

IoT and machine learning for enabling sustainable development goals

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The United Nations created an agenda for 2030 that includes 17 clearly defined objectives for sustainable development. These goals are a pressing call to action that needs cooperation and creativity among nations and organizations. The suggested agenda will be completed by the year 2023. However, the globe is still behind schedule in achieving any objectives. With concrete use examples that connect, this article explores the prospects presented by the development of artificial intelligence and the Internet of Things in achieving these aims. To cities, energy, and health. Additionally, the piece highlights the difficulties that arise from using these technologies to achieve the Sustainable Development Goals (SDGs), emphasizing the risks of bias, security, privacy of data, and multi-objective optimization of sometimes conflicting SDGs.

Keywords : data privacy, SDG, e-health, IoT, ML, and bias in data

Overview

An urgent “code red” warning about global warming and climate change was raised in the most recent report released by the United Nations (UN) in 2022 on the progress achieved toward the sustainable development goals (SDG) (United Nations, 2022a). The year 2023 represents the halfway point between the goals set for 2030 and the original UN agenda drafted in 2015. The globe is having difficulty recovering from the COVID-19 epidemic and is well behind schedule in reaching the defined markers. In light of this, scientifically

supported, realistic solutions for the SDGs are desperately required and are seen to be essential to quickening the transition¹.

It follows that throughout the last ten years, the research community has strongly emphasized innovation in science and technology to advance the SDG objectives. One study looks at the possibility of robots to help achieve the SDGs (Mai et al., 2022). Likewise, Jiang et al. (2022) examine disruptive blockchain technology's contribution to achieving the Sustainable Development Goals. While the software itself runs the danger of not being sustainable, it is shown to play a critical role in enabling SDG technologies (Calero et al., 2022). Enabling data/knowledge-sharing platforms that facilitate cooperation, cooperative innovation, and technology transfer across nations/institutions is a crucial issue within SDGs' technological innovation scope (Zhao et al., 2022).

The meeting point between artificial intelligence (AI) and the Internet of Things (IoT) is fundamental to the technologies above. The Internet of Things (IoT) is a network of physically linked items with sensors and actuators. These things may be used to monitor and alter the natural environment via apps remotely. Over 15 billion IoT devices are now linked, spanning various gadgets and uses. The promise of having access to information from the physical world at any time and place and the capability of acting promptly on that information makes the Internet of Things valuable. When IoT and AI are combined to create Intelligent IoT, which can offer actionable insights and deduce meaning from the acquired data, the promise may be realized (López-Vargas et al., 2021). 95% of people worldwide have access to a mobile broadband signal, including 88% who have fast 4G (fourth generation of mobile networks), according to the UN's most recent survey (United Nations, 2022a). A baseline of this kind is necessary to enable almost universal IoT connection (Wu et al., 2018); any gaps in coverage may be filled using non-terrestrial networks or other alternative systems (Thangavel et al., 2023) (Feltrin et al., 2021).

Prominent studies like (Barakat et al., 2021) provide an extensive analysis of a particular facet of IoT systems; in

this instance, it is the IoT's connection with the sixth mobile network generation (6G) as a technological enabler for use cases connected to the SDGs, such as transportation, smart grids, and healthcare. Some studies examine the relevance of IoT for a particular Sustainable Development Goal (SDG), such as the green energy paradigm study by Salam (2020). (Et al., Vinuesa, 2020). Examine AI as an additional facet of IoT systems and its potential to help achieve SDG objectives. The authors discover that although AI may help achieve around 80% of these goals, it may simultaneously hinder about 35%.

Unlike the previous research, which focuses on certain SDGs, this study looks at the IoT system, including connectivity and artificial intelligence (see Section 3.1). Novel IoT-driven SDG solutions are shown and juxtaposed with the standard system to emphasize the opportunities and challenges from an SDG standpoint. To support the SDGs, we first provide a system model based on the nexus of IoT and AI (see Table 1 for a complete list of the 17 SDGs). We then provide three examples that highlight how this paradigm may be used to alter remote health and wellbeing (SDG 3, 4, and 10), responsible energy usage (SDG 7, 9, and 12), and urban mobility (SDG 9, 11, and 13). Next, the dangers and difficulties associated with this system are explored by looking at IoT security, data privacy, and the consequences of SDG-driven intelligent IoT, such as postponing other SDGs.

