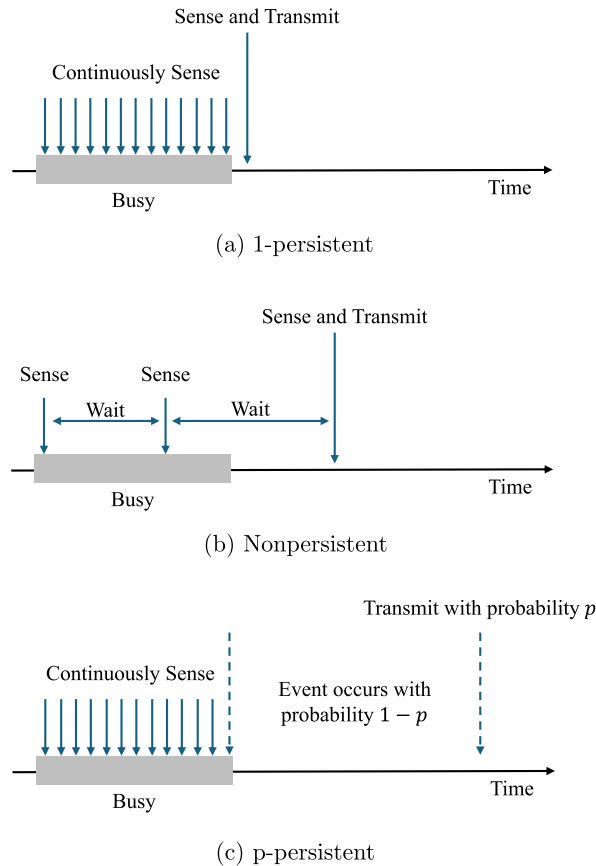
On the other hand, various backoff algorithms for optimizing retransmission rates have been proposed in [42,43] to maximize the throughput of unslotted ALOHA systems. Van der Vleuten et al. [42] leverages information about the number of backlogged devices. An observation period is required to estimate backlog information. Seo et al. [43] proposed a particle filter (PF) algorithm to estimate the number of backlogged devices by monitoring idle period durations.

Additionally, studies in [44–46] apply multipacket reception (MPR) techniques to unslotted ALOHA systems. MPR-capable systems can decode multiple packets simultaneously using advanced signal processing methods, such as successive interference cancellation (SIC). Specifically, interference can be partially mitigated to enable successful decoding even when packets are transmitted during an ongoing transmission.

- **Carrier Sense Multiple Access:** CSMA, developed in the early 1970s, is a protocol designed to improve the efficiency of random access communication by introducing carrier sensing. It is widely used in wired networks such as Ethernet and can also be applied to wireless networks such as Zigbee. The fundamental concept of CSMA is carrier sensing. Before transmitting, a device checks whether the communication channel is free. If the channel is clear, the device transmits immediately. If the channel is busy, the device waits until the channel becomes available.

As described in Fig. 8.6, the protocol operates as follows: Devices check whether the channel is idle before transmission.

If the channel is busy, the device waits and periodically checks again. If a collision occurs, the device stops transmitting and waits for a random backoff time before attempting to retransmit. Different variations of CSMA employ distinct algorithms to decide when to begin transmission over a shared medium. The primary differentiator among these algorithms is their level of aggressiveness or persistence in initiating transmission. More aggressive algorithms tend to start transmission sooner and make more efficient use of the available bandwidth. However, this increased utilization often comes with a higher risk of collisions with

**FIGURE 8.6**

Timing diagram by CSMA method.

other transmitting devices. Probabilistically, they can be categorized into three main categories 1-persistent, non-persistent, p -persistent [47].

1-persistent CSMA is considered an aggressive transmission algorithm. When the transmitting node is ready to send data, it first checks the transmission medium to determine if it is idle or busy. If the medium is idle, the node transmits immediately. If the medium is busy, the node continues to monitor it until it becomes idle, at which point it transmits the frame without any further conditions. In the event of a collision, the sender waits for a random period before attempting to retransmit using the same procedure. This method is commonly used in CSMA/collision detection (CD) systems, such as Ethernet.

Non-persistent CSMA is a less aggressive transmission algorithm. When the transmitting node is ready to send data, it first checks whether the transmission medium is idle or busy. If the medium is idle, it transmits immediately. If the medium

is busy, the node skips to the final random waiting step of 1-persistent CSMA before restarting the entire logic cycle. Unlike 1-persistent CSMA, it does not continuously monitor the busy channel in an attempt to transmit, which is why it is considered non-persistent. This method reduces the chance of collisions and increases overall throughput, but it incurs a longer initial delay compared to 1-persistent CSMA.

p -persistent CSMA lies between 1-persistent CSMA and pure non-persistent CSMA in terms of behavior. In this protocol, when the node is ready to transmit, it first checks the channel. If the medium is idle, the transmission proceeds immediately. If the medium is busy, the node waits until the channel becomes idle and then transmits with a probability p . If it does not transmit (i.e., $1 - p$), the node waits for a random period before attempting the process again, with the same probability. This probabilistic backoff continues until the frame is transmitted, or if the medium becomes busy again, in which case the node restarts the entire procedure. p -persistent CSMA is commonly used in CSMA/collision avoidance (CA) systems, including Zigbee and other packet radio systems.

In [48], the authors introduced a memorized backoff scheme that utilizes the exponentially weighted moving average (EWMA) method to dynamically adjust the contention window size. This adaptive approach enables more efficient handling of network congestion by smoothing past transmission outcomes and optimizing the backoff interval based on recent network conditions.

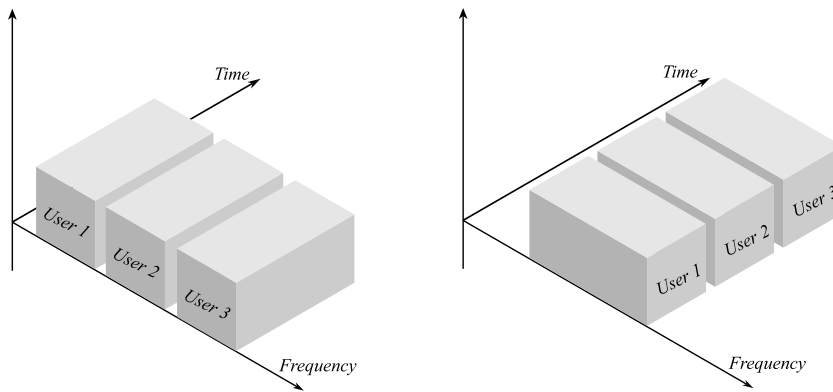
In [49], the authors derived contention window sizes optimized for both energy efficiency and delay performance as functions of the number of contending devices. This optimization addresses the critical trade-off between collision probability and idle listening time, where a larger contention window reduces collisions but increases idle listening, and a smaller window lowers idle time but raises the risk of collisions.

Jing et al. [50] optimized network throughput using an analytical model formulated through convex optimization and proposed an adaptive backoff mechanism to maximize performance. This algorithm is based on an approximate and simple Markov model to achieve adaptive backoff for maximum throughput.

Shakir et al. [51] proposed a hybrid node prioritization technique based on IEEE 802.15.6 CSMA/CA. By prioritizing nodes based on the power and size of the contention window and restricting channel access according to their priorities, the proposed technique reduces the average backoff time for channel access and minimizes the number of retransmissions. The authors provide experimental results on various network metrics such as throughput, bandwidth efficiency, energy usage, and network lifetime.

- **Multiple Access:** Efficient allocation of communication resources is critical in communication systems. For certain applications, there are constraints on continuous connectivity and quality, and the allocation of dedicated resources to specific users is commonly referred to as multiple access. Dedicated channels can be obtained by partitioning resources, typically using time, frequency, or code. Frequency-division multiple access (FDMA) is a method of assigning different frequency channels to each user by organizing non-overlapping channels along the

frequency axis. Guard bands are often set up to compensate for interference from channels in the frequency band, imperfections in filters, spectrum spreading due to Doppler, etc. It is also commonly used for analog signals, but can be used for both analog and digital signals. Unlike FDMA, TDMA organizes non-overlapping channels along the time axis, so that each user is assigned a different timeslot that repeats periodically. The advantage of TDMA is that by assigning multiple timeslots, the effect of assigning multiple channels can be achieved. However, in periodically repeating timeslots, the channel characteristics can change from period to period, making channel estimation techniques such as equalization essential in each period.



(a) Frequency-division multiple access

(b) Time-division multiple access

These methods have been widely used as core technologies in communication systems, with various techniques such as orthogonal frequency division multiple access (OFDM), frequency division duplexing (FDD), and time division duplexing (TDD). In particular, OFDM has been a crucial technology in LTE systems, where it utilizes a large number of orthogonal subcarriers to significantly increase data transmission rates and effectively mitigate the challenges posed by multipath fading. Additionally, narrowband IoT (NB-IoT) is designed to be suitable for IoT environments with a focus on low power consumption and cost-efficiency, following the architecture of LTE systems. As a result, the MAC protocol of NB-IoT adopts the single carrier frequency division multiple access (SC-FDMA), which is also a key feature of LTE [52].

Time allocation

With the rapid advancement of smart grid services such as demand response, precision load control, and advanced metering infrastructure, each IoT device generates a large volume of computation-intensive and delay-sensitive tasks such as demand response, precision load control, and advanced metering infrastructure. However, as the number of devices grows exponentially, the conflict between massive connectivity

demands and limited spectrum resources becomes more pronounced. Multi-timescale resource allocation, as noted in [53], significantly reduces interactions and signaling overhead, ensuring reliable service delivery for large-scale connectivity. Therefore, optimizing resource block allocation in each timeslot is crucial for effective task splitting. This time slot allocation enables seamless resource distribution and task splitting, optimizing factors like energy consumption, queuing delay, queue backlog, and connection success rate in massive IoT networks.

Subchannel allocation

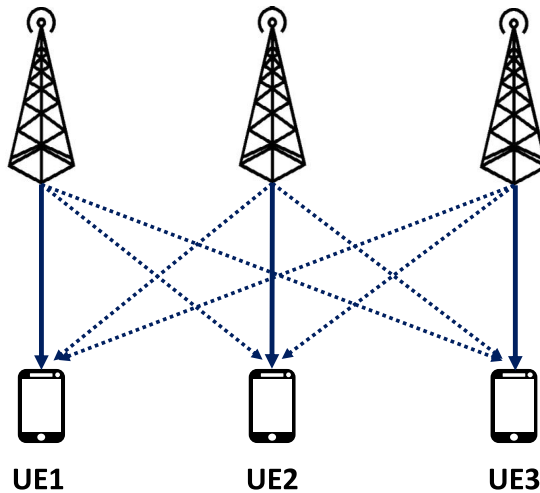
Many studies on NOMA-enabled IoT networks have focused on enhancing resource allocation to efficiently support large-scale connectivity of IoT devices, which can be an effective solution for ultra-dense network scenarios. To accommodate a high number of users, multicarrier NOMA (MC-NOMA) has been introduced, where users are assigned to different subchannels, each acting as an isolated resource block. In MC-NOMA, proper management of subchannel allocation is crucial to fully exploit the multiplexing gain from the fading channel. Various strategies for subchannel allocation, such as heuristic approaches, greedy algorithms, genetic algorithms, and matching algorithms, have been proposed. However, these methods often fall short due to the complexity of mixed-integer nonlinear programming (MINLP) problems. In response, [31] presents a mathematical analysis of optimal power allocation and reformulates the joint subchannel and power allocation problem in MC-NOMA into a binary decision problem for subchannel allocation, which can be easily integrated into heuristic algorithms. This reformulation allows the proposed scheme to effectively support massive IoT connectivity while maintaining feasible complexity in real-world applications. This work is anticipated to inspire future studies on efficient resource allocation in more complex network environments.

Coordinated multi-point transmission

To cope with the rapid increase in network traffic, the deployment of heterogeneous networks (HetNets) has emerged as a promising approach. HetNets help address the growing number of network devices and the rising demand for massive IoT network services. In HetNets, coordinated multi-point (CoMP) transmission has been introduced to improve both coverage and energy efficiency. CoMP transmission allows heterogeneous base stations to work together at the symbol level to transmit data to a user. CoMP methods are generally categorized into three types: dynamic point selection, coordinated scheduling/beamforming, and joint transmission. Given the strong potential of NOMA and RSMA, incorporating these CoMP techniques has demonstrated their ability to meet the diverse user requirements of future communication networks.

Rate splitting

In RSMA, the transmitted message is divided into a common message and a private message. The common message is decoded by multiple users, while the private message is intended for and decoded by a specific user. By adjusting the division

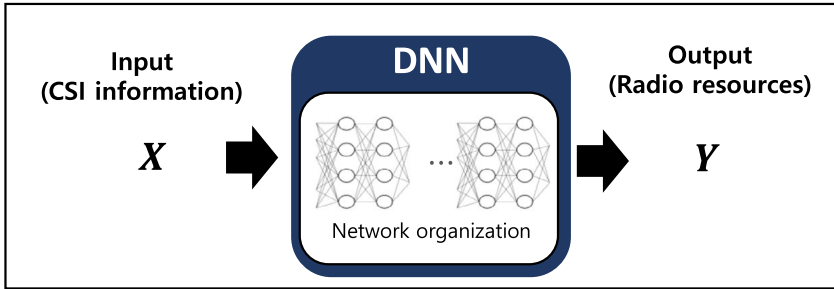
**FIGURE 8.7**

Multi-cell-based CoMP transmission.

between common and private messages, it is possible to manage both the computational complexity and the data rate achieved by RSMA. However, implementing RSMA in wireless networks poses several challenges, including how to optimally split the common and private messages, managing resources for efficient private message transmission, and ensuring synchronization during message transmission. To address these challenges, an optimal rate allocation for a fixed common message is derived based on mathematical analysis [30]. This approach enables seamless spectral efficiency for users in RSMA-assisted IoT networks [54].

Machine learning

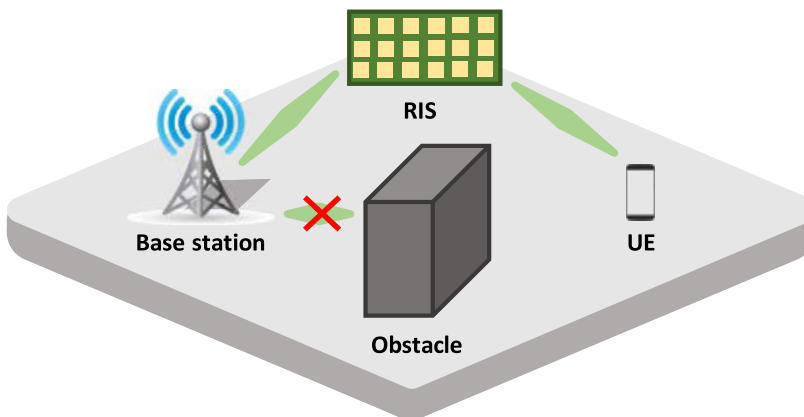
Recently, to overcome the high complexity of traditional approaches in practical applications such as voice and image recognition, language interpretation, and semantic analysis, various machine learning-based resource allocation techniques have been developed, enabling efficient management of large and complex data sets. In particular, deep learning, through the use of pre-trained DNN, can deliver superior performance without requiring an iterative convergence process, which can be a promising solution for traditional resource allocations. Machine learning algorithms are categorized into three types based on their training strategies: supervised learning, unsupervised learning, and reinforcement learning. Given its ability to reduce the challenges of iterative algorithms, many deep learning-based resource allocation methods have been proposed. Moreover, due to the SIC decoding process in NOMA and RSMA, optimizing resource allocation is generally more challenging than in conventional OMA. As a result, DNN-based training algorithms are essential for addressing the optimization challenges in NOMA and RSMA-enabled IoT networks, which tend to introduce significant complexity in practical scenarios [31,55].

**FIGURE 8.8**

A concept of machine learning-enabled resource allocations.

8.4.3 IRS

The unprecedented demand for ubiquitous wireless services and high-quality data poses significant challenges for existing cellular networks. Applications such as rate-centric enhanced mobile broadband (eMBB), ultra-reliable low-latency communications (URLLC), and massive machine-type communications (mMTC) have shaped the design targets for 5G systems. In contrast, 6G wireless communication systems aim to be transformative, focusing on applications like data-driven, instantaneous, ultra-massive, and pervasive wireless connectivity, as well as integrated intelligence. To support these advanced applications, innovative transmission technologies are required. Reconfigurable intelligent surfaces (RISs) consist of a 2D array of reflective elements designed to adjust the phase and amplitude of incident signals [56]. Given their ability to actively reshape the wireless environment, RISs have garnered significant interest as a solution to various challenges across diverse wireless networks.

