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Analysis of Challenges and Solutions of IoT in Smart Grids Using AI and Machine Learning Techniques: A Review

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Abstract: With the assistance of machine learning, difficult tasks can be completed entirely on their own. In a smart grid (SG), computers and mobile devices may make it easier to control the interior temperature, monitor security, and perform routine maintenance. The Internet of Things (IoT) is used to connect the various components of smart buildings. As the IoT concept spreads, SGs are being integrated into larger networks. The IoT is an important part of SGs because it provides services that improve everyone's lives. It has been established that the current life support systems are safe and effective at sustaining life. The primary goal of this research is to determine the motivation for IoT device installation in smart buildings and the grid. From this vantage point, the infrastructure that supports IoT devices and the components that comprise them is critical. The remote configuration of smart grid monitoring systems can improve the security and comfort of building occupants. Sensors are required to operate and monitor everything from consumer electronics to SGs. Network-connected devices should consume less energy and be remotely monitorable. The authors' goal is to aid in the development of solutions based on AI, IoT, and SGs. Furthermore, the authors investigate networking, machine intelligence, and SG. Finally, we examine research on SG and IoT. Several IoT platform components are subject to debate. The first section of this paper discusses the most common machine learning methods for forecasting building energy demand. The authors then discuss IoT and how it works, in addition to the SG and smart meters, which are required for receiving real-time energy data. Then, we investigate how the various SG, IoT, and ML components integrate and operate using a simple architecture with layers organized into entities that communicate with one another via connections.

Keywords: Artificial Intelligence (AI); Internet of Things (IoT); machine learning; Smart Grid (SG); smart buildings

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1. Introduction

The invention of the Internet of Things (IoT) is one of the most significant technological advances of the 21st century. The IoT is a network of linked hardware, software, and physical nodes that enables data gathering and distribution. The exchanging of data amongst multiple infrastructures and devices is referred to as the "IoT" [1]. Without them, Internet access is impossible. The Internet Protocol monitors Internet devices. The Internet allows user-to-user online communication. The networked “things” aspire to provide everyday objects with the ability to share data and information on their own and at regular intervals. A structure that uses connected data, technology, and machinery is called an “intelligent building.” Analytics and automation for controlling essential services, including HVAC, lighting, heating for safety equipment, and air conditioning HVAC devices with intelligent controls [2]. It is highly beneficial for HVAC systems to utilize less energy if they have authorities implemented when energy is in high demand. The problematic parts of this duty include recognizing and locating defects and minimizing power consumption in vacant portions of the facility [3].

The integration of renewable energy sources, Smart Grid (SG) management, energy trading, power system flexibility and negative pricing, energy management, arbitrage and pricing, and SG financial transactions are some recommendations for enhancing the performance of SG block chain technology and cryptocurrencies may lead to a flatter load profile and economic advantage. In addition, previous researchers [make changes to the block chain’s algorithms so that communities of online users may use Bitcoin to transact in marketplaces and energy systems using more secure methods [4]. The writers also use digital money in their energy infrastructure. A longer-term viewpoint may be just as helpful as a more immediate one when attempting to detect and mitigate possible hazards. The writers pay little attention to enduring challenges, well-known problems, or feasible remedies. Using block chain-based digital currencies, participants in the energy industry must solve security problems if they want to be effective and competitive.

Many more articles are available that cover a wide range of topics that impact all human cultures. For instance, the essay highlights the issue of global warming, which is leading to substantial changes in almost every part of the world. In this research, the electrical power utilized by ordinary home appliances is broken down using the Electrical Line Disaggregation (ELD) method. ELDs today depend on computer science techniques and Artificial Intelligence (AI). Optimized complete set empirical model decomposition and wave packet transformation, or OCEEMD-WPT, is also used. This idea was developed to show how the end user might perceive changes in power-line noise. Consequently, gathering vital information required for network operation is significantly more effective [5].

Using sensors or smart meters, a power grid might become an SG. These robust sensors transmit a lot of data. This helps understand network behavior and make assumptions. The vast data required to join and store thousands of IoT nodes makes this impossible [6]. Automatic Encoders (AE) approach encoding data entropy to represent previously compressed content with fewer data. These strategies use AI and deep learning. Until recently, data spectrum made compression impossible. The suggested data compression method leverages AE models. Spectral windows improve compression and entropy.