System model of the junction of ML and IoT

As shown in Figure 1, an IoT system comprises IoT devices that use gateways to connect to cloud-based servers. An Internet of Things (IoT) system is a network of interconnected gadgets that enable the Hyper-Connected Intelligent World (HIW)³. Smart homes, smart cities, smart agriculture, innovative health, and many more are examples of SDG-driven HIW use cases. While they employ different IoT devices that monitor application-specific data to allow specific goal-driven automation, they have comparable architectures and networking protocols. An Internet of Things (IoT) device is essentially a sensor or actuator equipped with a microprocessor and communication hardware that collects data from its surroundings, transmits and receives data to

and from the server, and acts based on the obtained data or instructions from the server. The Internet of Things gateway serves as a hub for data, sending information gathered by IoT devices to a cloud server for analysis. The IoT gateway hosts edge intelligence and performs local data processing in some HIW applications. Similarly, IoT devices may speak with one another directly and take action based on data collected. IoT devices often feature modest processing power, little memory, and a small energy source, making them lightweight and inexpensive. These features enable SDG-driven HIW systems to be fully automated with the option for human involvement where and when necessary. They also make them inexpensive, deployable, and flexible. This section looks at the many technologies that work together to create the Internet of Things system, as shown in Figures 2 and 3 (Lv, 2022). IoT devices: An IoT device is a linked smart sensor or actuator. Thus, they are gadgets with a CPU and wired or wireless connection capacity. Sensors such as temperature, moisture, luminosity, motion, audio, chemical, water level, presence, image, gyroscope, and actuators to alter their surroundings are employed by commonly used IoT devices to monitor their surroundings. Most IoT devices have the robustness and affordability necessary to support the extensive and profound reach of SDG-driven HIW applications.

- **Internet of Things connectivity:** A few IoT gadgets are linked via wired technologies, but of the 27 billion connected gadgets expected in 2025⁴, they will probably make up less than 7%. According to their coverage range, the remaining devices are wirelessly linked using various technologies that fall into the following categories (Vaezi et al., 2022).

- **Short-range (~ 10 m):** These use unlicensed airwaves, including WiFi, Bluetooth, and ZigBee. More than 82% of anticipated wireless Internet of Things (IoT) devices in 2028 are anticipated to connect using short-range technology (Ericsson, 2022).

- **Wide-range (~ 5 km):** LoRa and Sigfox use unlicensed frequencies, the two most popular technologies in this range. In 2028, it is anticipated that 17% of wireless Internet of Things (IoT) devices will connect using wide-range technology (Ericsson, 2022).

- **Cellular (~100 km):** In addition to two cellular technologies—NB-IoT and LTE-M—that are intended to link IoT devices with narrow-band and long-range mobile network technologies spanning from the second generation (2G) to the fifth generation (5G) might be used to enable IoT connection. About 15.6% of wireless IoT devices are connected by mobile technologies; fewer than 4% utilize old 2G and 3G, 35% use NB-IoT or LTE-M, and the remaining devices use 4G or 5G (Ericsson, 2022).

- **Non-terrestrial (~ 700 km):** The Definition Satellite Scenario, included in Release 17 of the 3GPP standard, provides enhanced support for NB-IoT and non-terrestrial networks (NTN). Here, 5G radio stations and NB-IoT traffic are channeled via low-Earth orbit (LEO) satellites without requiring any modifications to IoT devices. NTN is anticipated to bridge the gaps left by current connection technologies, enabling establishing a worldwide, ubiquitous communication network over land, sea, and space (Ericsson, 2022). By 2028, there will be 21 million users of satellite IoT connection, up from 5 million in 2023 (Mordor Intelligence, 2023).

- **Security and Privacy :** Internet of Things (IoT) devices are used in distant locations with sometimes difficult access to provide vital functions like data sensing and responsive action in vital applications like e-health, driverless vehicles, and instances of human-robot collaboration in industry. Consequently, private information (such as biometric data) may be carried in the transmitted data, making IoT communication security critical. Due to their low computing, storage, and power capabilities and their distant and often exposed locations, IoT devices are frequently seen as the weakest link in systems subject to various security risks (Alrubayyi et al., 2021a). Various dangers, such as eavesdropping, bogus data injection, and private data leakage, affect the Internet of Things communication network. This means that when choosing the technology for connection, factors about communication security are just as crucial as those about coverage range. Utilizing licensed frequency bands, cellular solutions include 3GPP security features such

as cryptographic algorithms, mutual authentication between terminal devices and networks, and a high degree of security while generating and transferring encryption keys because of the SIM card. On the other hand, wide-range solutions were initially intended to function without a SIM card on unapproved frequencies, thereby jeopardizing encryption and security measures.

This study looks at three SDG-driven HIW applications: Responsible Cities, which are predicted to house 70% of the world's population by 2050, and Urban Mobility (see Section 3). Cities are responsible for 70% of the world's greenhouse gas (GHG) emissions and more than 80% of the world's gross domestic output. Thus, it should come as no surprise that, according to the United Nations (2022a), 99 percent of urban residents reside in places with poor air quality. Transportation contributes significantly to greenhouse gas emissions; in the UK, it accounts for 24% of total emissions, with vehicles and taxis accounting for more than 50% (Department for Transport, 2022). The lack of alternative public transportation in 37% of the world's regions prevents the WHO air quality objectives from being met until the transportation issue is resolved (United Nations, 2022a). As any method of transportation based on physical activity, such as walking, cycling, micro-mobility, and skating, active travel is a possible alternative for transportation. Exercise that has been shown to enhance physical and mental health, such as active travel, lowers the need for medical care and boosts happiness and productivity⁵. Anybody can fulfill most of their daily demands with a 15-minute commute from their residence in a 15-minute city. Figure 4 illustrates the three layers of the 15-minute city concepts: active travel, public transportation, and private transportation. The first aims to fulfill everyday necessities in a 15-minute active travel trip. The second expands the core region to include other locations within a 15-minute commute via public transportation. After fifteen minutes of traveling in a private vehicle or cab, the last level covers a greater region. The SDGs about transportation and associated emissions are addressed by developing 15-minute cities linked by high-quality bicycle and public transit infrastructure. To achieve the Sustainable Development Goals (SDGs) for Sustainable Cities

and Communities and to attain 15-minute cities, it is crucial to make cost-effective investments in urban transformation that might encourage the adoption of active travel and enhance public transportation.