**FIGURE 8.9**

An illustration of RIS-assisted wireless systems.

For their superior functionality, RIS-enhanced IoT networks are viewed as a promising technology for 6G, particularly useful in intelligent wireless sensor networks, smart agriculture, and intelligent manufacturing. Additionally, RISs can align users' channel directions, reinforcing the potential for NOMA and RSMA technology implementation. Further, RIS can create a virtual line-of-sight (LoS) link in NOMA and RSMA systems. Therefore, combining the benefits of RIS with NOMA and RSMA technologies is crucial for advancing future IoT networks [55,57]. However, research on RIS-enhanced wireless networks remains in the early stages, with substantial room for contributions in areas like channel state information (CSI) acquisition and Pareto optimization for balancing multiple objectives.

8.4.4 AmBS / backscatter

BackCom technology, leveraging passive radio frequency (RF) identification (RFID), has become a promising approach for IoT systems. A standard BackCom system consists of three key components: a signal source, a backscatter transmitter with antennas, and a backscatter receiver. In BackCom, there are two path-loss effects to consider: one from the signal source to the backscatter transmitter and another from the transmitter to the receiver. Enhanced configurations across these components can help reduce or compensate for path loss, boosting communication performance. Many studies have explored ambient backscatter communications, covering system design, coherent, semi-coherent, and non-coherent signal detection, coding, and modulation. Extensive research has also focused on energy harvesting within backscatter, addressing energy harvesting module design, system design, and analysis. Given its low cost and flexibility, ambient backscatter with energy harvesting offers a viable solution for future low-power, widespread communications, including IoT applications.

Due to its compatibility, BackCom is often integrated with RIS to extend cell coverage. The BackCom RIS-NOMA-based system discussed in [13] has been extensively studied, demonstrating that this approach significantly improves the performance of IoT devices. Despite significant progress in BackCom research, further advancements are needed to meet the practical demands of future green and ubiquitous communication, especially in IoT applications. Four primary challenges persist: data transmission rate, coverage, energy efficiency, and deployment cost. To address these, future BackCom systems should integrate essential techniques such as energy harvesting, backscatter relays, full-duplex communication, millimeter-wave communications, hybrid backscatter, and quantum communications.

8.4.5 CF-mMIMO

The IoT requires low power usage, extremely low latency, and support for numerous devices. CF-mMIMO is a strong candidate for achieving ultra-low latency by minimizing the distance between access points (APs) and devices, thus reducing power consumption. NOMA's high connectivity potential is well-suited to IoT needs, and when combined with CF-mMIMO, it enhances system spectral efficiency through

non-orthogonal transmission. Notably, NOMA and RSMA can be used for both fronthaul and backhaul links. In the fronthaul, where APs communicate with users wirelessly, NOMA and RSMA serve as effective user access methods. In backhaul, if the AP-CPU connection is wireless, NOMA and RSMA can facilitate access for both uplink and downlink. Although NOMA and RSMA improve spectral efficiency, they introduce complexity, particularly in designing efficient resource allocation mechanisms for NOMA and RSMA-based CF-mMIMO networks.

The CF-mMIMO architecture is pivotal for its potential to revolutionize future mobile networks by resolving challenges faced by cell-edge users and the uneven coverage typical of current cellular networks. It also enhances network performance by boosting connectivity, signal strength, interference control, and macro-diversity. Research, including the study of estimator impacts on system spectral efficiency, has laid a foundation for further work to maximize the potential of CF-mMIMO systems. Research examines a wide array of issues within CF-mMIMO networks, such as system models, communication techniques, channel estimation, pilot contamination, deployment challenges, and downlink potential. Additionally, applications and avenues for future research are highlighted, promising advancements for next-generation solutions.

8.5 Conclusion

The evolution of the Internet of Things (IoT) has ushered in a transformative paradigm within the domain of wireless communications, presenting unprecedented opportunities for enabling intelligent automation across diverse industries. By facilitating massive interconnectivity, IoT systems have the potential to redefine operational efficiencies and processes, paving the way for fully automated, data-driven environments. Central to this revolution is the concept of machine-to-machine (M2M) communication, which underpins the functionality of IoT systems. The requirements and capabilities of M2M communications have been effectively addressed through the development of massive, interconnected networks, marking a significant milestone in the advancement of communication technologies.

Market trends unequivocally underscore a growing demand for IoT systems, driven by their ubiquity and potential to seamlessly integrate into various facets of daily life. However, the large-scale deployment of IoT systems introduces critical challenges, particularly in terms of energy efficiency, scalability, and sustainability. These challenges necessitate focused optimization efforts to ensure the practical feasibility of Green IoT systems. Green IoT, as a paradigm, emphasizes the efficient use of resources and minimal environmental impact, making optimization a fundamental requirement for its widespread adoption and long-term viability.

In this chapter, we systematically introduced foundational concepts integral to the design and realization of Green IoT systems. The discussion encompassed opportunities and challenges that are pivotal in making these extensive networks feasible

and sustainable. Furthermore, we identified emerging technologies, such as reconfigurable intelligent surfaces (RIS) and backscatter communications, that hold immense potential in enhancing the performance and energy efficiency of Green IoT systems. These technologies, when integrated into IoT networks, can play a transformative role in achieving cohesive, adaptive, and high-performance communication architectures.

Looking forward, the synergy between Green IoT systems and enabling technologies is expected to form the backbone of next-generation intelligent networks. This convergence will not only address the operational and environmental challenges of IoT deployments but also open new avenues for research and development. The practical realization of these systems, driven by increasing consumer demand and market dynamics, underscores the need for continued exploration of optimization techniques and resource allocation strategies. Ultimately, Green IoT systems, coupled with advanced technological solutions, will be instrumental in shaping the future of intelligent, sustainable, and connected ecosystems.

References

- [1] Ke Xu, Yi Qu, Kun Yang, A tutorial on the Internet of Things: from a heterogeneous network integration perspective, *IEEE Network* 30 (2) (2016) 102–108, <https://doi.org/10.1109/MNET.2016.7437031>.
- [2] Worldwide IoT revenue 2033, <https://www.statista.com/statistics/1194709/iot-revenue-worldwide/> (visited on 01/24/2025).
- [3] Mahnoor Anjum, et al., RSSI fingerprinting-based localization using machine learning in LoRa networks, *IEEE Internet of Things Magazine* 3 (4) (2020) 53–59, <https://doi.org/10.1109/IOTM.0001.2000019>.
- [4] Muhammad Abdullah Khan, et al., Machine learning-based resource allocation for IRS-aided UAV networks, in: *GLOBECOM 2023–2023 IEEE Global Communications Conference*, 2023, pp. 3051–3057, <https://doi.org/10.1109/GLOBECOM54140.2023.10437224>.
- [5] Mahnoor Anjum, Deepak Mishra, Aruna Seneviratne, Power-efficient transceiver design for full-duplex dual-function radar communication systems, in: *2024 IEEE 25th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*, 2024, pp. 11–15, <https://doi.org/10.1109/SPAWC60668.2024.10694318>.
- [6] Mahnoor Anjum, et al., Theoretical landscape of LPWANs, in: *Low-Power Wide-Area Networks: Opportunities, Challenges, Risks and Threats*, Springer International Publishing, 2023, pp. 3–37, https://doi.org/10.1007/978-3-031-32935-7_1, ISBN: 978-3-031-32935-7.
- [7] Mohammed H. Alsharif, et al., Symmetry 15.3, in: *Green IoT: A Review and Future Research Directions*, ISSN 2073-8994, 2023, <https://doi.org/10.3390/sym15030757>, <https://www.mdpi.com/2073-8994/15/3/757>.
- [8] Binnan Zhuang, Dongning Guo, Michael L. Honig, Energy-efficient cell activation, user association, and spectrum allocation in heterogeneous networks, *IEEE Journal on Selected Areas in Communications* 34 (4) (2016) 823–831, <https://doi.org/10.1109/JSAC.2016.2544478>.
- [9] Kun Wang, et al., Green industrial Internet of things architecture: an energy-efficient perspective, *IEEE Communications Magazine* 54 (12) (2016) 48–54.

- [10] Annu Malik, Rashmi Kushwah, A survey on next generation IoT networks from Green IoT perspective, *International Journal of Wireless Information Networks* (ISSN 1572-8129) 29 (1) (Mar. 2022) 36–57.
- [11] Gaofeng Cui, et al., Latency and energy optimization for MEC enhanced SAT-IoT networks, *IEEE Access* 8 (2020) 55915–55926.
- [12] Asif M. Yousuf, et al., Throughput, coverage and scalability of LoRa LPWAN for Internet of Things, in: 2018 IEEE/ACM 26th International Symposium on Quality of Service (IWQoS), 2018, pp. 1–10.
- [13] Iqbal Alam, et al., A survey of network virtualization techniques for Internet of things using SDN and NFV, *ACM Computing Surveys* (ISSN 0360-0300) 53 (2) (Apr. 2020), <https://doi.org/10.1145/3379444>.
- [14] Sha Zhu, Kaoru Ota, Mianxiong Dong, Green AI for IIoT: energy efficient intelligent edge computing for industrial Internet of things, *IEEE Transactions on Green Communications and Networking* 6 (1) (2022) 79–88.
- [15] Mohammed Laroui, et al., Edge and fog computing for IoT: a survey on current research activities & future directions, *Computer Communications* (ISSN 0140-3664) 180 (2021) 210–231.
- [16] Hadi Zahmatkesh, Fadi Al-Turjman, Fog computing for sustainable smart cities in the IoT era: Caching techniques and enabling technologies – an overview, *Sustainable Cities and Society* (ISSN 2210-6707) 59 (2020) 102139.
- [17] Ke Han, et al., Open framework of gateway monitoring system for Internet of Things in edge computing, in: 2020 IEEE 39th International Performance Computing and Communications Conference (IPCCC), 2020, pp. 1–5.
- [18] Ahmadreza Montazerolghaem, Mohammad Hossein Yaghmaee, Alberto Leon-Garcia, Green cloud multimedia networking: NFV/SDN based energy-efficient resource allocation, *IEEE Transactions on Green Communications and Networking* 4 (3) (2020) 873–889.
- [19] Neetesh Kumar, Deo Prakash Vidyarthi, A green routing algorithm for IoT-enabled software defined wireless sensor network, *IEEE Sensors Journal* 18 (22) (2018) 9449–9460.
- [20] Muhammad Abdullah Khan, et al., Applications of LPWANs, in: Ismail Butun, Ian F. Akyildiz (Eds.), *Low-Power Wide-Area Networks: Opportunities, Challenges, Risks and Threats*, Springer International Publishing, Cham, 2023, pp. 171–209, https://doi.org/10.1007/978-3-031-32935-7_6, ISBN: 9783031329357 (visited on 01/27/2025).
- [21] Jetmir Haxhibeqiri, et al., A survey of LoRaWAN for IoT: from technology to application, *Sensors* (ISSN 1424-8220) 18 (11) (2018).
- [22] Hafiz Husnain Raza Sherazi, et al., Energy-efficient LoRaWAN for industry 4.0 applications, *IEEE Transactions on Industrial Informatics* 17 (2) (2021) 891–902.
- [23] M.R. Poornima, H.S. Vimala, J. Shreyas, Holistic survey on energy aware routing techniques for IoT applications, *Journal of Network and Computer Applications* (ISSN 1084-8045) 213 (2023) 103584.
- [24] Mahmoud A. Albreem, et al., Green Internet of Things (GIoT): applications, practices, awareness, and challenges, *IEEE Access* 9 (2021) 38833–38858.
- [25] Yijie Mao, et al., Rate-splitting multiple access: fundamentals, survey, and future research trends, *IEEE Communications Surveys and Tutorials* 24 (4) (2022) 2073–2126, <https://doi.org/10.1109/COMST.2022.3191937>.
- [26] Sepehr Rezvani, et al., Optimal SIC ordering and power allocation in downlink multi-cell NOMA systems, *IEEE Transactions on Wireless Communications* 21 (6) (2022) 3553–3569, <https://doi.org/10.1109/TWC.2021.3120325>.

- [27] Donghyeon Kim, et al., DNN-based algorithm for joint SIC ordering and power allocation in downlink NOMA-enabled heterogeneous networks, *ICT Express* (2024), <https://doi.org/10.1016/j.ict.2024.06.004>, <https://www.sciencedirect.com/science/article/pii/S2405959524000754>.
- [28] Sibozhang, et al., Rate-splitting multiple access: finite constellations, receiver design, and SIC-free implementation, *IEEE Transactions on Communications* 72 (9) (2024) 5319–5333, <https://doi.org/10.1109/TCOMM.2024.3383102>.
- [29] Robert-Jeron Reifert, et al., A practical study of rate-splitting multiple access: single vs. multiple common messages, in: *2024 IEEE 25th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*, 2024, pp. 596–600, <https://doi.org/10.1109/SPAWC60668.2024.10694543>.
- [30] Zhaohui Yang, et al., Optimization of rate allocation and power control for rate splitting multiple access (RSMA), *IEEE Transactions on Communications* 69 (9) (2021) 5988–6002, <https://doi.org/10.1109/TCOMM.2021.3091133>.
- [31] Donghyeon Kim, et al., Novel resource allocation algorithm for IoT networks with multicarrier NOMA, *IEEE Internet of Things Journal* 11 (18) (2024) 30354–30367, <https://doi.org/10.1109/JIOT.2024.3413344>.
- [32] Qiao Qi, Xiaoming Chen, Derrick Wing Kwan Ng, Robust beamforming for NOMA-based cellular massive IoT with SWIPT, *IEEE Transactions on Signal Processing* 68 (2020) 211–224, <https://doi.org/10.1109/TSP.2019.2959246>.
- [33] Bho Matthiesen, et al., Globally optimal beamforming for rate splitting multiple access, in: *ICASSP 2021–2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2021, pp. 4775–4779, <https://doi.org/10.1109/ICASSP39728.2021.9413616>.
- [34] Muhammad Mahtab Alam, Elyes Ben Hamida, Performance evaluation of IEEE 802.15.6 MAC for wearable body sensor networks using a space-time dependent radio link model, in: *2014 IEEE/ACS 11th International Conference on Computer Systems and Applications (AICCSA)*, IEEE, 2014, pp. 441–448.
- [35] Muhammad Mahtab Alam, Elyes Ben Hamida, Surveying wearable human assistive technology for life and safety critical applications: standards, challenges and opportunities, *Sensors* 14 (5) (2014) 9153–9209.
- [36] Kyung Sup Kwak, Sana Ullah, Niamat Ullah, An overview of IEEE 802.15.6 standard, in: *2010 3rd International Symposium on Applied Sciences in Biomedical and Communication Technologies (ISABEL 2010)*, IEEE, 2010, pp. 1–6.
- [37] Lawrence G. Roberts, ALOHA packet system with and without slots and capture, *ACM SIGCOMM Computer Communication Review* 5 (2) (1975) 28–42.
- [38] Christian Namislo, Analysis of mobile radio slotted ALOHA networks, *IEEE Journal on Selected Areas in Communications* 2 (4) (1984) 583–588.
- [39] J. Metzner, On improving utilization in ALOHA networks, *IEEE Transactions on Communications* 24 (4) (1976) 447–448.
- [40] Junhee Lee, Wun-Cheol Jeong, Byeong-Cheol Choi, A scheduling algorithm for improving scalability of LoRaWAN, in: *2018 International Conference on Information and Communication Technology Convergence (ICTC)*, IEEE, 2018, pp. 1383–1388.
- [41] Tommaso Polonelli, et al., Slotted aloha on lorawan-design, analysis, and deployment, *Sensors* 19 (4) (2019) 838.
- [42] René J. van der Vleuten, Wim C. van Etten, P.A. van den Boom, Optimal controlled ALOHA for two-way data communication in a cable television network, *IEEE Transactions on Communications* 42 (7) (1994) 2453–2459.