IoT devices and technology may improve SG via real-time monitoring, new pricing methods, dynamic energy management, and self-healing. Intrusions are more significant in SG-converted grid components and services. Researchers studied attacker and defender payoffs using actual devices and honeypots. Both attacked and defended games contain uncertain NE and Bayesian NE matching conditions. The authors suggested increasing worst-case outcomes in non-equilibrium circumstances. If the defendant accepts the onslaught and gives up, he may submit. Simulations show that both games were balanced offensively and defensively. Defense recognizes and rewards aggressors. By interacting with a certain number of actual devices and honeypots, previous research looked at how an attacker and defense may cooperate to maximize their payoffs [7].

SGs use automation, sensors, and remote controls to increase comfort, security, and energy efficiency. IoT sensors monitor “smart” construction elements. This knowledge can enhance interiors. IoT-based “SG’s,” which monitor a building’s temperature, security, and maintenance, are made more accessible by smartphones and tablets. The IoT’s ability to link many sensors allows it to collect and analyze data in real time, leading to more innovative and user-friendly buildings [8]. For SGs, fire alarms are essential. A smart IoT fire alarm system is required to prevent property damage and save lives. Weka and J48 are used; previous research demonstrated energy-use patterns and behaviors. These were then categorized according to how much energy they used [9]. With machine learning and big data for the home, the HEMS-IoT smart energy management system lowers the home's overall energy consumption while ensuring the comfort and security of its residents. The system relies heavily on machine learning and large amounts of data to analyze and categorize how effectively energy is utilized, identify trends in human behavior, and maintain a high degree of comfort for building occupants [10]. The authors investigated many security holes in IoT software. The following survey was used to find workable security solutions. Previous researchers outlined a process for creating web services and apps for SGs using the IoT as an example [11]. Another research team developed an innovative structure employing mobile applications and open-source server software. This proves that intelligent buildings can be created using the IoT [12]. They built a method to implement their device management approach using relays and a low-cost Arduino microcontroller board. The purchase comes with an Android application that the customer may use to access the intelligent system. Using machine learning methods, a previous study provided an overview of how a large-scale IoT deployment may be accomplished [13]. These technologies and application areas are projected to dominate IoT research in the following years. The authors of used machine learning methods to create an intelligent controller for HVAC systems in homes and businesses. When confronted with resource allocation problems, IoT networks must make judgments according to the circumstance and context, as detailed in. Machine learning models can adapt to changing environmental conditions in real time, providing them with an advantage over optimization heuristics, game theory, and other methodologies [14]. Self-adjusting models can retrain. Machine learning can analyze and decide on resources in complex, dynamic, globally dispersed IoT systems. Urban regions are adopting smart grids, sensor appliances, and building management systems. The research examines the IoT and SGs. AI and IoT may affect businesses and jobs. AI protects computers, networks, and IoT devices that can mimic human brain processes and make decisions, enabling IoT [15].

We explored various subjects, including AI, IoT, and smart structures. The articles that helped us decide are mentioned in the following paragraphs for convenience. According to the IoT links various high-tech devices, including smartphones, sensors, and other types of cutting-edge technology [16]. These gadgets can interact with one another and exchange information. By connecting already online devices, the IoT is a system that enables inanimate things in the real world to interact and share data. According to the authors, there are several areas where the IoT may be employed, including agriculture, the military, home appliances, and personal healthcare [11]. These are a few of the many uses of the IoT to provide and maintain ubiquitous connection, real-time applications, and solutions to transportation system demands. A previous study offers a novel architecture based on machine learning and IoT capabilities. Figure 1 depicts a graphical representation of all the sections of this paper, and Table 1 show a list of abbreviations used in the manuscript [17].

Table 1. List of abbreviations.

Abbreviations	Full Form
IoT	Internet of Things
AI	Artificial intelligence
SG	Smart grid
SB	Smart buildings
HVAC	Heating, ventilation, and air conditioning
ELD	Electrical Line Disintegration
OCEEMD-WPT	Optimized complete set empirical model decomposition and wave packet transformation
AE	Automatic Encoders
NE	Network

Table 1. *Cont.*

Abbreviations	Full Form
HEMS	Home energy management system
PC	Personal computer
IETF	Internet Engineering Task Force
ROC	Receiver Operating Characteristic
V2V	Vehicle-to-vehicle
LPWAN	Low-power wide area networks
LTE	Long-Term Evolution
Ml	Machine learning
SGMS	Smart grid management system
CR AMI	Capability requirement for Advanced Metering Infrastructure
EVD	External ventricular drain
RPL	Routing Protocol for Low-Power and Lossy Networks
PMU	Phasor measurement unit
CAMS	Comprehensive area monitoring system
SCADA	Supervisory control and data acquisition
IED	An intelligent electronic device
HAN	Home-area network
WAN	Wide-area network
FIDO2	Password-less authentication