3.1 Urban mobility modeling for successful change

Reliable modeling is necessary for determining an investment plan that is both cost-effective and likely to vary based on the characteristics of the city and its citizens. (Tran et al., 2022) examines the influence of surrounding factors on the efficacy of suggested urban mobility solutions. It emphasizes the relationship between economic factors, government policies, transportation infrastructure, urban planning, and the preparedness to adopt suggested mobility solutions. When integrated with AI (i.e., Intelligent IoT), IoT systems can gather and analyze pertinent data anytime and anywhere. This might result in high-fidelity and real-time (or right-time) modeling of many city features. As a result, more studies and field tests are being conducted that use Intelligent IoT to solve SDG 11's innovative city-related issues. (Bellini et al., 2022) Offers a current analysis of significant studies in this area, outlining the key developments and unresolved issues with using Intelligent IoT to create sustainable and effective smart cities. Urban mobility is one of the eight SDG-driven HIW covered in this paper. In addition to more conventional sensors such as pneumatic road tubes (Liu et al., 2010), several traffic detectors are often employed for traffic flow monitoring. Examples include remote traffic microwave sensors (Jin et al., 2019) and magnetic sensors (Fomin & Braeunig, 2019). However, the information in these sensors' data is often restricted, making them useful primarily for simple tasks like counting cars (see Table 3). The bulk of HIW solutions connected to mobility are predicated on gathering data from computer vision Internet of Things devices, such as cameras. These have a wealth of information and can be applied to a variety of urban mobility applications, such as traffic optimization (Worrawichaiapat et al., 2021), multi-modal urban mobility modeling (Yasir et al., 2022), surveillance for safety/security remote monitoring (Shambharkar & Goelcorresponding, 2023), and so on (Xiao et al., 2022). However, cameras for such HIW systems

present several difficulties (see Table 3). Covering and analyzing kilometers of road networks with video cameras is very difficult and expensive, and there are unavoidable limits because of blind spots and subpar performance in unfavorable light and weather conditions (Liu et al., 2023). In addition, the public's resistance to the proliferation of video sensors is a consequence of privacy concerns brought on by the ubiquitous cameras in metropolitan areas and associated laws like the General Data Protection Regulation (GDPR) (Al-Turjman et al., 2022). Table 3 summarizes the benefits and limitations of IoT sensors that simulate urban transportation. In this part, we provide a novel research path that solves the challenges experienced by cameras by modeling urban movement using distributed acoustic sensor (DAS) systems as an alternate data source (see Figure 5).

3.2 The system of distributed acoustic sensors (DAS)

A strain distribution system (DAS) is an optoelectronic device that can detect strain throughout an optical fiber up to 40–50 km long (Hartog, 2017). The technology is based on Optical Time Domain Reflectometry (OTDR), in which a coherent light pulse (laser pulse in Figure 5) is periodically injected into a fiber. A photodetector at the launching end records some light refracted via the Rayleigh (elastic) scattering mechanism (see Figure 5). Each probing pulse produces a continuous time series of back-scatter intensity, commonly called a fiber shot. The time of the back-scatter intensity is proportional to the distance the pulse has traveled along the fiber. In a DAS system, the intensity of the back-scatter signal (see Figure 5) is a random function of fiber position and the cumulative phase of the interference of light scattered back by the fiber within the interrogating pulse. A resolution cell is the fiber interval that generates the backscatter interference (see Figure 5). Because of the random molecular structure of the fiberglass, the back-scatter phase from each resolution cell is intrinsically random. However, it remains constant if the fiber state within the associated resolution cell does not change. However, a bribe would experience a fluctuation in the back-scatter phase and, consequently, back-scatter intensity if exposed to dynamic strain or an auditory event (such as a passing car

or person in Figure 5). As a result, information on the strain development applied at the relevant fiber position may be obtained from a series of back-scatter measurements at a certain fiber distance.

3.3 DAS for Urban Mobility Modeling

3.3.1 Inspiration

As discussed in Section 3.1, DAS addresses the drawbacks of using cameras as the primary data source for urban mobility modeling. First of all, it is feasible to conceal up to Fifty kilometers of road with one DAS interrogator linked to a subterranean fiber connection (Hartog, 2017). As a result, DAS provides a continuous data source utilizing a single system for up to 50 kilometers. To cover the route that connects London and Oxford, for example, two DAS interrogators would be sufficient (approximately 100 km), while (assuming a 100 m gap between two successive cameras) at least 1,000 surveillance cameras would be required for the same distance. Furthermore, unutilized optical fiber cables – known as “dark fiber” – are often placed alongside lighted fiber on purpose in case they are needed later. These may then be used again to activate a DAS system and reduce the expenses associated with putting a DAS solution into place.