- [43] Jun-Bae Seo, Hu Jin, Optimally controlled pure ALOHA systems for wireless sensor networks, *IEEE Communications Letters* 21 (11) (2017) 2460–2463.
- [44] Andrea Baiocchi, Fabio Ricciato, Analysis of pure and slotted ALOHA with multipacket reception and variable packet size, *IEEE Communications Letters* 22 (7) (2018) 1482–1485.
- [45] Wang Hai, Abraham O. Fapojuwo, Design and performance evaluation of successive interference cancellation-based pure ALOHA for Internet-of-Things networks, *IEEE Internet of Things Journal* 6 (4) (2019) 6578–6592.
- [46] I.B. Arun, T.G. Venkatesh, Order statistics based analysis of pure ALOHA in channels with multipacket reception, *IEEE Communications Letters* 17 (10) (2013) 2012–2015.
- [47] Leonard Kleinrock, Fouad Tobagi, Packet switching in radio channels: part I-carrier sense multiple-access modes and their throughput-delay characteristics, *IEEE Transactions on Communications* 23 (12) (1975) 1400–1416.
- [48] Ai-Chun Pang, Hsueh-Wen Tseng, Dynamic Backoff for Wireless Personal Networks, *IEEE Global Telecommunications Conference, 2004. GLOBECOM'04*, vol. 3, IEEE, 2004, pp. 1580–1584.
- [49] Ilker Demirkol, Cem Ersoy, Energy and delay optimized contention for wireless sensor networks, *Computer Networks* 53 (12) (2009) 2106–2119.
- [50] Hui Jing, Aida Hitoshi, An analytical approach to optimization of throughput for IEEE 802.15. 4 slotted CSMA/CA networks, in: 2011 IEEE Consumer Communications and Networking Conference (CCNC), IEEE, 2011, pp. 1021–1025.
- [51] Mustafa Shakir, et al., Performance optimization of priority assisted csma/ca mechanism of 802.15. 6 under saturation regime, *Sensors* 16 (9) (2016) 1421.
- [52] Rapeepat Ratasuk, et al., Overview of narrowband IoT in LTE Rel-13, in: 2016 IEEE Conference on Standards for Communications and Networking (CSCN), IEEE, 2016, pp. 1–7.
- [53] Haijun Yu, et al., Multi-timescale multi-dimension resource allocation for NOMA-edge computing-based power IoT with massive connectivity, *IEEE Transactions on Green Communications and Networking* 5 (3) (2021) 1101–1113, <https://doi.org/10.1109/TGCN.2021.3076582>.
- [54] Jihan Feng, et al., Optimal trajectory and resource allocation for RSMA-UAV assisted IoT communications, *IEEE Transactions on Vehicular Technology* 73 (6) (2024) 8693–8704, <https://doi.org/10.1109/TVT.2024.3354329>.
- [55] Ruichen Zhang, et al., Energy efficiency maximization in RIS-assisted SWIPT networks with RSMA: a PPO-based approach, *IEEE Journal on Selected Areas in Communications* 41 (5) (2023) 1413–1430, <https://doi.org/10.1109/JSAC.2023.3240707>.
- [56] Mahnoor Anjum, et al., Dedicated versus shared element-allotment in IRS-aided wireless systems: when to use what?, in: 2023 IEEE 97th Vehicular Technology Conference (VTC2023-Spring), 2023, pp. 1–6, <https://doi.org/10.1109/VTC2023-Spring57618.2023.10200209>.
- [57] Minh-Sang Van Nguyen, et al., Enhancing NOMA backscatter IoT communications with RIS, *IEEE Internet of Things Journal* 11 (4) (2024) 5604–5622, <https://doi.org/10.1109/JIOT.2023.3308786>.

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Role of artificial intelligence in supporting the development of Green IoT

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9.1 Introduction

The Internet of Things (IoT) has transformed global connectivity by integrating physical objects with sensors and software to facilitate data exchange, driving efficiency and performance across several domains. The concept of the IoT was formalized by British technologist Kevin Ashton in 1999, envisioning a global network of interconnected devices capable of autonomous communication without human intervention. The advancement of high-speed internet, ubiquitous smartphone and wearable adoption, and the development of communication protocols have facilitated the rapid expansion of IoT. As a result, IoT has evolved into a vast ecosystem encompassing billions of interconnected devices across diverse domains, including personal, residential, industrial, and urban environments. On an individual level, IoT systems include health and lifestyle tracking to improve quality of life. The Healthcare Internet of Things (H-IoT) revolutionizes healthcare by enabling remote patient monitoring, personalized treatment, and improved diagnostics. Wearable devices track vital signs, activity levels, and sleep patterns, transmitting data to healthcare providers for continuous monitoring. IoT facilitates telemedicine, allowing patients to receive care from remote locations. Smart pills with embedded sensors track medication adherence, and connected medical equipment enhances hospital efficiency and patient outcomes. Key applications of IoT in the residential sphere or “smart homes” include smart systems such as adaptive lighting systems that adjust to ambient light levels or mood settings, smart thermostats that optimize energy consumption based on occupancy and user preferences, and connected security systems with real-time monitoring through cameras and sensors. Additionally, IoT facilitates predictive maintenance in household appliances and integrates voice-activated assistants for seamless task management. These innovations collectively contribute to developing intelligent and automated living environments. The Industrial Internet of Things (IIoT) enhances productivity,

safety, and efficiency through sensor-equipped industrial facilities, which enable predictive maintenance, minimizing downtime and costs. Real-time monitoring and analytics optimize production, supply chain management, and inventory control, while automation and robotics improve operational efficiency, safety, and product quality in manufacturing and industrial environments. IoT enhances agricultural efficiency by optimizing resource use and increasing yield. Soil sensors enable precise irrigation and fertilization through real-time moisture, nutrients, and temperature data. Drones and satellite imagery monitor crop health and detect issues early, while livestock tracking improves animal health, location monitoring, and overall productivity. Smart governance leverages IoT to facilitate data-driven decision-making, improve public services, and enhance citizen engagement through digital platforms. IoT supports intelligent transportation by enabling real-time traffic monitoring, adaptive traffic signal control, and smart parking solutions, optimizing mobility and reducing congestion. Security is strengthened through IoT-based surveillance, predictive policing, and emergency response systems, ensuring safer urban environments. Furthermore, IoT enhances essential services such as waste management, energy distribution, and water supply by enabling predictive maintenance and efficient resource allocation. Networks of sensors detect air and water quality, radiation levels, and weather conditions. IoT devices can monitor deforestation levels, glacier movements and melting rate, and wildlife habitats, providing data essential for environmental protection and climate research. Collectively, these advancements contribute to the sustainability, efficiency, and resilience of our human habitation and ecosystems.

The rapid expansion of the IoT offers significant benefits; however, it also raises critical concerns regarding environmental sustainability. The energy consumption required to power billions of connected devices, the increasing strain on data centers, and the growing volume of electronic waste (e-waste) contribute to ecological challenges. According to the International Energy Agency (IEA), data centers and data transmission networks accounted for approximately 1% of global electricity consumption in 2022, with projections indicating continued growth as IoT adoption increases [1]. Additionally, the International Telecommunication Union (ITU) reports that global e-waste reached 62 million metric tons in 2022, with only 22.3% being formally recycled [2]. The World Health Organization (WHO) reports that the informal dumping of waste leads to adverse health effects, especially in women and children [3]. In response to these concerns, the Green Internet of Things (G-IoT) has emerged as a sustainable alternative that integrates energy-efficient technologies, eco-friendly materials, and optimized data processing strategies to mitigate IoT's environmental impact. G-IoT focuses on reducing the environmental impact of IoT technologies through key strategies like energy-efficient communication and data processing protocols, using sustainable materials to manufacture sensors and communication devices, and improving lifecycle management. Energy-efficient devices, powered by low-power designs and energy harvesting methods such as solar and kinetic energy, help to minimize electricity consumption. Optimized communication protocols like Zigbee, LoRaWAN, and NB-IoT further reduce energy use during data transmission. Sustainable manufacturing practices emphasize using eco-friendly materials, such as biodegradable and recyclable components, and cleaner production

methods to reduce emissions. G-IoT also promotes design for longevity, encouraging modularity to extend device lifespans and prevent e-waste. Responsible recycling and disposal systems reclaim valuable materials and mitigate environmental harm. IoT applications in environmental monitoring and resource optimization further support sustainability by tracking pollution, conserving resources, and enhancing energy and water efficiency. By integrating these approaches, G-IoT aims to minimize the ecological footprint of IoT devices while supporting sustainability and conservation efforts across industries.

Artificial Intelligence (AI) is critical in enhancing the performance and reliability of wireless communication systems in the IoT domain. AI techniques such as supervised learning and deep neural networks are used for tasks like channel estimation, which improves real-time prediction of channel responses, and beamforming, which optimizes signal transmission to reduce interference. Reinforcement learning (RL) is also applied in dynamic resource allocation, ensuring efficient utilization of spectrum and bandwidth based on users' data rate requirements and channel conditions. Furthermore, AI facilitates data acquisition and pre-processing from IoT sensors, followed by pattern recognition through deep learning (DL) algorithms to detect anomalies and predict trends. AI-driven predictive models analyze data from IoT devices to anticipate potential failures, enabling proactive actions that enhance operational efficiency. These techniques collectively contribute to advancing smarter, more efficient wireless communication networks for IoT.

This chapter presents an overview of G-IoT, its definition, architecture, and key enablers. It primarily focuses on the role of AI in supporting its development within the constraints of sustainability and compliance with the quality of service (QoS).

9.2 Green-Internet of Things

G-IoT refers to designing, deploying, and operating IoT systems that focus on energy efficiency, reduced carbon emissions, and sustainable practices. G-IoT aims to minimize the environmental impact of IoT systems while maintaining their functionality and scalability. G-IoT can be pivotal in advancing several of the United Nations Sustainable Development Goals (UN-SDGs). Goal 7 — Affordable and Clean Energy — optimizes energy usage and integrates renewable sources like solar and wind through smart grids and energy management systems. G-IoT supports efficient energy distribution and consumption by leveraging the smart grid paradigm. For Goal 9 — Industry, Innovation, and Infrastructure — G-IoT contributes by improving industrial sustainability with eco-friendly technologies and optimized processes, while real-time monitoring ensures resilient infrastructure. In alignment with Goal 11 — Sustainable Cities and Communities — G-IoT supports smart mobility, pollution management, and urban planning through data analytics, fostering efficient and sustainable urban development. In relation to Goal 12 — Responsible Consumption and Production — G-IoT encourages sustainable consumption by promoting circular economy models, improving supply chain transparency, and empowering consumers

with data on environmentally conscious choices. Finally, in line with Goal 13 — Climate Action — G-IoT facilitates climate monitoring and mitigation by providing data on emissions and climate predictions and offering early warning systems for natural disasters. Overall, G-IoT drives progress in sustainability and environmental stewardship across diverse sectors, demonstrating its alignment with the UN SDGs.

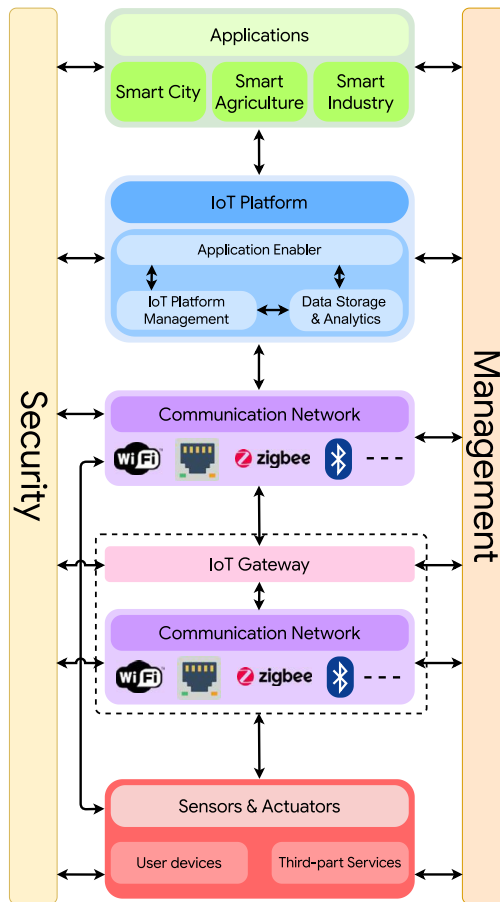


FIGURE 9.1

A General IoT architecture framework.

The advancement of green IoT necessitates robust standardization frameworks and collaborative global initiatives to address energy efficiency challenges across heterogeneous networks and devices. A general IoT system architecture can be drawn up from recommendations from the Institute of Electrical and Electronics Engineers (IEEE) [4] and the International Telecommunication Union (ITU) [5] as illustrated in Fig. 9.1, which considers existing IoT architectures [6]. Efficient protocols and

technologies support each layer of this architecture, some of which are standardized. Several standardization and innovation efforts have begun since the inception of IoT. Earlier research efforts like the Energy Aware Radio and neTwork tecHnologies (EARTH) project pioneered energy-efficient broadband systems by optimizing network architectures and adaptive management strategies, reducing operational energy consumption by 50% while maintaining quality of service (QoS) [7]. Toward Real Energy-Efficient Network Design (TREND) project evaluates and proposes energy-saving potentials in network protocols and architectures, emphasizing scalable solutions for IoT ecosystems [8]. The GreenTouch Consortium proposed an end-to-end network power model to evaluate energy consumption and minimize the carbon footprint through innovations in spectrum efficiency and low-power hardware design in optical networks [9]. Japan's Green IT Initiative was among the pioneering initiatives that prioritized environmental protection while achieving economic growth using information technology (IT) [10]. Standardization bodies such as the IEEE Technical Subcommittee on Green Communications and Computing (TSCGCC) and the Internet Engineering Task Force (IETF) have established the IPv6 over Low-Power Wireless Personal Area Networks (6LoWPAN) [11] and Routing Over Low-Power and Lossy Networks (ROLL) [12], respectively, enabling energy-aware communication in resource-constrained IoT devices. Radio Frequency Identification (RFID) innovations by government agencies, industry, and non-profits promote sustainable designs such as biodegradable RFID tags, energy-harvesting sensor nodes, and broader operating frequency ranges.

The key technologies pushing energy efficiency in G-IoT were explored in [13]. These enablers can be classified into three categories: green tags, green sensing technologies, and green internet technologies as illustrated in Fig. 9.2. Green tags like RFID and Near-Field Communication (NFC) are foundational for G-IoT. RFID tags are essentially microchips, which are passive devices that harvest energy for their operation from an RFID reader, while NFC, being active, is powered by a battery. RFID can identify and track objects without a direct line of sight. NFC operates at a shorter range of up to 20 cm and is particularly customer-oriented due

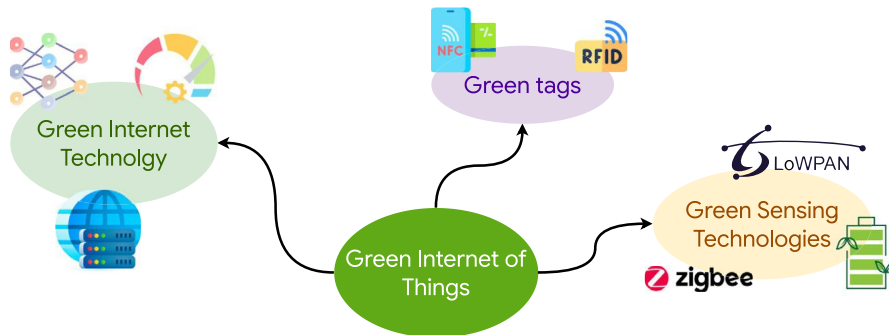


FIGURE 9.2

Enabling technologies for G-IoT.

to its integration into mobile devices, allowing for seamless interaction with hyper-connected environments. These devices are used to monitor vehicle emissions, track waste disposal, waste management and recycling, and energy management systems in buildings and public spaces. However, the enormous number of these tags used in such applications may contribute to e-waste. Therefore, paper-based, printable, or biodegradable RFIDs are proposed as a potential solution. The sheer number of these devices may increase the complexity of such systems.