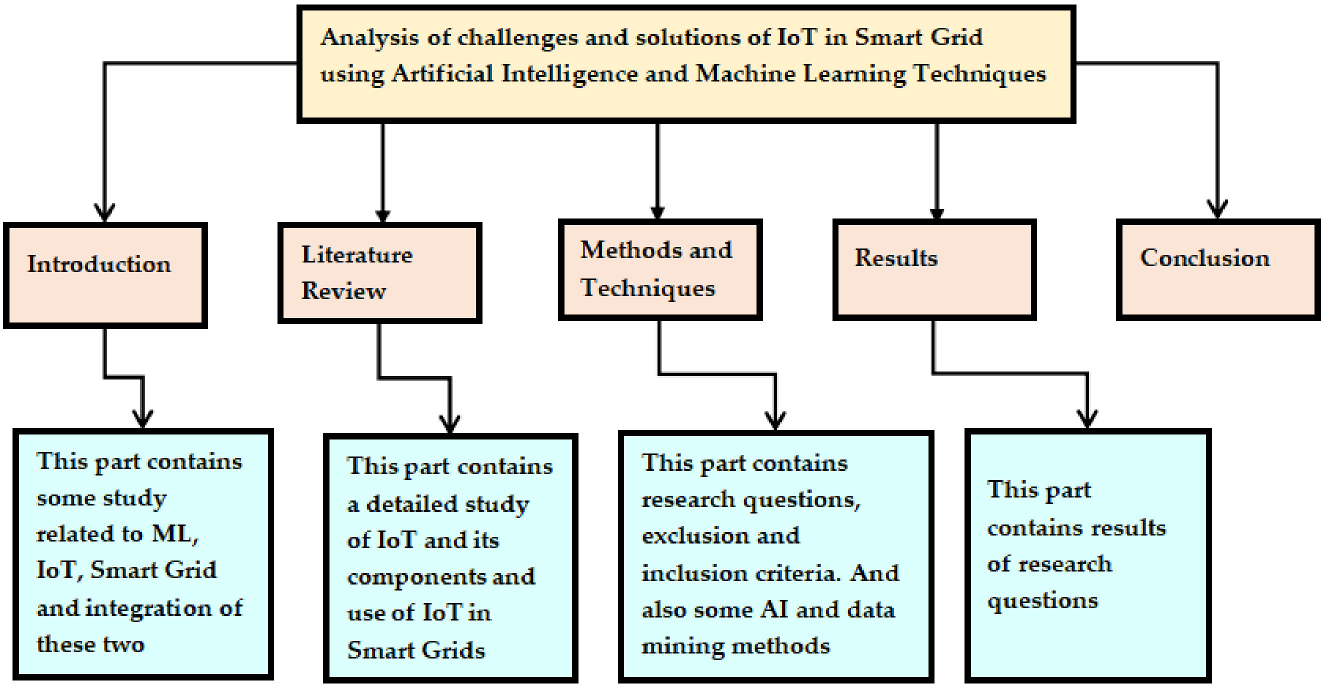

Figure 1. Taxonomy of the proposed work.

The remainder of this paper is organized as follows. Section 2 describes the related work in detail, and Section 3 discusses the methodology, in which research questions, exclusion and inclusion of AI, and data mining techniques are discussed. Section 4 discusses the results of the research questions, and Section 5 concludes the work.

2. Literature Review

Including full-duplex or bidirectional contacts is the subject of further research [18]. The research-recommended interactions increase network asset management. Both money and time are spent on administration and upkeep. Intelligent real-time monitoring is vital yet complex. The authors recommend starting with electrical system basics. AI can recognize incomplete discharges, which are hazardous to the system. Smart sensors throughout the SG can monitor partial discharges and grid sections. Real-time sensor assessment ensures network performance.

One of the many demands that today's customers have of businesses is maintaining the privacy of sensitive information sent across electrical networks. The IoT is a system of interconnected, high-tech gadgets that can communicate, share information, and control one another. The sensitivity and energy consumption of the data must be disclosed to higher-layer applications through the IoT networks. We could control how much power each request and program used if we were aware of this. The administration should happen quickly if the device creates consumption profiles for each user and monitors regular usage. Malicious software, such as a virus, or a system failure may threaten these profiles. In this article, two computers perform identical tasks in the same order across time. The experiment's results are noteworthy since one PC carries a virus [19]. The research discovered that energy consumption rises when a computer performs duplicate or unreliable tasks.