Unfavorable weather, lighting, and impediments from moving objects like wind-blown tree branches affect cameras and computer vision. In contrast, as mentioned in (Chiang et al., 2023), DAS signals are far less, if impacted at all, by these problems. Because of the underground optical fiber line’s nature, the DAS signal is unaffected by lighting conditions either during the day or at night. A fiber splice or break might disrupt the DAS signal, but mitigating their effects is relatively easy compared to unforeseen camera obstructions because their positions are known. Regarding the weather, the authors of Chiang et al. (2023) suggest that simple signal processing methods may be used to prevent the periodic signal created by rain, mitigating the possible influence of rainfall on the quality of the DAS signal. To be confirmed, further data collecting and processing would be necessary since this notion has not yet been proven.

Camera-based data-driven HIW systems are susceptible to malicious deepfake assaults, which manipulate reality to lead the application astray (Mitra et al., 2022). Deepfake attacks continue to be a threat and cause significant danger in high-impact wireless (HIW) applications related to intelligent transportation systems (may cause fatal accidents), surveillance (may conceal unlawful events from surveillance), and modeling of urban mobility, despite research efforts to reduce their effectiveness, such as those conducted by Güera and Delp (2018). On the other hand, a DAS signal indicating a specific moving item is complicated, if not impossible, to spoof. The authors (Zitt et al., 2023) present a new method for denoising DAS seismic data using synthetic DAS data at the European Geosciences Union general assembly in 2023. However, it should be highlighted that manipulating a DAS signal to be mistaken for a particular vehicle or mode of transportation is far more complex than manipulating seismic signals. Until such technology is developed, DAS-based HIW solutions for urban mobility are not vulnerable to malicious fake attacks.

As previously stated, camera signals include a wealth of data and might be used to inform many HIW applications at once. However, in urban transportation, camera signals provide more information than is necessary for precise modeling. More significantly, the extra information is often exclusive and private, such.

The color of their skin (Heh & Wainwright, 2022), people's faces (Doberstein et al., 2022), and others (Al-Turjman et al., 2022). Widespread HIW solutions for urban mobility are hampered by intrusions into personal information and the possibility of data privacy breaches, given GDPR compliance and public acceptance of intrusive monitoring. On the other hand, DAS signals cannot uniquely identify a person and do not contain personal information, making them inherently privacy-preserving.

DAS-driven urban mobility is a potential new study area since it is affordable, continuous, resistant to unfavorable circumstances, deepfake, and privacy-preserving.

3.3.2 A Pilot Study Using DAS to Mimic Motorized Mobility

In the groundbreaking work, (Chiang et al., 2023) provide a proof of concept study in which they show that these DAS signals include distinct information about the moving object—known as the signature—that enables accurately and reliably recognizing the kind of moving vehicle. Based on actual DAS data gathered in a controlled setting, the authors pose two problems: 1) Identifying a particular vehicle type, and 2) Classifying vehicles according to their size. Figure 6 displays a snapshot of the associated DAS data. A blur shot indicates the time component (1 shot equals $1/1,000.4$ s), and a blur bin indicates the position of the acoustic event along the blur (the distance between two successive bins is equal to 0.68 meters). Each pixel's color represents the phase strength of the radians of the backscatter signal. In this figure, five cars go from the end of the fiber line to the DAS interrogator in a queue at the same pace.

One-dimensional convolution neural network (1D-CNN) is the foundation of a deep learning strategy that is suggested to represent the unique latent characteristics of DAS signals produced by various moving vehicles, which, taken together, make up their distinguishing signature. Depending on the kind of vehicle, the authors arrive at 83% to 92% accuracy for the first issue. Regarding the second issue, 89% of the time, it is accurate to identify big (or heavy) cars, and 92% of the time, it is accurate to identify little (or light) vehicles. In HIW applications about intelligent transportation, these two issues are significant. Using their signatures found in the DAS data, the first may be used to track and prioritize the flow of specific vehicles (such as fire trucks or ambulances) anywhere in the monitored region. The second might be used to monitor and manage metropolitan regions accessible only to emergency vehicles and small cars. In a different study (Chiang et al., 2022), a two-dimensional CNN (2D-CNN) is suggested as an alternative to the one-dimensional CNN to detect vehicle occupancy while determining the kind of vehicle in question via examining the associated DAS signal. It is shown that distinguishing between high occupancy vehicles (HOV) (cars carrying more than two people) and light occupancy vehicles