The second category, green sensing technologies, includes Wireless Sensor Networks (WSNs), which are critical for enabling IoT applications in environmental monitoring, industrial automation, and smart cities. WSNs comprise sensor nodes that collect data from the environment and communicate it to a central base station or a sink. These networks are typically characterized by low-power, low-bit-rate communication and energy-efficient protocols. They are primarily based on the IEEE 802.15.4 standard. WSNs can leverage energy harvesting techniques, such as solar, kinetic, and thermal energy, to power the sensing nodes, reducing the reliance on batteries and minimizing environmental impact. However, true battery-free operation has yet to be achieved. Furthermore, As the number of IoT devices increases, spectrum congestion and interference will become significant issues. Cognitive Radio (CR) technologies, which allow devices to select communication channels dynamically, are being explored to ensure efficient spectrum utilization. Protocols like 6LoWPAN and ZigBee are designed to optimize energy usage in low-power devices, enabling seamless integration into the IoT ecosystem.

Finally, the third enabler—green internet technology—includes several innovative solutions to support energy-efficient operations without compromising performance. Cloud computing is pivotal in G-IoT by providing scalable, on-demand computing resources and storage. Additionally, edge computing further improves the performance of G-IoT systems, offering some of the advantages of cloud computing. This shift from on-device infrastructure to remote services reduces energy consumption by consolidating resources in centralized or distributed, energy-efficient data centers or devices [14]. However, the energy demands of data centers remain a concern, necessitating further innovations in low-power processing hardware, efficient data processing algorithms, and lightweight software. Using renewable energy to power and cool data centers is a significant step towards sustainable technology. There are efforts to develop cooling systems for data centers to maintain stable performance with a minimal carbon footprint.

AI is becoming integral to wireless network design and deployment and has become a key enabler of G-IoT. It plays a crucial role in improving the efficiency and functionality of IoT systems. AI is primarily used to process and analyze large volumes of data generated by IoT devices, thus enabling real-time decision-making and automation. This is particularly important in G-IoT, where energy consumption and resource management are critical. For instance, AI algorithms can optimize energy usage in smart grids, reducing waste and promoting sustainability. The decision support capability is vital for predictive maintenance, where AI algorithms can predict equipment failures and schedule maintenance activities, thereby reducing downtime

and extending the lifespan of devices. This improves operational efficiency and minimizes the environmental impact by reducing the need for frequent replacements and repairs. AI enhances the security of IoT systems by detecting and mitigating potential threats, such as cyber-attacks and data breaches. This is crucial for maintaining the integrity and reliability. Additionally, AI can enhance user experience and accessibility, making it easier for network designers and administrators to interact with intelligent environments. AI-driven automation reduces the need for human intervention in routine tasks, allowing for more efficient and sustainable operations [15], [14].

9.3 Artificial intelligence models for Green-Internet of Things

AI is a key enabler of G-IoT by improving data management, energy efficiency, security, and decision-making across various application domains. AI-driven machine learning (ML) and DL techniques facilitate the analysis of vast amounts of IoT-generated data, enabling efficient data filtering and reducing redundancy. AI minimizes bandwidth usage and improves response times by optimizing the data offloading mechanisms and processing data at the network edge. Additionally, AI plays a crucial role in energy optimization by monitoring real-time power consumption and performing predictive analysis to adjust energy usage dynamically. ML models can anticipate environmental conditions and system load variations, allowing IoT devices to optimize power allocation and minimize energy waste. Beyond efficiency improvements, AI enhances the security and reliability of IoT networks. Artificial neural networks (ANNs) and AI-driven anomaly detection systems can identify potential cyber threats, enabling proactive security measures. The use of federated learning (FL) ensures the security of data by leveraging its capacity for “distributed learning”, which shares the learning parameters without requiring the transfer of data between the nodes and sink in an IoT system. AI is also instrumental in optimizing fog and edge computing architectures, alleviating the computational burden on cloud data centers. By distributing data processing closer to the source, AI mitigates network congestion, reduces latency, and improves system responsiveness, particularly in applications requiring real-time decision-making. This further reduces the burden on communication networks, significantly improving energy and spectral efficiency. Furthermore, AI can proactively perform predictive maintenance to enhance IoT devices’ reliability and longevity. AI minimizes downtime and reduces maintenance costs by identifying anomalies and diagnosing faults before they lead to failures. Therefore, AI integration into G-IoT fosters an energy-efficient, secure, and scalable ecosystem, ensuring the sustainable deployment of IoT technologies across diverse applications [16]. Based on the discussion presented in [16], the key AI models that enable G-IoT can be grouped under the following categories:

1. Supervised learning models.
2. Unsupervised learning models.

3. Semi-supervised learning models.
4. Deep learning models.
5. Reinforcement learning models.
6. Federated learning models.

In general, we can classify the AI into three broad functional categories, further divided into sub-categories, as illustrated in Fig. 9.3. A summary of the key ideas and applications of these models in G-IoT system are tabulated in Table 9.1.

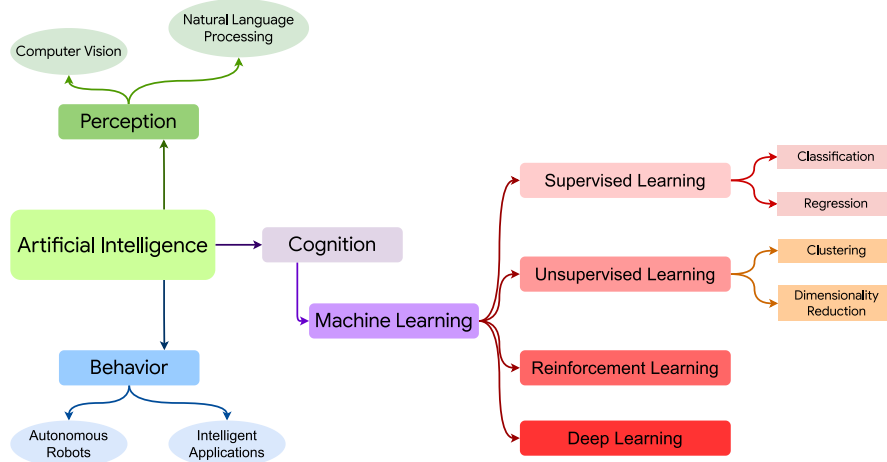


FIGURE 9.3

Functional classification of AI. ML models can be further classified on the basis of the learning models.

9.3.1 Supervised learning

Supervised learning (SL) [17] is a type of ML in which a model is trained on labeled datasets containing samples of input data paired with a label. The model learns from these labeled samples to make accurate predictions or classifications of unseen samples or test data. During the training process, the model iteratively adjusts its parameters to minimize the difference between the predicted and actual labels using techniques such as regression and classification. SL is primarily used for pattern recognition, predictive modeling, and decision-making tasks.

SL models can be used in G-IoT applications by leveraging historical data for accurate predictions and decision-making. In energy consumption optimization, SL models can predict energy demand based on past usage patterns, optimize power consumption in smart grids and buildings, and automate electrical systems to minimize energy waste. Additionally, in predictive maintenance, these models detect potential faults in IoT-connected devices before failures occur and utilize sensor data to

Table 9.1 AI Models with their working principles, their applications, and key benefits in G-IoT summarized.

AI Model	Working Principle	Applications	Key Benefits
Supervised Learning	Trains models on labeled datasets to predict or classify unseen data.	– Energy consumption optimization – Predictive maintenance in IoT devices – Environmental monitoring and pollution control – Smart agriculture – Traffic management	– Optimal decision-making – Reduced energy waste – Enhanced fault detection – Optimized traffic flow and resource allocation
Unsupervised Learning	Analyzes unlabeled data to find hidden patterns, structures, or relationships within datasets.	– Energy distribution optimization – Predictive maintenance – Environmental monitoring – Smart agriculture – Smart city traffic and public transport analysis	– Reduced energy consumption – Fault detection and prediction – Improved resource allocation
Semi-supervised Learning	Combination of small labeled datasets with large unlabeled datasets for better efficiency.	– Predictive modeling for energy usage – Load balancing in smart grids – Energy optimization in residential/commercial settings – Applications in smart cities, smart agriculture, and smart living	– Lower resource utilization – Improved learning accuracy – Enhanced adaptability in G-IoT systems – Optimized energy patterns and consumption prediction
Reinforcement Learning	An agent learns by interacting with its environment and receiving rewards or penalties for its actions.	– Resource Allocation – Routing and congestion control – Sustainable agriculture – Traffic management	– Optimized resource utilization – Continuous learning and adaptation – Reduced energy consumption – Minimal environmental impact – Efficient network operation
Federated Learning	Trains models locally on devices with only model parameters shared with a central server.	– Wireless communication optimization by CSI prediction and resource allocation – Predicting real-time network traffic flows – Energy-efficient communication – Secure IoT applications	– Reduced energy consumption – Enhanced privacy and security – Reduced network congestion – Improved scalability – Sustainable and efficient IoT networks

forecast industrial equipment maintenance needs, thereby reducing downtime and conserving energy. Environmental monitoring and pollution control also benefit from SL models by analyzing sensor data from air and water quality monitoring systems,

which helps predict pollution levels and classify regions based on environmental risks for improved decision-making. In smart agriculture, SL models can predict crop yields by analyzing weather patterns, soil quality, and historical production data while detecting plant diseases through image analysis from IoT-connected cameras and drones. Furthermore, SL models can analyze traffic congestion patterns in traffic management to optimize vehicle routing and dynamically adjust traffic light operations to minimize fuel consumption and emissions.

9.3.2 Unsupervised learning

Unsupervised learning (UL) [17] is a type of ML where models analyze unlabeled datasets to identify hidden patterns, structures, or relationships without predefined output labels. Unlike SL, UL uses self-organizing techniques to classify data or extract insights. It is primarily used for clustering and dimensionality reduction. UL includes algorithms such as K-means clustering, hierarchical clustering, principal component analysis (PCA), and autoencoders.

UL supports G-IoT by improving energy efficiency, security and building fault tolerance. Clustering techniques are used to analyze consumption patterns of users and devices, enabling efficient power distribution while detecting inefficiencies in smart grids through the identification of anomalies in power usage. Additionally, behavioral pattern analysis facilitates the implementation of optimized energy-saving protocols. UL can predict issues by detecting unusual sensor readings that indicate impending equipment failures. Clustering device performance data can identify potential faults before they cause disruptions. Environmental monitoring and pollution control benefit from clustering techniques applied to air and water quality data, allowing for the detection of pollution hotspots. Anomaly detection in climate sensor data enables the prediction of environmental hazards. Clustering can be applied to segment agricultural land based on soil quality and crop health patterns, enabling targeted interventions. Furthermore, clustering image data from IoT-connected drones enhances the early detection of plant diseases. Similarly, irrigation systems can be optimized by analyzing water usage patterns across different clusters of agricultural facilities. Clustering techniques can be used in smart cities to analyze traffic flow data, optimize urban transportation systems by identifying congestion hotspots, and improve route planning. Additionally, trends in public transport usage can be analyzed by UL models to ensure optimal resource allocation, thereby contributing to sustainable and efficient mobility solutions.

9.3.3 Semi-supervised learning

Semi-supervised learning [18] is an ML approach that combines SL and UL. It leverages a small amount of labeled data combined with a large volume of unlabeled data to improve learning accuracy and efficiency. This approach mitigates training costs in the absence or shortage of labeled data, as it allows the model to generalize from a limited set of labeled samples while learning patterns from the vast pool of unlabeled data. Semi-supervised learning techniques include self-training,

co-training, and graph-based methods, which help to refine decision boundaries and improve model performance.

Semi-supervised learning can play a critical role in enhancing the efficiency, adaptability, and accuracy of G-IoT applications by using labeled and unlabeled data collected by the sensors and managing underlying network usage patterns. Semi-supervised learning enables predictive modeling of energy usage trends, improves load balancing in smart grids by identifying consumption patterns and anomalies, and optimizes energy patterns in residential and commercial settings to reduce energy waste. Semi-supervised learning can offer benefits in smart cities, smart agriculture, and smart living settings by leveraging its capabilities to use a small set of labeled data to learn patterns in the vast unlabeled datasets with a higher accuracy and lower resource utilization.

9.3.4 Reinforcement learning

Reinforcement learning (RL) [17] is a type of ML where an agent learns to make decisions by taking actions in an environment to maximize some notion of a cumulative reward. The agent receives feedback in the form of rewards or penalties based on its random actions and learns to optimize its policy over time. Unlike SL or UL, where the model learns from pre-existing datasets, RL uses trial and error to discover the best policy. Applications of RL span several domains, including robotics, gameplay, autonomous vehicles, and natural language processing (NLP). These applications benefit from RL's ability to optimize performance through continuous learning and adaptation.

In G-IoT, RL presents significant potential for advancing sustainability and efficiency. Key applications include smart grid management, building energy management, sustainable agriculture, traffic management, and supply chain optimization. By leveraging RL, G-IoT systems can optimize resource utilization, reduce energy consumption, and minimize environmental impact, thus contributing to greener and more sustainable technological ecosystems. RL models are inherently lightweight compared to the previously stated models due to the absence of explicit training datasets. Therefore, RL is integrated with the network design without increasing the operation cost of underlying wireless networks powering the G-IoT systems. RL can be integrated into channel access methods, routing, and congestion control to ensure efficient network operation.

9.3.5 Federated learning

Federated learning (FL) [17] decentralizes the training of models by leveraging distributed data across multiple devices or agents. Contrary to centralized learning, where the training and test data is sent to a central server for processing, FL allows the model to be trained locally on the sensor or edge nodes, with only model parameters shared with a central server. This approach addresses significant privacy, security, and data efficiency challenges while offering solutions for network management and data processing at the same time. FL enhances wireless communication

by improving channel state information (CSI) prediction, optimizing resource allocation, and reducing interference through personalized, locally trained models. It also aids in predicting real-time network traffic flows and adapting to local conditions. FL enables more accurate device behavior modeling, supporting personalized services like adaptive streaming and energy-efficient communication, while minimizing privacy risks by keeping user data on-device. Additionally, FL improves security by ensuring that sensitive data does not leave the user's device, reducing the risk of data breaches and complying with privacy regulations.

FL contributes to energy-efficient and sustainable solutions in the G-IoT paradigm significantly. The local model training in FL minimizes energy consumption, especially for battery-powered devices, by reducing the need for continuous communication with central servers and utilization of resource-heavy data processing. Additionally, FL optimizes data efficiency and bandwidth usage by limiting network transmission to just model parameters, alleviating congestion in bandwidth-constrained G-IoT networks. FL usually employs edge processing, which enables decision-making within the network to optimize energy consumption without overwhelming the central servers. This decentralization reduces latency, enhances scalability, and supports sustainability by lowering the carbon footprint through decreased data transfer and less reliance on centralized data centers, thereby promoting greener IoT infrastructures.

9.4 Leveraging AI for Green-Internet of Things

The scope of sixth-generation (6G) cellular networks, especially machine-type communication (MTC), includes support for 1000 devices per square meter, delivering high data rates and reliability. Energy efficiency and sustainability are integral to the network design, especially for IoT networks [19]. AI models are widely adopted to transform IoT to G-IoT at all layers of the IoT architecture, as illustrated in Fig. 9.1. Furthermore, AI models are evolving to achieve higher energy and computational efficiency. Green AI development necessitates optimizing computational efficiency across dimensions. Algorithm optimization techniques, such as sparse training, quantization, and pruning, reduce the memory requirements and computational complexity, thereby lowering energy consumption. Hardware efficiency can be enhanced by utilizing energy-efficient hardware, leveraging parallelization, and implementing edge computing to process data locally, minimizing energy-intensive cloud transmissions. Data center optimization strategies, including dynamic server load balancing, cooling system adjustments, and efficient resource allocation, further reduce energy demands. Finally, scaling reductions, such as limiting algorithm iterations and hyper-parameter tuning, help mitigate unnecessary computational overhead while maintaining performance [20]. The available research literature on the convergence of AI and IoT to manifest G-IoT can be arranged according to each layer of Fig. 9.1. Each application requires a minimum performance, which the underlying layers can deliver. These layers work in tandem with each other, supporting a critical function enabling an application. Therefore, the contributions of AI in supporting G-IoT, which translates to energy-efficient operation, can be summarized under the following headings.

9.4.1 IoT architecture

AI techniques are predominantly centralized, i.e., the models are run on a central server. However, this architecture faces challenges in terms of accuracy, computational complexity, power consumption, memory constraints, and explainability. Edge computing moves the computational process from a central server to the “edge of the network”. Therefore, this shift warrants a similar distributed AI paradigm, with fragmented training and inference processes to optimize computation and memory while maintaining privacy and low latency. As large-scale IoT applications drive further decentralization, the need for interoperability, scalability, and dynamic resource allocation has led to the emergence of Pervasive AI, which integrates AI with pervasive computing to manage resource constraints intelligently [21].