To better comprehend how to handle outlier data, this was undertaken using data-driven analytics, data mining, and information security technologies. They examine how outlier mining and denial are used in an SG setting, and conclude that operational security and power system reliability are the biggest obstacles to intelligent energy management [20].

Many tiny devices are included in different IoT systems. The numerous problems with low-power, lossy networks (LLNs) are partly due to the devices' limited capabilities. Routing over IPv6 is made possible via the RPL protocol. The Internet Engineering Task Force (IETF) created it as a simple, global networking standard for resolving resource-related concerns such as congestion. The RPL uses objective functions to decide the best way to proceed. The best possible parents are chosen by the OFs while choosing a path. The metrics that were used to build the OF must be carefully chosen in order to find the route that meets all requirements. The different node metrics that can be used in RPL OFs are listed, along with details on how to calculate them [21]. To stop or lessen assaults on the network control system's integrity, availability, and confidentiality, it must be protected. If these assaults are not stopped or neutralized, they might harm the economy, human life, and public health. The author then proposes a systematic strategy for mitigating controls by examining recent and impending cyber-attacks against SGs.

Using sensors and technology from the IoT, an SG may be able to set up real-time monitoring, complicated pricing schemes, dynamic power management, and self-healing features. However, switching from a regular grid to an SG puts the grid's parts and services at risk of cyber-attacks. By interacting with one another, assaults and defenses may be strengthened [7]. The benefits for the attacker and victim are enhanced with real devices and honeypots. The authors devised the Nash Equilibrium (NE) and Bayesian NE since the attacker's reward was uncertain. The non-equilibrium design is presented. The defender may accept a phony equilibrium—balanced attack and defense simulations if the attacker shoots low. Logic chooses the best attacker.

We created an intelligent system for the lab that provides real-time monitoring and management of a range of innovative home equipment using a free and open-source IoT platform [17]. Every room has sensors and cameras to monitor occupants' daily routines, lighting, temperature, and activity levels. If the data surpasses the threshold, homeowners will receive an email or text message telling them to make interior improvements. The AI is trained to identify unexpected events. Recent advances in big data analytics, sensor technology, machine learning (ML), and the IoT may make SGs affordable. Minimal effort is needed to make minor infrastructure changes [22]. This paradigm is proposed as a workable solution in. We can find significant clinical indicators that might indicate the existence of heart illness using Receiver Operating Characteristic (ROC) analysis and a three-tier expandable architecture based on the IoT [23].

Using "smart lighting" reduces the need for unnecessary artificial light by using natural light and improving functionality in areas such as occupancy detection and dimming.

Increasingly, dim lighting conditions are becoming the norm in public places. Companies that employ step and continuous dimmer control may make money using demand-response systems [24]. The many configuration possibilities of lighting control systems allow for comprehensive remote control of intelligent lighting systems. Due to lighting management features, customers now have access to web-based dashboards for controlling lights, and the usage of wireless controllers makes retrofit deployment easier. IoT-based smart buildings and grid systems are presented in Figure 2.

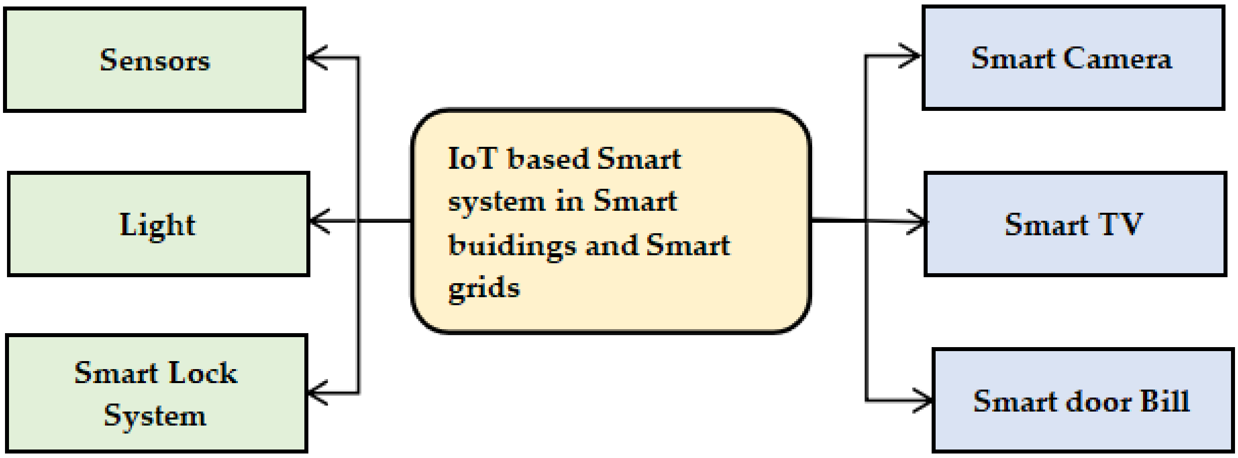

Figure 2. IoT-based smart buildings and grid systems [25].