(LOV) can be done with an accuracy of around 65%. However, determining the number of passengers is more difficult since additional training data is needed to prevent overfitting. The challenge of large-scale HOV/LOV distinction is essential to achieving SDG targets for sustainable transportation, where maximizing travel utility while minimizing emissions is vital. This issue has two immediate applications. To promote sustainable alternatives like ride-sharing, the first involves modeling the occupancy of private automobiles and developing urban transformation interventions and legislation (Diana & Ceccato, 2022). Given that ride-sharing shortens travel times, (Tavory et al., 2023) identify dedicated lanes for HOV as an effective intervention to encourage ride-sharing. Continuous, economical, and privacy-preserving HOV/LOV detection via DAS provides a way to manage lane utilization and guarantee a better experience for ride-share users than solutions relying on cameras or people. Note that for the DAS-enabled HOV/LOV detection to work in this situation, it could be helpful to employ a video sensor at the HOV lane entry to identify the kind of vehicle (because the kind of vehicle is necessary a priori for valid results). Public bus routes and timetables are optimized in the second application to optimize occupancy and user experience while minimizing lengthy trips using LOV (Lotze et al., 2022). To do this, monitoring the occupancy of public buses is a crucial need. Because the kind of vehicle is known in advance, DAS provides a continuous, economical, and private way.

3.3.3 Persistent difficulties

The outcomes of the two studies discussed in Section 3.3.2 prove that the DAS signal contains distinct moving object characteristics that may be recovered and used to differentiate between comparable occurrences (for example, two identically sized automobiles). Further research is necessary to determine if DAS can be used to inform HIW applications in real-world scenarios with uncontrolled traffic, various road kinds, and optical fibers. The DAS data from five pre-selected cars and a controlled environment where traffic was limited to one way at a time is used in both works. Additionally, the training dataset's labeling was made more accessible by

the scripted nature of the trials (see Figure 6). It follows that specific significant concerns remain unsolved despite the encouraging findings found in these two groundbreaking works:

- The suitability of a model for roads and optical fiber circumstances that vary from those in the training dataset. It is well known that the physical properties of the fiber impact the DAS signal, the kind of road, and the depth of the fiber. Therefore, the model should be retrained for each installed DAS system to consider these physical attributes. This would result in a very dependable way to identify and follow cars on the roadways that the system spans.
- The model's accuracy in actual traffic situations with uncontrolled vehicle flow. As seen in Figure 6, the suggested strategy effectively differentiates the vehicle kinds in the face of external activities like those produced by other automobiles, even if the pilot research is based on a controlled trial with few undesired movements. Due to the well-labeled data and a priori knowledge of the desired automobile and speed. Without such knowledge, a target vehicle's unique and clean DAS signature would be required beforehand. The signature may be recognized again if any other moving cars are nearby. Considering the DAS system's tens of kilometers in length, this is a reasonable assumption in an urban setting.
- Increasing the model's size to include every car on the road. Since the dataset under study only includes five vehicle types, it is not easily generalizable to identify any vehicle model currently on the road. Although it would need extensive data collecting and expensive model training, increasing the number of vehicle models in the dataset would probably provide a more representative model. Airports, industrial facilities, energy plants, and other related connected settings are among the applications where recognizing a specific vehicle is necessary. These applications need a predetermined list of authorized cars. The suggested DAS-driven method would work well to describe mobility specific to a particular location in these situations.

4. Use case 2: accountable energy usage

Responsible energy usage is critical to achieving SDG 7: Affordable and Clean Energy. Target 7.3 of the defined SDG 7 objectives states that by 2030, the worldwide rate of progress in energy efficiency will have doubled from 2010 levels, reaching 2.6%. Primary energy and GDP are quantified using the energy indicator Energy Intensity (EI), which was 5.6 MJ/USD in 2010 and 4.7 MJ/USD in 2019 (United Nations, 2022b). While preliminary EI predictions for 2020 show a significant decline, the pandemic is the leading cause. The values for 2021 indicate a mere 1.9% improvement, far less than what is required. Thus, to meet the SDG 7.3 objective, an accelerated yearly improvement of 3.2% is needed. A path to achieve Net Zero Emissions by 2050 was published by the International Energy Agency in 2022; to fulfill this ambitious goal, an even quicker (and potentially disruptive) 4% yearly increase in EI is required (International Energy Agency, 2022).

The residential sector accounts for around one-third of the energy use.

Consumption is the only industry with a decline in acceleration between 2010 and 2019 (see Figure ES10 in (United Nations, 2022b)). Consumption occurs globally. The increased need for appliances, heating, and cooling systems in residential structures is the cause of this disadvantage. Therefore, reducing domestic energy demand and consumption via innovation is essential to achieving large-scale energy efficiency. As an example of intelligent energy IoT systems, innovative grid advancements provide a way to track, manage, and control household energy use (Zhang T. et al., 2022).

This section shows two use scenarios within the energy-driven HIW paradigm. The first, covered in Section 4.1, attempts to control household energy use to reduce overall demand and prevent peaks associated with wasteful energy generation. The second, covered in Section 4.2, deals with energy theft detection and is another major contributor to energy waste and subpar, inefficient energy output.