Edge computing reduces latency and computational burden by bringing computational resources closer to IoT devices, enabling real-time decision-making while reducing data transfer to cloud servers, thereby freeing up bandwidth and reducing hardware requirements. This localized processing lowers the power consumption associated with cloud infrastructure and network transmission. Additionally, AI algorithms in the edge nodes facilitate intelligent resource management, optimizing energy consumption in IoT networks. Techniques such as DL-based predictive analytics enable devices to operate in an energy-efficient manner by dynamically adjusting their processing loads based on demand. Furthermore, model partitioning and offloading strategies allow computationally intensive tasks to be distributed between edge and cloud servers, balancing efficiency and accuracy [22][23]. FL reduces redundant data movement by training models locally on edge devices, further enhancing energy efficiency while preserving data privacy. Low-power AI models designed for edge deployment, such as quantized DL models and lightweight neural networks (NNs), ensure reduced computational complexity without compromising accuracy performance. Software optimization techniques make AI-driven edge computing solutions more sustainable. Adaptive energy management strategies within IoT systems leverage RL and heuristic optimization algorithms to dynamically allocate resources, reducing overall power consumption. Additionally, edge computing facilitates event-driven architectures, where data processing is performed only when necessary, minimizing idle power usage in IoT devices. Context-aware AI models running at the edge can predict optimal operating conditions, enabling proactive energy-saving measures in applications such as smart grids, intelligent transportation systems (ITS), and industrial automation. AI-driven edge computing enhances real-time load balancing and renewable energy forecasting, improving energy efficiency in smart grid applications. AI models optimize proactive predictive maintenance to minimize energy-intensive downtimes in industrial settings [23].

9.4.2 Communication networks

The radio access technologies powering G-IoT communication include low-power technologies including Wi-Fi, Zigbee, and Bluetooth Low Energy (BLE). However, regardless of the underlying communication standard, AI is increasingly integrated in

the design of IoT systems. In the context of wireless communication, AI offers several advantages. The growing data traffic load and the complexity of modern wireless applications have made it difficult for traditional systems to meet demands. AI aids at the physical layer in signal processing by enabling adaptive channel modeling, reducing reliance on accurate mathematical models. The intelligent methodologies for accurate channel modeling and estimation use models including generative networks and deep learning methods. These methods can accurately predict the channel conditions and adapt the transmission parameters, which help in improving energy efficiency, especially for battery-powered nodes. However, the NN-based models require a significant computational resources. Gathering accurate channel conditions through the channel state information (CSI) leveraging deep NNs. In addition, learning models improve data processing by identifying patterns and reducing redundancy, optimizing data storage and processing. Furthermore, AI supports network optimization and resource allocation, which are crucial for the efficiency and scalability of wireless systems. Traditional optimization tools struggle to handle large-scale, real-time applications, especially with complex objectives and constraints in next-generation wireless systems. RL-based resource allocation reduces reliance on training, and considering the distributed nature of the WSNs with resource constraints, RL provides the required performance without reliance on computational resources. AI integration into wireless communications also enhances practical applications, such as localization and positioning accuracy, which are vital for indoor navigation and asset tracking. AI algorithms can dynamically optimize beamforming and antenna adjustments to reduce interference and enhance network performance. Additionally, AI enables better allocation of wireless resources such as bandwidth, power, and frequency spectrum, ensuring more efficient use and improving overall network performance [24]. RL models further optimize routing decisions in WSN by reducing the signaling overhead and remove network congestion. This reduces “sinkholes” and energy consumption, and increase network life.

Despite these advances, the deployment of in wireless networks faces several challenges. Effective reasoning of signal meanings remains difficult, and the scarcity of computing resources poses significant hurdles, limiting the robustness of networks. Efficient management of computing resources is just as critical as wireless resource management. Furthermore, the selection of appropriate ML algorithms for specific tasks remains an ongoing challenge. While data-driven ML methods have proven successful in many contexts, model-driven methods are still relevant in some cases, making algorithm selection a key consideration.

9.4.3 Security

There is an inherent risk of sensitive and private data exposure during its transmission and storage. For critical applications, ensuring users’ privacy and data security is of the utmost priority. Among the most prevalent security and privacy concerns are eavesdropping, data record exposure, user identity exposure, and location information exposure features across the literature. The commonly adopted solutions

to these issues include data encryption during storage and transmission, assigning pseudo identities, and distribution of data at several remote locations [25].

AI offers several advantages over traditional methods for ensuring network and data security. AI-based methods have yielded a high accuracy rate in intrusion detection systems (IDS) [26] [27]. These methods employ SL, UL, and several RL algorithms against denial of service (DoS), jamming, spoofing, intrusion and malware detection, and eavesdropping attacks. Q-Learning is an RL method that is employed successfully to authenticate sensor nodes, avoid signal jamming, and prevent man-in-the-middle attacks. NN offer very high accuracy in data offloading and intrusion detection. While UL can provide a lightweight solution for encrypting the sensed data at the sensor nodes before transmission [28]. However, non-RL methods require resource-intensive training and datasets. Therefore, there is a tradeoff in accuracy and computational cost in the case of SL, UL, and DL methods. Therefore, including edge computing can help offset these tradeoff losses [29].

9.5 Conclusion

The fast paced adaption of AI in several faculties of IoT systems have yielded an energy efficient and sustainable paradigm called G-IoT. The exponential growth of sensor devices including trackers, climate and environment monitors, camera, and imaging sensors are contributing to the enormous levels of e-waste. The improvements in battery technology and software design can significantly improve the energy efficiency. AI can further improve the energy efficiency when integrated in the IoT-system operation and design. The distributed computing architectures decentralize the processing hardware. Intelligent algorithms offload the processes to the edge nodes to reduce communication bandwidth and computational resources. Additionally, light-weight AI models reduce the energy and computational requirements. At the network level, AI models can optimize channel access and data transmission to reduce the transmission overhead and maximize throughput. Furthermore, AI-based encryption algorithms foster data and network security.

This integration also opens up several challenges, including energy efficiency, limited computing resources, scalability, privacy risks, and interoperability issues [30]. The heterogeneity of IoT devices and network technologies further complicates this integration, as variations in hardware and communication protocols can affect model performance. Moreover, AI models must be sustainable, as AI training and inference can have a high carbon footprint. The lack of standardized protocols for AI-powered G-IoT systems hinders seamless integration, leading to interoperability issues. Explainability and trust in AI decisions are also critical, especially in applications such as smart grids and healthcare, where regulatory compliance and user confidence are essential. Cost constraints present a significant challenge in developing economies, as AI-based G-IoT solutions require investments in energy-efficient hardware and infrastructure. Furthermore, AI models must adapt to dynamic environmental conditions, such as fluctuating energy availability and changing network loads, without excessive retraining.

Future research should focus on developing lightweight and energy-efficient AI models optimized for resource-constrained IoT devices. Advancements in FL and edge-based AI can help reduce dependency on centralized computing while enhancing data privacy. Standardization efforts should be prioritized to ensure interoperability across diverse IoT ecosystems. Additionally, explainable AI techniques should be explored to improve transparency and trust in AI-driven decisions. Sustainable AI training methodologies, such as low-power neural networks and green computing frameworks, can help mitigate the environmental impact of AI deployment. Finally, adaptive AI models capable of learning in real time with minimal retraining should be developed to address the challenge of dynamic environmental conditions.

References

- [1] Tracking clean energy progress 2023, IEA, <https://www.iea.org/reports/tracking-clean-energy-progress-2023>, 2023.
- [2] C.P. Baldé, R. Kuehr, T. Yamamoto, R. McDonald, E. D'Angelo, S. Althaf, G. Bel, O. Deubzer, E. Fernandez-Cubillo, V. Forti, V. Gray, S. Herat, S. Honda, G. Iattoni, D.S. Khatriwal, V.L. di Cortemiglia, Y. Lobuntsova, I. Nnorom, N. Pralat, M. Wagner, Global E-waste Monitor 2024, International Telecommunication Union (ITU) and United Nations Institute for Training and Research (UNITAR), 2024, <https://www.itu.int/hub/publication/d-gen-ewaste-01-2024>.
- [3] Electronic waste (e-waste), WHO, [https://www.who.int/news-room/fact-sheets/detail/electronic-waste-\(e-waste\)](https://www.who.int/news-room/fact-sheets/detail/electronic-waste-(e-waste)), 2024.
- [4] IEEE, IEEE standard for an architectural framework for the Internet of Things (IoT), in: IEEE Std 2413-2019, 2020, pp. 1–269, <https://doi.org/10.1109/IEEESTD.2020.9032420>, <https://ieeexplore.ieee.org/document/9032420>.
- [5] ITU-T telecommunication standardization sector of ITU, in: ITU-T Y.2060- Overview of the Internet of Things, Series Y: Global Information Infrastructure, Internet Protocol Aspects and Next-Generation Networks Next Generation Networks – Frameworks and Functional Architecture Models, 2012, pp. 1–269, <https://doi.org/10.1109/IEEESTD.2020.9032420>, <https://ieeexplore.ieee.org/document/9032420>.
- [6] T. Domínguez-Bolaño, O. Campos, V. Barral, C.J. Escudero, J.A. García-Naya, An overview of IoT architectures, technologies, and existing open-source projects, Internet of Things 20 (100626) (2022), <https://doi.org/10.1016/j.iot.2022.100626>.
- [7] Energy Aware Radio and neTwork tecHnologies, EU FP7 Grant Number:247733, <https://cordis.europa.eu/project/id/247733/reporting/fr>, 2012.
- [8] M.A. Marsan, S. Buzzi, L. Chiaraviglio, M. Meo, C. Guerrero, F. Idzikowski, Y. Ye, J.L. Vizcaíno, Trend: toward real energy-efficient network design, in: 2012 Sustainable Internet and ICT for Sustainability (SustainIT), 2012, pp. 1–6.
- [9] S. Lambert, P. Ananth, P. Vetter, K.-L. Lee, J. Li, X. Yin, H. Chow, J.-P. Gelas, L. Lefevre, D. Chiaroni, B. Lannoo, M. Pickavet, Road to energy-efficient optical access: greentouch final results, Journal of Optical Communications and Networking 8 (11) (2016) 878–892, <https://doi.org/10.1364/JOCN.8.000878>.
- [10] Establishment Outline, Green IT promotion council, <https://greenit-pc.jp/e/about>, 2008.
- [11] C.H. Lakshmi Veenadhari, S. Kandasamy, A comprehensive survey on ipv6 over low power wireless personal area networks (6lowpan), in: 2024 International Conference on

- Social and Sustainable Innovations in Technology and Engineering (SASI-ITE), 2024, pp. 78–83, <https://doi.org/10.1109/SASI-ITE58663.2024.00021>.
- [12] A.N. Abbou, Y. Baddi, A. Hasbi, Routing over low power and lossy networks protocol: overview and performance evaluation, in: 2019 International Conference of Computer Science and Renewable Energies (ICCSRE), 2019, pp. 1–6, <https://doi.org/10.1109/ICCSRE.2019.8807584>.
- [13] F.K. Shaikh, S. Zeadally, E. Exposito, Enabling technologies for green Internet of Things, *IEEE Systems Journal* 11 (2) (2017) 983–994, <https://doi.org/10.1109/JSYST.2015.2415194>.
- [14] P. Fraga-Lamas, S.I. Lopes, T.M. Fernández-Caramés, Green IoT and edge AI as key technological enablers for a sustainable digital transition towards a smart circular economy: an industry 5.0 use case, *Sensors* 21 (17) (2021), <https://doi.org/10.3390/s21175745>, <https://www.mdpi.com/1424-8220/21/17/5745>.
- [15] U. Khadam, P. Davidsson, R. Spalazzese, Exploring the role of artificial intelligence in Internet of Things systems: a systematic mapping study, *Sensors* 24 (20) (2024), <https://doi.org/10.3390/s24206511>.
- [16] M.A. Albreem, A.M. Sheikh, M.H. Alsharif, M. Jusoh, M.N. Mohd Yasin, Green Internet of Things (GIoT): applications, practices, awareness, and challenges, *IEEE Access* 9 (2021) 38833–38858, <https://doi.org/10.1109/ACCESS.2021.3061697>.
- [17] B.A. Salau, A. Rawal, D.B. Rawat, Recent advances in artificial intelligence for wireless Internet of Things and cyber–physical systems: a comprehensive survey, *IEEE Internet of Things Journal* 9 (15) (2022) 12916–12930, <https://doi.org/10.1109/JIOT.2022.3170449>.
- [18] J.E. van Engelen, H.H. Hoos, A survey on semi-supervised learning, *Machine Learning* (2020), <https://doi.org/10.1007/s10994-019-05855-6>.
- [19] X. Shen, W. Liao, Q. Yin, A novel wireless resource management for the 6g-enabled high-density Internet of Things, *IEEE Wireless Communications* 29 (1) (2022) 32–39, <https://doi.org/10.1109/MWC.003.00311>.
- [20] V. Bolón-Canedo, L. Morán-Fernández, B. Cancela, A. Alonso-Betanzos, A review of green artificial intelligence: towards a more sustainable future, *Neurocomputing* 599 (2024) 128096, <https://doi.org/10.1016/j.neucom.2024.128096>, <https://www.sciencedirect.com/science/article/pii/S0925231224008671>.
- [21] E. Baccour, N. Mhaisen, A.A. Abdellatif, A. Erbad, A. Mohamed, M. Hamdi, M. Guizani, Pervasive AI for IoT applications: a survey on resource-efficient distributed artificial intelligence, *IEEE Communications Surveys and Tutorials* 24 (4) (2022) 2366–2418, <https://doi.org/10.1109/COMST.2022.3200740>.
- [22] S. Zhu, K. Ota, M. Dong, Green AI for IIoT: energy efficient intelligent edge computing for industrial Internet of Things, *IEEE Transactions on Green Communications and Networking* 6 (1) (2022) 79–88, <https://doi.org/10.1109/TGCN.2021.3100622>.
- [23] Z. Chang, S. Liu, X. Xiong, Z. Cai, G. Tu, A survey of recent advances in edge-computing-powered artificial intelligence of things, *IEEE Internet of Things Journal* 8 (18) (2021) 13849–13875, <https://doi.org/10.1109/JIOT.2021.3088875>.
- [24] Z. Qin, L. Liang, Z. Wang, S. Jin, X. Tao, W. Tong, G.Y. Li, Ai empowered wireless communications: from bits to semantics, *Proceedings of the IEEE* 112 (7) (2024) 621–652, <https://doi.org/10.1109/JPROC.2024.3437730>.
- [25] I. Keshta, Ai-driven IoT for smart health care: security and privacy issues, *Informatics in Medicine Unlocked* 30 (2022) 100903, <https://doi.org/10.1016/j.imu.2022.100903>, <https://www.sciencedirect.com/science/article/pii/S2352914822000545>.

- [26] L. Xiao, X. Wan, X. Lu, Y. Zhang, D. Wu, IoT security techniques based on machine learning: how do IoT devices use AI to enhance security?, *IEEE Signal Processing Magazine* 35 (5) (2018) 41–49, <https://doi.org/10.1109/MSP.2018.2825478>.
- [27] K.A. Shukla, S. Ahamad, G. Rao, A.J. Al-Asadi, A. Gupta, M. Kumbhkar, Artificial intelligence assisted IoT data intrusion detection, in: 2021 4th International Conference on Computing and Communications Technologies (ICCCT), 2021, pp. 330–335, <https://doi.org/10.1109/ICCCT53315.2021.9711795>.
- [28] I. Keshta, Ai-driven IoT for smart health care: security and privacy issues, *Informat-ics in Medicine Unlocked* 30 (2022) 100903, <https://doi.org/10.1016/j.imu.2022.100903>, <https://www.sciencedirect.com/science/article/pii/S2352914822000545>.
- [29] H. Wu, H. Han, X. Wang, S. Sun, Research on artificial intelligence enhancing Internet of Things security: a survey, *IEEE Access* 8 (2020) 153826–153848, <https://doi.org/10.1109/ACCESS.2020.3018170>.
- [30] I. Ahmad, S. Shahabuddin, T. Sauter, E. Harjula, T. Kumar, M. Meisel, M. Juntti, M. Ylianttila, The challenges of artificial intelligence in wireless networks for the Internet of Things: exploring opportunities for growth, *IEEE Industrial Electronics Magazine* 15 (1) (2021) 16–29, <https://doi.org/10.1109/MIE.2020.2979272>.

Road ahead for Green IoT technologies

10

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10.1 Introduction

The road ahead for Green IoT (GIIoT) technologies has many challenges and promising ways to innovation and environmental benefits. With the rapid expansion of connected devices, there is an increasing urgency to tackle issues related to energy use, resource management, and ecological consequences. GIIoT seeks to balance technological growth with sustainability by adopting energy-saving methods, leveraging renewable energy, and prioritizing environmentally conscious designs.

The Internet of Things (IoT) is a transformative technology that connects a wide network of devices, enabling them to communicate and exchange data over the Internet [1][2]. These interconnected devices, such as sensors, actuators, and software, operate autonomously through Machine-to-Machine (M2M) communication, allowing them to collect, share, and analyze data without human intervention. This capability drives efficiency and automation across various sectors, including healthcare, transportation, agriculture, and industrial operations. For example, IoT enables smart home systems to automate lighting and heating, while in agriculture it optimizes irrigation and crop monitoring. One of the most significant contributions of the IoT is its role in the development of smart cities, where it improves resource management, improves public services, and elevates overall quality of life by optimizing energy use, traffic flow, and waste management [3]. The rapid increase in IoT devices is changing the way we interact with technology and our environment. By 2030, it is estimated that more than 100 billion devices will be connected globally, creating an extensive ecosystem of smart, data-driven solutions [4]. However, this growth comes with challenges, particularly in terms of energy consumption and resource management. The increasing number of connected devices demands substantial energy, raising concerns about sustainability and environmental impact [5–7]. As IoT continues to expand, there is a pressing need to adopt greener practices, such as energy-efficient hardware, integration of renewable energy, and sustainable design principles, to ensure that technological progress aligns with environmental preservation. Addressing these challenges will be crucial for realizing the full potential of IoT while minimizing its ecological footprint.

The rapid expansion of IoT has significantly transformed various industries by enhancing efficiency and connectivity. However, this technological advancement also brings serious environmental concerns, primarily due to the high energy consumption and carbon emissions associated with connected devices [8,9]. Each IoT device requires power to function, and with billions of these devices in operation, the cumulative energy demand becomes substantial. Large-scale IoT applications, particularly those involving extensive data processing and analytics, require considerable computational power, further increasing energy consumption. This contributes to an increase in CO₂ emissions, which can undermine sustainability efforts. Projections indicate that carbon dioxide emissions from cellular networks alone could reach hundreds of millions of tons annually, emphasizing the environmental burden posed by IoT expansion [10].

Beyond energy consumption, IoT devices also impact the environment through the extraction and disposal of materials used in their production. The demand for raw materials, including rare earth metals, leads to resource depletion and environmental degradation. Furthermore, improper disposal of obsolete IoT devices contributes to Electronic Waste (e-waste), posing further ecological risks. Without sustainable management, the widespread adoption of IoT could exacerbate existing environmental problems rather than alleviate them. While IoT has the potential to optimize resource use and reduce inefficiencies, its environmental footprint must be addressed through sustainable practices. Adopting renewable sources of energy, integrating green technologies, and better managing e-waste are all critical measures to lessen these impacts. It is crucial that IoT has both an innovative and a sustainable approach, in order to develop in harmony with the resonating environmental objectives around the world aligning with global environmental goals [11].

As a new concept, GIoT addresses the shortcomings of traditional IoT frameworks for environmental issues. It shifts the design thinking of IoT systems architecture towards an energy-centric vertical to empower efficiency and sustainability at all stages of IoT spanning design, production, operation, and even decommissioning. GIoT aims to reduce the carbon footprint and other resources utilized in supporting IoT infrastructure and integrating eco-friendly approaches. The main directions of such an approach are reconsidering modern methods of software development, adopting energy-efficient, low-power computing technologies such as microcontrollers and wireless sensors, and solar powering of the devices. For instance, innovations like green Radio Frequency Identification (RFID) tags and energy-sensitive sensing networks reduce energy demands without compromising functionality. GIoT also emphasizes “smart” resource management, where context-aware systems dynamically adjust operations, such as sleep modes during inactivity, to conserve energy. Furthermore, cloud-based solutions enable centralized data processing, reducing the energy burden on individual devices [12].

A core principle of GIoT is the adoption of sustainable design frameworks, ensuring devices are built with recyclable or biodegradable materials and engineered for longevity to curb electronic waste. Lifecycle management practices, such as efficient recycling protocols, further mitigate environmental harm. By reimagining communication protocols—like Low-power Wide-area Network (LPWAN) or edge computing

GIoT minimizes data transmission energy and latency. Such innovation not only reduces costs, but also integrates the expansion of the IoT with international sustainability targets like cutting down greenhouse gas emissions and advancing circular economies. In the end, the GIoT achieves a balance between fostered climate and technological development, which results in smarter cities and industries while conserving natural resources. As evolution progresses within this domain, prospective work could consider components such as Artificial Intelligence (AI)-controlled energy optimizers, biodegradable sensors and devices, or even decentralized renewable energy IoT ecosystem. Embracing GIoT is not just an environmental imperative, but a strategic pathway to ensure that the scalability of IoT remains compatible with a sustainable future.

10.1.1 Motivation and objectives

The rapid proliferation of IoT technologies has revolutionized global connectivity, yet their environmental costs, escalating energy demands, carbon emissions, and electronic waste pose significant threats to ecological balance. With billions of devices projected to dominate infrastructure by 2030, the urgency to align IoT innovation with sustainability principles is critical. This research is motivated by the imperative to transform conventional IoT into environmentally responsible systems, ensuring technological progress does not compromise planetary health.

The primary objective of this work is to explore and systematize strategies for advancing GIoT technologies—innovations that prioritize energy efficiency, renewable resource integration, and lifecycle sustainability. This research seeks to:

- Investigate energy-efficient technologies and systems, including low-power hardware, renewable energy integration, and intelligent algorithms, to minimize the ecological footprint of IoT operations.
- Develop holistic frameworks for sustainable IoT design, emphasizing lifecycle management, recyclable materials, and circular economy practices to reduce waste and extend device longevity.
- Advocate for cross-disciplinary strategies that combine policy reforms, industry standards, and ethical innovation to address scalability challenges and steer IoT growth toward global sustainability goals.

By addressing these objectives, this research aims to bridge the gap between IoT's transformative potential and environmental stewardship, empowering stakeholders to adopt solutions that harmonize connectivity, efficiency, and ecological preservation.

10.1.2 Chapter organization

This chapter is structured to systematically explore the multi dimensions of GIoT, guiding readers through technological innovations, practical implementations, and policy-driven strategies for sustainability. Section 10.2 examines emerging technologies for GIoT systems, introducing cutting-edge advancements such as energy-efficient hardware, low-power communication protocols, and AI-driven optimisation

tools that form the backbone of sustainable IoT ecosystems. Section 10.3, Collaborative Intelligence and Software Optimization, explores intelligent algorithms and distributed computing frameworks that enhance energy efficiency by minimizing computational redundancy and enabling adaptive resource management. Section 10.4, Energy Harvesting and Renewable Integration, addresses methods to power IoT devices through renewable energy sources like solar, kinetic, and thermal harvesting, reducing reliance on non-renewable power. Section 10.5, Sustainable System Design, focuses on lifecycle-aware engineering principles, emphasising recyclable materials, modular architectures, and circular economy practices to control electronic waste. Section 10.6, Regulatory and Policy Frameworks for GIoT, analyzes global standards, government incentives, and industry regulations necessary to align IoT growth with environmental goals. Section 10.7, Future Challenges and Opportunities, identifies unresolved issues such as scalability, interoperability, and ethical considerations, while highlighting pathways for innovation in biodegradable electronics and decentralized energy systems. Finally, Section 10.8, Conclusion: Path to a Sustainable Future, synthesises key insights and outlines actionable strategies to harmonize IoT's transformative potential with planetary sustainability. Each section builds on the previous, offering an organized roadmap for researchers, policymakers, and industry stakeholders to advance GIoT technologies responsibly.

10.2 Emerging technologies for Green IoT systems

Emerging technologies play a crucial role in the advancement of GIoT systems by focusing on enhancing energy efficiency and promoting sustainable practices within interconnected networks.

The fundamental part is the wireless identification and tracking of objects with the use of eco-friendly tagged RFID systems, which significantly enhance the resource management level. Green RFID tags, which obtain power from the reader's signal instead of batteries, are an important example of this. These tags enable effective tracking and identification processes in various applications while further reducing energy use. Green RFID tags require no batteries; furthermore, these tags reduce energy while retrieving information through lightweight power collection. These tags not only facilitate seamless data collection but do so with a significantly lower power footprint, thereby contributing to overall energy conservation. Near Field Communication (NFC) is similar to RFID, but designed for short-range communication, NFC enables interactions between devices within a close distance. This technology is particularly useful in smart devices and payment systems, where it operates efficiently with low power usage, contributing to the overall energy efficiency of IoT applications. Alongside this, Green Wireless Sensor Network (WSN) play a crucial role by optimizing the energy usage of wireless sensors that gather extensive data without adverse ecological impacts. By leveraging advanced algorithms and efficient device management, these networks ensure that significant amounts of information can be

collected while keeping power consumption at a minimum. These networks are designed to operate with minimal power consumption, intelligently managing energy use while providing robust data collection and monitoring capabilities. WSNs allow for real-time data analysis and decision-making processes that optimize energy use. Applications in agriculture, smart cities, and industrial monitoring demonstrate how WSNs can enhance efficiency and sustainability by enabling adaptive management based on sensor feedback [13].

Moreover, Cloud Computing: The backbone of modern IoT systems, cloud infrastructure supports vast amounts of data generated by IoT devices while providing necessary computational resources. Therefore, Green Cloud Computing focuses on creating hardware and software solutions that minimize energy usage and utilize environmentally sustainable resources, ensuring high performance with a lower carbon footprint. The growth of low-power Microcontroller Unit (MCU)s and Integrated Circuits (IC)s designed for energy efficiency is driving the development of sustainable IoT applications. Coupled with innovations in low-power communication protocols, these advancements are transforming how devices interact, ensuring that data transmission is both efficient and energy-saving. Additionally, the shift towards edge computing enables data processing to occur closer to its source, reducing reliance on centralized servers and conserving energy. Context-aware systems further enhance these capabilities by dynamically adjusting device operations based on environmental conditions, enabling real-time optimizations that minimize energy consumption [14].

Furthermore, advanced communication networks enhance data transmission efficiency, minimizing energy consumption and supporting sustainable smart cities. As urban areas change into smarter ecosystems, integrating energy-efficient technologies becomes crucial for reducing CO₂ emissions and achieving sustainability goals. However, a key focus is developing low-power communication protocols that maintain seamless device connectivity while minimizing energy use. Given the vast number of connected IoT devices, these protocols are essential for efficient data exchange. Smart algorithms using AI and machine learning further optimize resource utilization by analyzing usage patterns and dynamically adjusting operations to reduce waste. Therefore, we have M2M Communication technology that facilitates direct communication between devices, allowing them to share information autonomously and its Green M2M communication version implements efficient protocols and optimization strategies to reduce energy consumption [15].

In GIoT systems, one of the important technologies is energy harvesting, which captures renewable energy from natural sources such as solar, wind, thermal, and kinetic energy to power IoT devices. This process significantly reduces dependency on conventional batteries, minimizing environmental impact and waste. Coupled with energy harvesting, renewable integration enables the seamless incorporation of these energy sources into IoT infrastructures, ensuring that devices can operate sustainably even in off-grid locations, thus significantly lowering the overall carbon footprint of IoT ecosystems. The use of biodegradable materials in the production of IoT hardware complements these efforts, focusing on sustainability not only during the device's operational life, but also at its end-of-life stage. This holistic approach reflects

a significant advancement towards achieving an eco-friendly IoT ecosystem, where technology and environmental responsibility coexist, driving the future of technology in a direction that emphasizes sustainability and resource efficiency. Finally, Green Data Centers prioritize energy efficiency by integrating renewable energy sources, recycling electronic waste, and using sustainable building materials to enhance their ecological impact [16].

These technologies collectively represent a strategic shift towards a more sustainable and resilient IoT infrastructure, addressing the challenges of energy consumption and environmental degradation. All emerging technologies for GIoT systems are illustrated in Fig. 10.1.

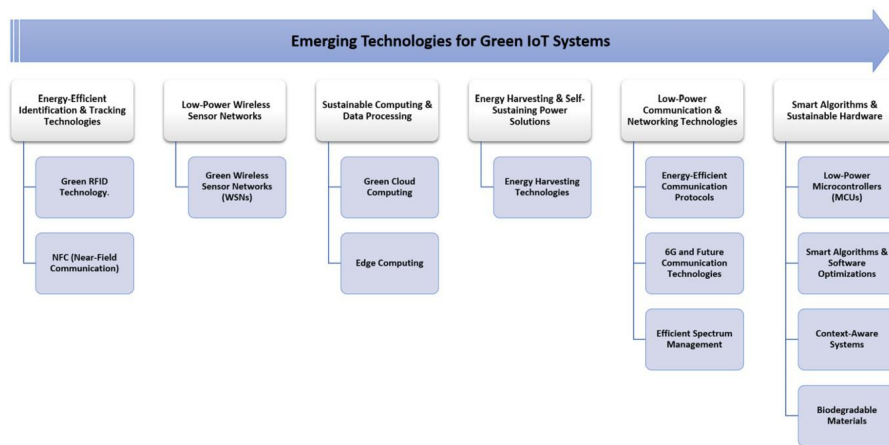


FIGURE 10.1

Emerging technologies for Green IoT systems.

10.3 Collaborative intelligence and software optimization

The rapid growth of IoT ecosystems has necessitated innovative approaches to manage energy consumption and computational resources effectively [17]. Collaborative intelligence and software optimization are emerging as critical enablers of GIoT, leveraging advanced algorithms, distributed computing, and adaptive frameworks to minimize energy waste while maintaining system performance. Let us explore key strategies and technologies driving this transformation. Federated Learning (FL) is a decentralized machine learning paradigm that enables IoT devices to collaboratively train models without sharing raw data. By processing data locally and transmitting only model updates, FL significantly reduces the energy overhead associated with data transmission to centralized servers. Federated Edge AI framework demonstrated a 60% reduction in energy consumption for IoT applications like smart healthcare

and predictive maintenance. FL also enhances privacy and scalability, making it ideal for large-scale IoT deployments [18]. Recent advancements in FL include adaptive aggregation algorithms that dynamically adjust the frequency and size of model updates based on device energy levels and network conditions.

Edge and fog computing architectures bring computational resources closer to IoT devices, reducing the need for energy-intensive data transmission to distant cloud servers. By processing data locally, these frameworks minimize latency and energy consumption while improving system responsiveness. For example, Amazon Web Services (AWS)'s Wavelength platform embeds micro-data centers in 6G towers, enabling real-time analytics for smart city applications with 30% lower energy use compared to traditional cloud-based systems [19]. Fog computing extends this concept by creating a distributed network of intermediate nodes that collaboratively process and store data. fog-based energy management systems optimize power distribution in smart grids, reducing energy losses by 22%. These architectures are particularly effective for applications requiring real-time decision-making, such as autonomous vehicles and industrial automation.

AI plays a key role in optimizing resource allocation and energy use in IoT systems. Reinforcement Learning (RL) algorithms, for instance, dynamically adjust device operations based on environmental conditions and energy availability. An RL-based system for smart agriculture that reduces irrigation energy use by 45% while maintaining crop yields [20]. AI-powered predictive maintenance is another key application, enabling IoT devices to anticipate failures and optimize energy use proactively. For example, Siemens MindSphere platform uses AI to monitor industrial equipment, reducing energy waste by 25% through timely maintenance interventions [21]. These intelligent systems not only enhance energy efficiency, but also extend the lifespan of IoT devices, contributing to sustainability goals. Table 10.1 showcasing energy savings achieved through AI-driven predictive maintenance in industrial IoT.

Table 10.1 Energy savings by industry and application.