4.1 Digital twin for controlling household energy consumption

One of the main obstacles to attaining cost-effective energy production is energy peak demands (Rana et al., 2022). Peak shaving, or the efficient regulation and nudging of energy usage to reduce overall demand, is made possible by the proliferation of smart meters and grids. There are two common ways to shave your peak. When there is a decrease in energy demand, the first method stores excess energy and uses it later (Grubler et al., 2018). The second strategy is built on a time-of-use pricing strategy that energy suppliers created to encourage customers to use their appliances during off-peak hours (Amiri-Pebdani et al., 2022). A time-of-use tariff is a billing system where the cost per joule, or energy cost rate, is determined by the time of day the energy is used. The rate is low during low energy demand and high during peak energy demand. Due to various residential regions' varying collective energy consumption patterns, traditional time-of-use pricing predetermines the time range of each energy cost rate, leading to inadequate energy savings.

A problem shared by the two approaches discussed is the need for regular and specific transmission of energy consumption (EC) data to the server/energy provider for efficient scheduling of energy demand and further energy supply optimization. Personal information about the residents is included in residential EC data, which may provide insight into their routines and habits. When this data is sent across the smart grid, it becomes vulnerable to unauthorized access and may be used for targeted marketing campaigns or well-timed break-ins. The smart meter data's greater temporal and geographical resolution corresponds to a greater privacy risk when EC data leaks. For example, minute- and room-based EC data may identify the presence of children in the home, provide information about their routines, and indicate potential abuse (De and Métayer, 2016). The adoption of smart meters is sluggish in light of these concerns; in the UK, only around 50% of electric meters will be competent in 2022⁷, partly because people are loath to embrace them (Gosnell & McCoy, 2023).

An additional obstacle stems from the intricacy of peak shaving.

The challenge in light of the interdependencies between the agents engaged and the underlying multi-objective optimization (Su et al., 2022) (Wynn et al., 2022). Thus, peak shaving optimization issues are computationally costly and involve time-consuming procedures. Because of this, these systems cannot respond quickly enough to control the overall energy demand, which prevents the intelligent grid's stability from erroneous or slow changes. To do this, Fathy et al. (2021) use a digital twin technique, which enables optimization to be carried out in a virtual duplicate before applying the results to the grid. A digital twin is an electronic copy of tangible assets that allows data-driven modeling of the state and actions of the system's physical elements and their interactions. In this instance, the complicated peak shaving system is effectively optimized by using an intelligent meter data-driven digital twin, which is shown to provide dependable and reasonably priced anticipatory solutions. A multi-layer digital twin of the energy system (Fathy et al., 2021) seeks to create a home digital twin (HDT) that reflects the actual EC of households. Connected to the digital twin of energy production (EDT), HDT enables the household-centric energy optimization model to attain the targeted efficiency in energy consumption. By lowering the daily levels of energy demand, the model aims to increase the efficiency of energy production. To prevent peak demands, residential households' EC patterns are cooperatively rearranged.

They are meeting the demands of the occupants and cutting their energy expenses. The first HDT model is included in the suggested system to assess how different modifications affect the family energy cost and, in turn, energy output. Before applying the final solution to the actual assets, a distributed reinforcement learning approach is suggested that operates in the virtual replica and optimizes the scheduling of the home appliances. The HDT protects all sensitive home data, and as Figure 7 illustrates, only aggregated data is sent to the central controller of the Energy DT (EDT). The central controller and many local transformers make up the energy provider EDT.

The former communicates with several regional transformers to determine the total energy consumption of every region. Then, it provides the optimized hourly energy cost rates based on the peak-to-average energy output ratio. With the help of machine learning algorithms, EDT and HDT are connected and able to dynamically optimize the energy supply-demand balance from the standpoints of both suppliers and customers. To do this, HDT would optimize the cost of home energy using the area-specific time-of-use energy rate that the EDT has computed.

Edge-distributed reinforcement learning's advantages

There are three methods. First, home consumers would be more likely to accept intelligent energy solutions as HDT edge computing preserves people's privacy. Secondly, reinforcement learning is a self-learning technique that adapts to a household's shifting preferences for using electric equipment. For example, the algorithm can quickly provide optimal outcomes whether there are new family members, renters, or appliances. Similarly, the algorithm will automatically be impacted by changing energy cost rates that the EDT may design, and the resultant schedule will be adjusted to minimize the household's energy costs. Thirdly, there is very little chance of unstable behavior or an undesirable consequence since the optimization is done in the virtual copy and only applies to the actual assets if the results are promising.

The suggested energy system is used with an actual Internet of Things dataset covering seventeen families over more than two years. The results of the studies indicate that the model successfully reduced overall energy usage by 20.4%. Concurrently, there was a 17.7% decrease in the typical household's energy costs.

4.2 Recognition of Energy Theft

Energy theft worsens the energy crisis by raising the danger of electric shocks and fires, increasing market instability, income loss, and cost increases. Energy theft mainly results from direct tapping from feeders, tampering with the electrical meter, adding magnetic material to slow down

metering and excessive line losses, and hacking attempts to modify intelligent meters. Traditional energy theft detection techniques require labor-intensive, expensive, time-consuming, and human error-prone physical on-site examinations.