Industry	Energy Savings (%)	Application
Manufacturing	25%	Equipment monitoring and maintenance
Energy	30%	Smart grid optimization
Transportation	20%	Fleet management
Healthcare	15%	Medical device maintenance

To address the computational constraints of IoT devices, researchers are developing lightweight algorithms that deliver high performance with minimal energy use. For instance, CRYSTALS-Kyber cryptographic algorithm provides robust security with 70% less computational overhead than traditional methods, making it ideal for energy-constrained IoT devices [22]. Energy-aware communication protocols, such as LPWAN and Bluetooth Low Energy (BLE), further optimize data transmission. LPWAN protocols reduce energy consumption by 90% compared to

Wireless Fidelity (Wi-Fi), enabling long-range communication for applications like environmental monitoring and asset tracking.

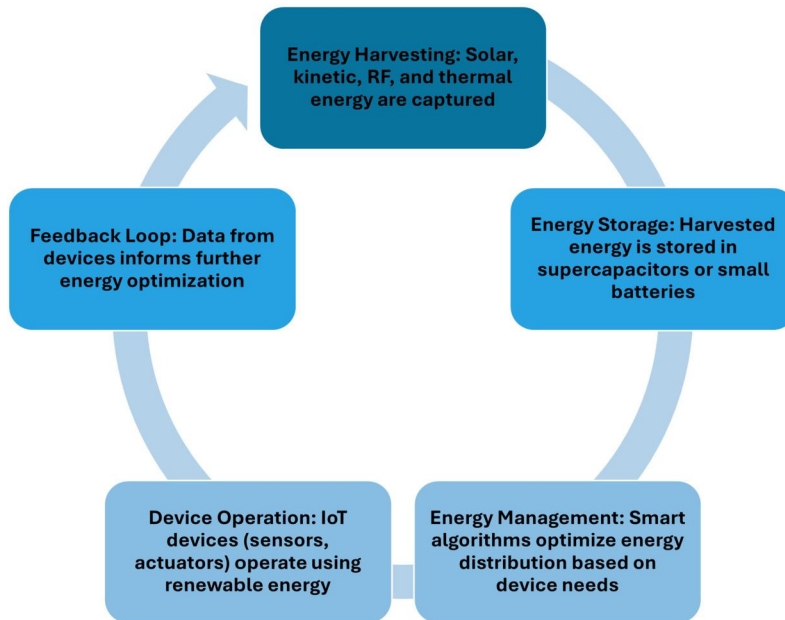
Blockchain technology is increasingly being integrated into IoT ecosystems to enable secure, transparent, and energy-efficient collaboration. Blockchain platform tracks the carbon footprint of IoT supply chains, ensuring compliance with sustainability standards. Blockchain also facilitates peer-to-peer energy trading in smart grids, allowing IoT devices to exchange surplus energy efficiently. Collaborative IoT ecosystems leverage blockchain to create decentralized networks where devices share resources and data securely with reduced energy waste. Collaborative intelligence and software optimization are transforming GIoT by enabling energy-efficient, adaptive, and scalable systems. From federated learning and edge computing to AI-driven resource management and blockchain integration, these technologies can unlock the full potential of GIoT while minimizing its environmental impact.

10.4 Energy harvesting and renewable integration

The components of GIoT systems include energy harvesting along with renewable integration, both of which actively work in capturing energy and integrating it in the best way possible for usage [23]. This in turn ensures that IoT devices are able to operate sustainably and with minimal environmental impact. Renewable sources of energy include solar, wind, thermal and even kinetic energy, all of which can be coupled to power IoT devices. This approach greatly reduces dependency on traditional batteries, and in turn, lowers carbon footprints and waste. Energy harvesting, on the other hand, uses solar panels or piezoelectric devices to power sensors and actuators in remote locations, bypassing off-grid limitations. Furthermore, efficient and sustainable device operations are also ensured through islands of renewable energy integrated into the IoT systems with the aid of sophisticated renewable energy management approaches through integration. Such levels of integration are made possible through the coordination of energy consumption and generation hosted through variable loads. These advanced algorithms and smart technologies greatly allow for greater utilization of renewable energy significantly improving eco-sustainability and energy efficiency in IoT environments. In conclusion, energy immersion and renewable integration together form an ecosystem through which the arcs of GIoT in energy balancing and restraining harmful energy consumption practices.

The use of RFID and NFC technologies is becoming increasingly popular within IoT systems, as technologies are capable of collecting information about objects wirelessly. The recent focus has been on improving the energy consumption of these technologies. Green RFID systems are now optimized through energy harvesting features and improved signal processing, allowing them to operate with minimal power consumption. For example, batteryless NFC sensors that harvest energy from ambient sources have been developed, eliminating the need for batteries and reducing environmental impact. The shift toward self-sustaining IoT systems is accelerating

with breakthroughs in energy harvesting. Solar-powered IoT nodes now leverage perovskite solar cells, which achieve 33% efficiency under low light conditions, making them viable for indoor or urban deployments. In one study, kinetic energy harvesting has advanced the prototype of a piezoelectric floor tile that generates 4 W per step, sufficient to power environmental sensors in smart buildings [24]. Meanwhile, Radio Frequency (RF) energy scavenging is gaining traction; researchers developed an RF harvester that extracts $1 \mu\text{W}/\text{cm}^2$ from ambient Wi-Fi signals, enough to sustain low-power sensors [25]. Thermal energy recycling is another boundary; therefore, researchers are Testing Thermoelectric Generators (TEGs) that convert industrial waste heat into electricity for IoT monitoring systems [26]. A report by the International Energy Agency (IEA) estimates that renewable energy-powered IoT could reduce global CO₂ emissions by 1.2 gigatons annually by 2030, underscoring their role in achieving net-zero targets [27]. These energy-efficient identification and tracking technologies not only minimize power consumption, but also contribute to the sustainability of IoT systems by reducing electronic waste. By leveraging energy harvesting mechanisms, these devices can operate indefinitely without the need for battery replacements, making them ideal for applications in logistics, inventory management, and environmental monitoring. In Fig. 10.2, a flowchart illustrates how renewable energy is integrated into IoT systems, from harvesting to consumption.

**FIGURE 10.2**

Integration of renewable energy into IoT systems, from harvesting to consumption.

The development of low-power MCU has enabled IoT devices to operate with minimal power. Advancements in MCU design, such as the integration of energy-efficient architectures and power-management features, have significantly reduced

the energy consumption of IoT devices. These developments are crucial for battery-powered applications, where energy efficiency directly impacts device longevity and environmental sustainability. Low-power MCUs, such as ARM’s Cortex-M55 with Ethos-U55 neural processing units, now integrate machine learning capabilities at under 1 milliwatt of power, enabling real-time data analytics without draining batteries. These MCUs are increasingly paired with biodegradable substrates; for instance, recently researchers developed transient circuits using silk proteins that dissolve harmlessly after use, reducing e-waste. Complementing these hardware innovations are ultra-efficient communication protocols like Long Range Wide Area Network (LoRaWAN) and Narrowband IoT (NB-IoT), which optimize data transmission ranges and frequencies to cut energy use by up to 90% compared to traditional Wi-Fi or Bluetooth [28]. One study highlighted passive backscatter systems, such as battery-free RFID tags powered by ambient radio waves, which are revolutionizing retail and logistics by eliminating the need for disposable batteries [29]. Further, energy-aware 5G/6G networks now employ dynamic spectrum sharing and AI-driven beamforming to reduce base station energy consumption by 30 to 40% [30]. These technologies collectively address the “energy paradox” of IoT, balancing functionality with sustainability by redefining how devices are built and communicate. Table 10.2 compares the efficiency, applications, and energy output of various energy harvesting methods. Energy harvesting and renewable integration are crucial for the advancement of GIoT

Table 10.2 Comparison of energy harvesting technologies.

Energy Source	Efficiency	Energy Output	Applications
Solar (Perovskite)	33% (low light)	10–20 mW/cm ²	Outdoor sensors, smart agriculture
Kinetic (Piezoelectric)	10–20%	4 W per step	Smart buildings, wearable devices
RF (Ambient Wi-Fi)	1 μW/cm ²	1–10 μW/cm ²	Low-power sensors, retail tracking
Thermal (TEGs)	5–10%	1–5 mW/cm ²	Industrial monitoring, waste heat recovery

systems, facilitating sustainable energy utilization while optimizing the efficiency of IoT devices. Through the deployment of energy harvesting solutions and intelligent energy management strategies, IoT systems can operate autonomously and sustainably, significantly contributing to a reduction in carbon emissions and energy waste. The implementation of these technologies supports the goal of creating environmentally friendly IoT solutions that enhance operational efficiency and promote a greener future.

10.5 Sustainable system design

Sustainable System Design in the context of GIoT focuses on creating systems that minimize environmental impact throughout their lifecycle, from design and production to utilization and disposal. At its core, this philosophy integrates energy

efficiency, resource optimization, and renewable materials to create an eco-friendly infrastructure. For example, low-power sensors and adaptive management systems significantly reduce energy consumption in smart cities, as demonstrated in Amsterdam's smart grid deployments, where energy use is optimized through decentralized renewable sources. Additionally, modular architectures enhance sustainability by enabling easy upgrades and repairs, extending device lifespans, and reducing e-waste [31].

A critical aspect of sustainable system design is the use of biodegradable materials such as cellulose-based circuits and organic semiconductors that decompose harmlessly after use. Researchers have developed transient electronics using silk proteins that dissolve within weeks post-deployment, reducing electronic waste accumulation. Circular economy principles are embedded into design frameworks, promoting material reuse and recycling. For example, Dell's closed-loop recycling program recovers plastics from retired IoT devices for reuse in new products, significantly reducing the demand for virgin materials and mitigating environmental degradation [32].

From a technical standpoint, sustainable system design incorporates hardware, software, and circular economy principles to enhance energy efficiency and reduce waste. On the hardware front, innovative energy-efficient components play a crucial role in reducing power consumption in IoT systems. Devices such as ARM's Cortex-M55 microcontroller operate at ultra-low power levels, enabling real-time analytics without excessive energy draw [33]. Renewable energy integration is another pivotal strategy; solar-powered IoT nodes using perovskite cells and piezoelectric floor tiles that generate energy from foot traffic exemplify how sustainable energy sources can support IoT infrastructures [34]. Meanwhile, software optimizations are crucial for energy conservation. Smart algorithms and communication protocols enhance IoT sustainability by optimizing resource use. Machine learning algorithms dynamically adjust energy consumption, as seen in Barcelona's smart streetlights, which automatically dim when no movement is detected, cutting energy costs by 30%. Additionally, lightweight communication protocols like LoRaWAN significantly reduce data transmission energy compared to Wi-Fi, making them ideal for remote agricultural sensors and industrial monitoring applications [35]. Furthermore, circular economy integration sustainable system design also emphasizes modular and recyclable hardware. Fairphone's modular smartphones serve as an inspiration for IoT architectures, promoting replaceable sensors and extendable device lifecycles. Additionally, smart recycling programs, such as sensor-equipped waste bins, optimize collection routes, reducing truck emissions by 40% [36]. Blockchain technology further supports sustainability by enabling lifecycle tracking of materials, ensuring compliance with environmental regulations and reducing illicit waste disposal.

Real-world implementations of sustainable system design showcase its practicality in various sectors, including smart agriculture, smart buildings, and urban waste management. Precision farming solutions, using soil moisture sensors enabled by the IoT, have helped reduce water consumption by 50% while maintaining crop yields [37]. Solar-powered microclimate monitoring nodes in vineyards have also slashed reliance on grid power, enhancing energy efficiency. In urban settings, smart

buildings like The Edge Building in Amsterdam leverage IoT-based Heating, Ventilation, and Air Conditioning (HVAC) and lighting systems, achieving 70% energy savings through automated adjustments based on occupancy patterns [38]. Table 10.3 comparing real-world applications of sustainable IoT systems, highlighting their environmental and operational benefits.. By embedding sustainability into the core of IoT development, GIoT technologies can drive significant environmental benefits, supporting global sustainability goals while enhancing efficiency and innovation.

Table 10.3 Comparison of sustainable IoT applications.

Application	Key Features	Environmental Benefits	Operational Benefits
Smart Agriculture	Soil moisture sensors, solar-powered nodes	50% reduction in water usage	Increased crop yields, reduced costs
Smart Buildings	IoT-enabled HVAC, occupancy sensors	70% energy savings	Lower utility bills, improved comfort
Urban Waste Management	Sensor-equipped bins, route optimization	35% reduction in fuel consumption	Cost savings, reduced emissions
Smart Grids	Real-time energy monitoring, renewable integration	30% reduction in energy waste	Stable energy supply, lower carbon footprint

10.6 Regulatory and policy frameworks for Green IoT

Regulatory and policy frameworks play a key role in shaping the development and deployment of GIoT technologies. These frameworks ensure that IoT systems align with global sustainability goals, such as reducing carbon emissions, minimizing e-waste, and promoting energy efficiency. Now more than ever, governments and global agencies appreciate encouraging the adoption of renewable energy sources, energy-efficient designs, and sustainable manufacturing processes. For instance, the Eco-design Directive of the European Union (EU) requires that IoT devices are manufactured with high energy efficiency and recyclability, which leads to less innovation, more adoption, and greater environmental protection [39]. One of the most important features of these frameworks is how they regulate socioeconomic development alongside environmental protection. Policies that define minimum energy consumption levels, maximum materials able to be used, and other such criteria enable policy-maker restrictions that serve concern for the environment in regard to IoT evolution. For instance, Energy Star for IoT certifies devices that are power efficient, thus limiting the number of such devices in circulation permits the devices to be more widely accepted [40]. Besides, the Circular Economy Action Plan as well as other initiatives emphasize the importance of IoT of components, minimizing e-waste and enabling a circular economy.

Internationally GIoT practices will require global standards. These objectives are being pursued by the International Organization for Standardization (ISO) and the

Institute of Electrical and Electronics Engineers (IEEE) through the establishment of protocols aimed at the interoperability and energy efficiency of IoT systems. For instance, the ISO 14000 series provides guidelines for environmental management systems, helping IoT manufacturers minimize their ecological footprint [41]. Similarly, the IEEE P2413 standard focuses on unifying IoT architectures to enhance energy efficiency and scalability [42]. International agreements, reinforce the importance of GIoT for achieving climate goals. Countries participating in these agreements are adopting policies that promote the research and development of sustainable IoT technologies. For example, Singapore's Smart Nation Initiative subsidizes IoT projects that align with carbon neutrality targets, fostering innovation in energy-efficient systems [43]. These collaborative efforts ensure that GIoT technologies are not only environmentally friendly, but also globally scalable and interoperable.

National governments play a critical role in driving the adoption of GIoT through targeted policies and incentives. For example, carbon tax rebates in different countries encourage companies to invest in energy-efficient IoT solutions. Similarly, e-waste legislation, such as the EU's Waste Electrical and Electronic Equipment (WEEE) Directive, mandates that IoT manufacturers manage end-of-life recycling of their products, reducing environmental degradation [44]. In addition, public awareness campaigns educate consumers and businesses about the benefits of GIoT, encouraging the adoption of energy-efficient practices. For example, the GIoT Initiative in the UK is helping organizations shift towards sustainable IoT solutions through dedicated resources and training [45].

The industry, through its corporate initiatives, is working hand in hand with the government to formulate best practice standards and sustainability frameworks for IoT implementation. Alliance for IoT Innovation (AIOTI) is one such organization that put together a GIoT best practices publication that focuses on energy efficiency, resource optimization, and lifecycle management. An equally important initiative is that of the GSMA that aims for IoT climate action, with a target of net-zero IoT networks by 2040. Achieving this goal would engrave the use of renewable energy and energy-efficient infrastructures. All these efforts highlight the necessity for a combined effort from all stakeholders, governments, industries, and academia, to drive initiatives on GIoT further. The above-mentioned initiatives cite the EU's Smart Cities and Communities Initiative, which collaborates with municipalities to create IoT solutions for cities like smart grids and energy-efficient lighting systems. Surely, such collaborations enable innovation; however, they also guarantee that GIoT technologies work practically, are scalable and, most importantly, environmentally friendly.

To foster sustainable development practices at the intersection of the regulatory, organizational and the IoT sectors, governments should support the GIoT by enhancing energy efficiency and reducing environmental impact. These frameworks will help IoT technology provide global solutions for sustainability and address significant environmental issues.

10.7 Future challenges and opportunities

The rapid innovation of GIoT technologies offers a unique blend of challenges and opportunities. Efforts on improving energy efficiency, integrating renewables, and promoting sustainable development provided a good starting point, but there are challenges still. It is essential to tackle these challenges while leveraging available opportunities in order to unlock the potential of GIoT towards the sustainability objectives.