Energy suppliers may get highly granularity and near-real-time EC data using HIW energy applications, including smart meters and grids. As seen in Figure 8, EC data may be distinguished from regular EC by several unique characteristics. EC data contains information about consumer patterns and energy theft.

Using incoming EC data, the authors of (Nadeem et al., 2023) provide a deep-learning method for identifying theft. Since there are more honest users than thieves (ten to one in the EC data obtained from actual home customers), the data is inherently skewed (Nadeem et al., 2023)). To do this, the authors develop a multi-objective measure that considers energy and compensates for the revenue loss caused by incorrectly classified EC data. Two misclassifications exist: an honest sample was mistaken for theft, and theft detection was overlooked. The most recent research from Ofgem (Smarter Markets, 2013) states that energy theft may go unreported for 1.4 years and incur expenses more than eight times higher than those incurred if a crime is mistakenly reported. An energy-aware deep model with weighted loss was developed in response to the substantial data bias and the conflicting goals of identifying theft without inadvertently accusing someone. This model surpassed all earlier models in minimizing the loss of energy theft by 30.4%.

5. Use case 3: Clever IoT for health

According to the World Health Organization's most recent research, women and young people are most affected by the prevalence of anxiety and depression worldwide (World Health Organization, 2023). 2019 will see 86 million.

Eighty million teenagers between the ages of 10 and 14 and fifteen to nineteen suffer from poor mental health (United Nations, 2022a). In 2020, there was a projected 25% rise in the total number of instances of anxiety and sadness after the

pandemic. Unfortunately, this rise resulted in a significant disruption to mental health services, widening the gaps in mental health treatment. Although there have been some slight gains since 2021, many individuals still cannot get the necessary treatment and assistance for both new and pre-existing mental health disorders. To assist nations in accelerating progress on health-related objectives, the Global Action Plan for Healthy Lives and Wellbeing for All, or SDG3 GAP, is a collection of commitments that play significant roles in health, development, and humanitarian responses. These are supported, although many accelerator working groups cooperate to fulfill these obligations. Among them, the working group for the Data and Digital Health Accelerator has made a significant contribution to the achievements listed in the World Health Organization (2023).

Within the scope of Data and Digital Health initiatives, Intelligent IoT for ubiquitous mental health assistance is relevant here and has the potential to close the gap by assisting people whom current mental health services have neglected. (Alshareef et al., 2022) the intelligent stress monitoring assistant uses affective computing to identify stress levels based on biological cues. The writers pose two distinct issues. The first seeks to identify stress in a pre-identified and familiar set of individuals; this might help keep an eye on the health of a team that performs a vital function, like air control or medical personnel. The second aims to identify stress in anybody not visible to the naked eye. This model might help understaffed service providers reach schoolchildren and other impacted populations. With an impressive accuracy of 96%, the authors train an attention-based transformer network on an open-source dataset to extract stress-specific characteristics.

Since 75% of individuals in contemporary culture believe they cannot manage their stress, identifying stress is an issue of utmost significance (Foundation, 2018). Although the development of intelligent IoT systems for ubiquitous and remote stress detection has great promise, given the growing prevalence of mental health illnesses and the urgent need for help, some difficulties must be resolved before

using such solutions. The security of sensitive patient data, which may be subject to abuse and unauthorized access when transported and kept, is a problem when HIW is used in the healthcare industry. Moreover, there are considerable privacy issues when training a model on sensitive data, such as that of Alshareef et al. (2022). Several sensors are used in this study, such as the electromyogram (EMG), electrodermal activity (EDA), and electrocardiogram (ECG). Accordingly, it is possible that the model would memorize or acquire specific attributes of particular patients, enabling the re-identification or deduction of sensitive data (Nadas et al., 2020). Therefore, it is essential to include robust security and privacy protections at every stage of creating and implementing machine learning models for use in healthcare settings.

6. Six Obstacles to Achieving the Multi-Objective SDGs

The governance problems unique to the application have been underlined in each of the use cases covered in Sections 3, 4, and 5. Two main concerns impact all SDG-driven HIW apps: 1) security and data privacy and 2) The interconnectedness and connection of the various SDGs. Table 4 enumerates broad open difficulties and intriguing research avenues. Every use case includes a discussion of data privacy, closely tied to security risks that might allow unauthorized access to private information (such as health, energy, or mobility data). Malware attacks may be used to compromise privacy and expose personal information by focusing on weak IoT devices or gateways (see Figure 1). Malware attacks may be prevented or detected using various techniques, but they are often too complicated for lightweight IoT devices (Alrubayyi et al., 2021a). Alrubayyi et al., 2021b) offer an artificial immune system approach for malware detection that is low-complexity and capable of identifying malware that is not readily visible, making it an excellent fit for Intelligent IoT systems. The danger of man-in-the-middle, a security breach that targets the communication network to eavesdrop on or modify the sent data—private or personal data in this case—is not addressed by malware detection. The literature has several strategies for reducing this risk, including preventing data transfer, safeguarding sent data, or doing both. For example,

the multi-layer digital twin with distributed reinforcement learning in Faithy et al., 2021 keeps the sensitive information close to the edge, or client, shielding it against man-in-the-middle assaults. Other techniques to prevent private data transfer across the Internet of Things use edge computing, including federated and distributed learning, which replaces actual data with synthetic data with the necessary latent properties. These techniques are often combined with data protection techniques, as described by Issa et al. (2023), which use blockchain in conjunction with federated learning for intelligent IoT systems due to the danger of deriving genuine data from synthetic data or model parameters. Additional techniques to safeguard data against man-in-the-middle attacks include encryption (Zhang L. et al., 2022), differential privacy (Wu et al., 2022), and data anonymization (Yang et al., 2022).

One major obstacle that has to be addressed is the interdependence and connectedness among the various SDGs. To achieve this, (Caldarelli et al., 2023) contend that the theories and techniques derived from complexity science are desperately required to direct the creation and use of digital technologies—in this example, digital twins—for the sustainable development of urban areas. The most frequent mistake made when using intelligent IoT to advance a sustainable development goal (SDG)—like SDG 11 or SDG 3—is that these goals need energy consumption, which puts SDG 7 in danger of being delayed. For example, deploying an efficient communication infrastructure for IoT equipment is one of the leading causes of energy consumption in all HIW applications. Nonetheless, energy-insensitive goals like latency, data throughput, and resilience are often the focus of communication provisioning. Consequently, energy efficiency has been given priority in the design of future wireless systems. For example, through reinforcement learning, authors (Liu et al., 2022) maximize energy efficiency in the user-beamform selection process in non-orthogonal multiple access systems. Similarly, additional publications (Ozturk et al., 2022) suggest using reinforcement learning to provide context-aware connection with multi-objectives, including energy efficiency.

Artificial Intelligence, including deep learning and reinforcement Intelligent IoT has been made possible via the enormous success of machine learning in several areas, not the least of which is the cost of computing time and associated emissions. (Strubell et al., 2019) It is shown in their groundbreaking work that training a single model for natural language processing may release as much carbon dioxide throughout its lifespan as five automobiles. There has been a further wave of research in which accuracy metrics are deemed crucial, and AI models are subjected to more strict efficiency constraints. The lead time for training a model, the associated carbon footprint, and the model's exportability or repeatability are used to determine efficiency (Schwartz et al., 2020). First and foremost, these specifications would guarantee that a model's utility is maximized at the lowest possible energy expense. Furthermore, lowering AI's processing cost has a direct financial effect and makes the technology more accessible to a larger audience.

7 Wrap-up

This study looks at cutting-edge research that uses artificial intelligence (AI) and Internet of Things (IoT) systems to construct intelligent IoT systems in the hyperconnected, intelligent future that will help achieve the Sustainable Development Goals (SDG). To do this, the leading IoT system components are first covered. Three crucial SDGs are examined, and newly developed, cutting-edge Intelligent IoT solutions are outlined. This study shows that Intelligent IoT systems are essential for any hope of reaching the set SDGs in 2030, especially after the slow progress achieved since 2015. Other challenges in each use case are exposed, along with general obstacles affecting all SDG-driven Intelligent IoT solutions. Despite this, security and privacy threats may seriously impair Intelligent IoT solutions. Consequently, reducing these risks is a crucial first step in creating practical SDG solutions. Furthermore, the interdependencies across the many SDGs make designing intelligent IoT systems more complex. The SDG aim of responsible energy usage may be negatively impacted by the carbon footprint of artificial intelligence model training and the interconnectedness of IoT devices.

Conclusion

This chapter has explored the transformative role of IoT and Machine Learning (ML) in accelerating progress toward the United Nations Sustainable Development Goals (SDGs). By integrating intelligent sensing, ubiquitous connectivity, and data-driven decision-making, IoT-ML systems offer scalable, cost-effective, and adaptive solutions across critical domains such as urban mobility, responsible energy usage, and digital healthcare. The discussed use cases demonstrate how Intelligent IoT can enhance operational efficiency, optimize resource utilization, reduce environmental impact, and improve quality of life while addressing SDGs related to health, energy, sustainable cities, and climate action.

However, the chapter also highlights significant challenges that must be addressed to ensure sustainable and ethical deployment of these technologies. Data privacy, cybersecurity vulnerabilities, algorithmic bias, high energy consumption of AI models, and the interdependence among SDGs pose non-trivial risks. If left unaddressed, these issues may undermine the very objectives that IoT and ML aim to support. Emerging approaches such as edge intelligence, federated learning, digital twins, energy-aware AI, and privacy-preserving analytics show strong potential to mitigate these risks.

In conclusion, IoT and ML are not standalone solutions but powerful enablers that must be embedded within responsible governance frameworks, inclusive policy design, and sustainability-aware system architectures. Future research should focus on multi-objective optimization across SDGs, low-carbon AI, interoperable IoT infrastructures, and ethical-by-design intelligent systems. With coordinated global efforts, Intelligent IoT can play a decisive role in bridging the gap between current progress and the ambitious targets of the 2030 Sustainable Development Agenda.

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