– Challenges in Green IoT Implementation

One of the primary challenges in GIoT is balancing performance with sustainability. Although the use of energy-efficient hardware and the integration of renewable energy have succeeded in power consumption efficiency, the power supply of many IoT devices is still based on traditional batteries or non-renewable energy sources. The high cost of sustainable materials, such as biodegradable circuits and graphene-based components, remains a barrier to mass adoption. For instance, biodegradable IoT sensors, while promising in reducing e-waste, are currently 2–3 times more expensive than traditional alternatives, limiting their large-scale deployment.

Another critical concern is the scalability of GIoT solutions. Many sustainable technologies, such as self-powered sensors and energy-harvesting devices, remain in the prototype or early adoption phase. Large-scale manufacturing of transient electronics and bio-based components faces production limitations, preventing their mainstream commercialization. Additionally, interoperability issues arise due to the diverse range of IoT communication protocols, such as Zigbee, LoRaWAN, and NB-IoT, which lack standardization. The absence of a unified framework for integrating different sustainable IoT systems makes deployment complex, particularly in large urban environments.

Additionally, the data security issues in GIoT bring forward privacy concerns that need to be addressed. Numerous communication protocols that design IoT devices focus on energy efficiency and neglect security, thus making these devices prone to hacking. For example, passive backscatter systems may inadvertently disclose important information when energy usage is minimized, due to their weak encryption. To resolve these issues, significant effort is needed in innovation, coordination, and development of overarching policies and regulations for GIoT.

– Opportunities for Growth and Innovation

Despite these challenges, GIoT offers vast opportunities for innovation, particularly in energy harvesting, sustainable computing, and AI-driven resource optimization. Recently developed self-sustaining IoT systems introduce revolutionary biohybrid sensors powered by algae, kinetic energy harvesting Triboelectric Nanogenerators (TENGs), and organic solar photovoltaics operating in low-light conditions. These technologies have great potential for powering remote or off-grid IoT systems without the use of conventional energy sources.

Another significant saturator is the IoT manufacturing and deployment models based on a circular economy. More and more firms are developing modular IoT architecture within which separate sensors and processors can be altered or upgraded. This design will greatly improve the efficiency of IoT systems, as well as extend the useful life of the devices and lessen electronic waste. Furthermore, blockchain-based IoT devices enhance the accountability of recycling and material recovery, thus improving sustainability and facilitating IoT lifecycle management.

The capability of AI-based means for sustainability optimization suggests GIoT may be transformed by the emerging need for vertically integrated power management for various components' energy consumption and system performance. Advanced machine learning techniques may process real-time data from a multitude of sensors and analyze energy demand prediction, thus boosting the dependability of power distribution, cutting the need for transmitting data, and significantly minimizing energy waste. For example, AI-powered dynamic spectrum sharing in 5G and 6G networks can optimize network resource allocation, reducing energy consumption by 30–40% while maintaining seamless IoT connectivity.

Policy and regulatory frameworks are also evolving to support sustainable IoT initiatives. Governments worldwide are implementing stricter regulations on e-waste management, energy efficiency standards, and carbon footprint reduction for electronic devices. The EU Ecodesign Directive mandates that IoT manufacturers adopt sustainable design practices, ensuring that devices are energy efficient, repairable, and recyclable. These regulatory measures provide a strong incentive for industries to transition toward GIoT solutions, driving large-scale adoption and innovation.

10.8 Conclusion: path to a sustainable future

The evolution of GIoT technologies marks a pivotal shift toward a more sustainable, energy-efficient, and intelligent digital ecosystem. The growth of IoT systems in industries calls for the combination of new technologies, collaborative intelligence, renewable energy, and design sustainability to decrease environmental impact. Overreliance on traditional power sources for GIoT systems is achieved through innovations like low-power MCUs, AI-enhanced edge computing, and self-sustaining sensors. With advanced hardware architectures, AI driven optimisations, and regulatory frameworks, the GIoT world is creating a reality where sufficiency meets ecological preservation.

Furthermore, biohybrid sensors, biodegradable circuits, and transient electronics have improved the sustainability of IoT. Collaborative intelligence coupled with software optimisation renders change in IoT performance while empowering AI-driven energy management. With the integration of lightweight communication protocols and intelligent data processing, devices consume fewer resources, which allows for efficient device usage.

The combination of energy harvesting and renewable energy approaches has become one of the primary methods within GIoT, allowing devices to operate without

frequent battery changes. Two technologies, namely RF energy scavenging, piezoelectric harvesting, and even perovskite solar cells are revolutionizing IoT applications with autonomous power supplies. In addition, the aspects of sustainable system design, such as modular designs, circular economy systems and material reprocessing, guarantee the sustainability and environmental friendliness of IoT implementations in smart cities, modern agriculture and industrial automation.

While GIoT presents remarkable opportunities, regulatory and policy frameworks remain essential in driving its large-scale adoption. Governments and international organizations are formulating eco-design mandates, energy efficiency standards, and lifecycle tracking regulations to ensure compliance and promote green innovation. However, challenges such as high costs, interoperability issues, and cybersecurity risks still pose hurdles that require collaborative efforts between industry leaders, researchers, and policymakers.

Looking ahead, GIoT is poised to redefine the future of smart systems by integrating AI-driven efficiency, renewable energy solutions, and sustainable system designs. Through continuous innovation, cross-sector collaboration and regulatory support, GIoT can help achieve global sustainability goals, reduce carbon footprints, and foster resilient, low-impact digital ecosystems. The road ahead for GIoT is both challenging and promising, but with the right technological and policy-driven strategies, it holds the potential to create a greener, smarter, and more sustainable future.

References

- [1] M.A. Jamshed, K. Ali, Q.H. Abbasi, M.A. Imran, M. Ur-Rehman, Challenges, applications, and future of wireless sensors in Internet of Things: a review, *IEEE Sensors Journal* 22 (6) (2022) 5482–5494.
- [2] M.A. Jamshed, F. Ayaz, A. Kaushik, C. Fischione, M. Ur-Rehman, Green UAV-enabled Internet-of-Things network with AI-assisted noma for disaster management, in: 2024 IEEE 35th International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), IEEE, 2024, pp. 1–6.
- [3] M.A. Albreem, A.A. El-Saleh, M. Isa, W. Salah, M. Jusoh, M. Azizan, A. Ali, Green internet of Things (IoT): an overview, in: 2017 IEEE 4th International Conference on Smart Instrumentation, Measurement and Application (ICSIMA), IEEE, 2017, pp. 1–6.
- [4] M. Elkhodr, S. Shahrestani, H. Cheung, The Internet of Things: vision & challenges, in: IEEE 2013 Tencon-Spring, IEEE, 2013, pp. 218–222.
- [5] M.A. Jamshed, F. Heliot, T.W. Brown, A survey on electromagnetic risk assessment and evaluation mechanism for future wireless communication systems, *IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology* 4 (1) (2019) 24–36.
- [6] M.A. Jamshed, F. Heliot, T.W. Brown, Unsupervised learning based emission-aware uplink resource allocation scheme for non-orthogonal multiple access systems, *IEEE Transactions on Vehicular Technology* 70 (8) (2021) 7681–7691.
- [7] M.A. Jamshed, Y.A. Qadri, A. Nauman, H. Jung, Electromagnetic field exposure-aware ai framework for integrated sensing and communications-enabled ambient backscatter wireless networks, *IEEE Internet of Things Journal* (2024).

- [8] B. Haq, M.A. Jamshed, K. Ali, B. Kasi, S. Arshad, M.K. Kasi, I. Ali, A. Shabbir, Q.H. Abbasi, M. Ur-Rehman, Tech-driven forest conservation: combating deforestation with Internet of things, artificial intelligence, and remote sensing, *IEEE Internet of Things Journal* (2024).
- [9] M.A. Jamshed, C. Theodorou, T. Kalsoom, N. Anjum, Q.H. Abbasi, M. Ur-Rehman, Intelligent computing based forecasting of deforestation using fire alerts: a deep learning approach, *Physical Communication* 55 (2022) 101941.
- [10] F.K. Shaikh, S. Zeadally, E. Exposito, Enabling technologies for Green Internet of Things, *IEEE Systems Journal* 11 (2) (2015) 983–994.
- [11] F.A. Almalki, S.H. Alsamhi, R. Sahal, J. Hassan, A. Hawbani, N. Rajput, A. Saif, J. Morgan, J. Breslin, Green iot for eco-friendly and sustainable smart cities: future directions and opportunities, *Mobile Networks and Applications* 28 (1) (2023) 178–202.
- [12] M.H. Alsharif, A. Jahid, A.H. Kelechi, R. Kannadasan, Green IoT: a review and future research directions, *Symmetry* 15 (3) (2023) 757.
- [13] B. Memić, A.H. Džubur, E. Avdagić-Golub, Green iot: sustainability environment and technologies, *Science, Engineering and Technology* 2 (1) (2022) 24–29.
- [14] F.A. Almalki, S.H. Alsamhi, R. Sahal, J. Hassan, A. Hawbani, N. Rajput, A. Saif, J. Morgan, J. Breslin, Green iot for eco-friendly and sustainable smart cities: future directions and opportunities, *Mobile Networks and Applications* 28 (1) (2023) 178–202.
- [15] M.H. Alsharif, A. Jahid, A.H. Kelechi, R. Kannadasan, Green IoT: a review and future research directions, *Symmetry* 15 (3) (2023) 757.
- [16] F.K. Shaikh, S. Zeadally, E. Exposito, Enabling technologies for Green Internet of Things, *IEEE Systems Journal* 11 (2) (2015) 983–994.
- [17] M.A. Jamshed, M.F. Khan, K. Rafique, M.I. Khan, K. Faheem, S.M. Shah, A. Rahim, An energy efficient priority based wireless multimedia sensor node dynamic scheduler, in: *2015 12th International Conference on High-Capacity Optical Networks and Enabling/Emerging Technologies (HONET)*, IEEE, 2015, pp. 1–4.
- [18] K.-H. Le, K.-H. Le-Minh, H.-T. Thai, Brainyedge: an Ai-enabled framework for IoT edge computing, *ICT Express* 9 (2) (2023) 211–221.
- [19] C. Centofanti, *Multi-Access Edge Computing: Performance Optimization via Orchestration and Virtualization*, 2023.
- [20] G. Sidiropoulos, C. Kiourt, Reinforcement learning agents in precision agriculture, in: *International Conference on Information, Intelligence, Systems, and Applications*, Springer, 2023, pp. 188–211.
- [21] S. Shi, Industrial cloud, automation: the industrial. Internet of Things (IIoT) is being embraced by manufacturers as a natural extension of automation and controls development, *Control Engineering* 70 (8) (2023) 31–32.
- [22] N. Madieta, G. Aymard, N. El Mrabet, D. Fronte, Memory-efficient implementations of crystals-kyber, in: *Cryptology and Information Security Conference 2024*, 2024, p. 12.
- [23] M.A. Jamshed, B. Haq, M.A. Mohsin, A. Nauman, H. Yanikomeroglu, Artificial intelligence, ambient backscatter communication and non-terrestrial networks: a 6g commixture, *arXiv preprint*, arXiv:2501.09405, 2025.
- [24] I. Allaire-MacDonald, *Increasing Power Output of a Shoe-Based Piezoelectric Energy Harvester Within a User Burden-First Design Perspective*, The University of Utah, 2022.
- [25] A. Sidibé, *Compact RF wireless power transmission system for battery-free geolocation tags*, PhD thesis, Université Paul Sabatier-Toulouse III, 2023.
- [26] J. Riggio, *The Development of a Thermoelectric Generator (teg) Concept for Recycling Waste Heat into Electricity*, 2020.

- [27] International Energy Agency, CO2 emissions in 2023, 2024. Licence, CC by 4.0.
- [28] Q. Lv, Q. Li, P. Cao, C. Wei, Y. Li, Z. Wang, L. Wang, Designing silk biomaterials toward better future healthcare: the development and application of silk-based implantable electronic devices in clinical diagnosis and therapy, *Advanced Materials* (2024) 2411946.
- [29] S.R. Khan, A.L. Bernassau, M.P. Desmulliez, Passive and battery-free rfid-based wireless healthcare and medical devices: a review, *IEEE Journal of Radio Frequency Identification* (2024).
- [30] H. Pennanen, T. Hänninen, O. Tervo, A. Tölli, M. Latva-aho, 6g: the intelligent network of everything—a comprehensive vision, survey, and tutorial, *arXiv preprint, arXiv:2407.09398*, 2024.
- [31] F. Norouzi, T. Hoppe, L. Kamp, C. Manktelow, P. Bauer, Diagnosis of the implementation of smart grid innovation in the Netherlands and corrective actions, *Renewable and Sustainable Energy Reviews* 175 (2023) 113185.
- [32] I. Pongen, P. Ray, K. Govindan, Creating a sustainable closed-loop supply chain: an incentive-based contract with third-party e-waste collector, *Journal of Cleaner Production* (2024) 142351.
- [33] C. Room, Article content menu, *Machine Learning* 12 (29) (2020) 32.
- [34] C. Chen, Ultra-High Energy Density Roadway Piezoelectric Energy Harvesting System, University of California, Merced, 2021.
- [35] M.A. Lodhi, M.S. Obaidat, L. Wang, K. Mahmood, K.I. Qureshi, J. Chen, K.-F. Hsiao, Tiny machine learning (tinyml) for efficient channel selection in lorawan, *IEEE Internet of Things Journal* (2024).
- [36] A. Addas, M.N. Khan, F. Naseer, Waste management 2.0 leveraging Internet of Things for an efficient and eco-friendly smart city solution, *PLoS ONE* 19 (7) (2024) e0307608.
- [37] V. Kumar, K.V. Sharma, N. Kedam, A. Patel, T.R. Kate, U. Rathnayake, A comprehensive review on smart and sustainable agriculture using iot technologies, *Smart Agricultural Technology* (2024) 100487.
- [38] M. Anjana, A.R. Devidas, M.V. Ramesh, Empowering sustainability: the crucial role of IoT-enabled distributed learning systems in reducing carbon footprints, *IEEE Access* (2025).
- [39] L. Krämer, Eu ecodesign and product policy: from energy efficiency to circular economy, *Journal for European Environmental & Planning Law* 21 (3–4) (2024) 343–360.
- [40] E. PROTECTION, Environmental protection agency (epa), 2022.
- [41] A. Barragán-Ocaña, P. Silva-Borjas, K.A. Luna-López, M.D.P. Longar-Blanco, Technological development and mitigation of environmental impact through iso 14000: a review, *International Journal of Productivity and Quality Management* 36 (1) (2022) 27–45.
- [42] P. Sangra, B. Rana, Y. Singh, Energy efficiency in iot-based smart healthcare, in: *Proceedings of Third International Conference on Computing, Communications, and Cyber-Security: IC4S 2021*, Springer, 2022, pp. 503–515.
- [43] Y.P. Foong, R. Pidani, V. Sithira Vadivel, Y. Dongyue, Singapore smart nation: journey into a new digital landscape for higher education, in: *Emerging Technologies in Business: Innovation Strategies for Competitive Advantage*, Springer, 2024, pp. 281–304.
- [44] L. Sasso, The eu e-waste policy and regulation, in: *Development in E-waste Management*, CRC Press, 2023, pp. 19–40.
- [45] I. Bortone, H. Sakar, A. Soares, Gaps in regulation and policies on the application of green technologies at household level in the United Kingdom, *Sustainability* 14 (7) (2022) 4030.

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Design and Analysis of Green and Sustainable IoT Technologies for Future Wireless Communications

EDITED BY **Muhammad Ali Jamshed and Awais Aziz Shah**

Key Features

- Comprehensive book dedicated to developing green and sustainable IoT systems
- Covers fundamentals and practical implementation
- Highlights the latest technological advances for designing and implementing Green IoT systems
- Presents future research challenges and gives a perspective of the road ahead for Green IoT technologies

To realise the 6G vision of hyper-human connectivity across smart environments, future IoT systems will require many devices and multi-access environments where different types of wireless spectrum need to be used efficiently. However, this increases the challenge of keeping a net zero emission carbon rate. **Design and Analysis of Green and Sustainable IoT Technologies for future Wireless Communication Systems** presents a wide range of technologies for the development of greener and sustainable IoT systems. It brings together multidisciplinary team of researchers to present the latest techniques to designing energy efficient IoT devices, laying the foundation for future advances in this important area.

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