2.1. Parts of IoT-Based Devices

A network of interconnected electronic devices known as the IoT collects and distributes data about human users to promote improved communication, coordination, and cooperation. An open and compatible collection of technologies and protocols known as the IoT enables the Internet connectivity of commonplace devices. An IoT platform might be used to build a network of sensors. After examining the data, it has acquired, the network chooses the best results [26]. The IoT technology is anticipated to have a wide range of future applications. These applications include detection systems, and location, cloud, and communication technologies.

2.1.1. Cloud Infrastructure

Regarding IoT services such as Vehicle-to-Vehicle (V2V) connections, real-time health monitoring, and commercial IoT, cloud infrastructure is even more important than computer services [27]. To make plans, people are increasingly using their mobile devices. With the help of intelligent device scheduling, it is possible to keep customers' devices functioning correctly while also saving money and using less energy overall. This is done without diminishing the product's usability for the consumer. By taking into account both the preferences of the users and the data gathered from other sources, the energy management system organizes the usage of the devices mentioned above in the most effective way possible [28].

2.1.2. Network Model

SG IoT connection is anticipated to be impacted by cellular-based technologies that will provide low-power wide area networks in the coming years (LPWAN). This effect will be developed gradually. LPWANs use less power and may support more devices. IoT enables several protocols to communicate between related items and the cloud. LTE and LoRA WAN are used in these strategies. These networks can operate over a substantially more comprehensive working range and at data transmission rates that are noticeably quicker [29].

2.1.3. IoT Gateways

A gateway's primary role in communications is to serve as a connecting point for various communication systems. Different systems may differ in their communication interfaces, protocols, and choices [30].

2.1.4. IoT Sensors

The server stores and makes accessible all sensor data. Examining the building's workloads may reveal energy utilization trends. Electricity utilization should be reduced. This development will help locals and guests [31]. The fundamental components that must be present to realize a fully functional IoT setup are shown in Figure 3.

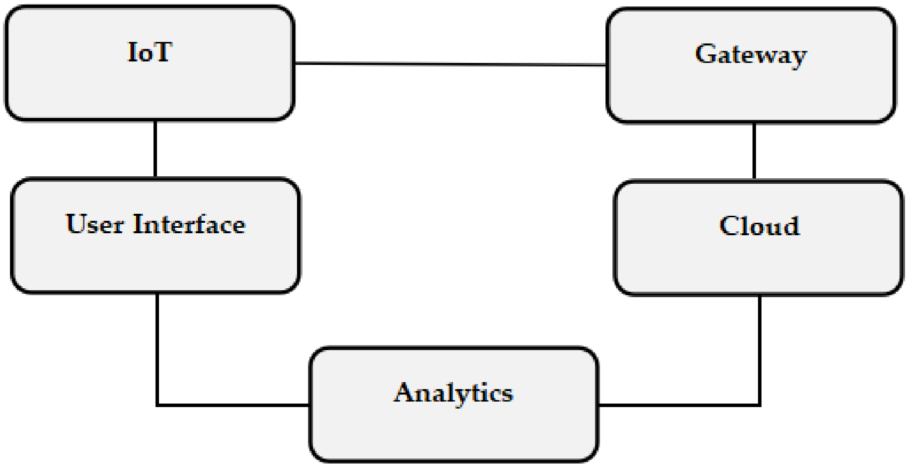

Figure 3. Essential components of IoT [32].

Computers and mobile devices may be used in "smart" buildings to monitor temperature more efficiently, control security, and perform maintenance. SG uses IoT to coordinate building activities. Building management systems, IoT sensors, AI, and machine learning are all used in intelligent buildings. A few such potential technologies include AI and ML.

2.1.5. SGMS

Building automation and management systems, or SGMS for short, are required to accurately keep track of the amount of energy used in residential, commercial, and industrial buildings [33]. These devices are called "building energy management systems" in certain localities. A building is considered to have "smart" qualities when automation, sensors, and other remote elements are used to improve the effectiveness of building administration, the level of tenant contentment, and the expenses associated with building maintenance.

2.1.6. Advances in Power Line Communication Technology

IoT technology may enhance and optimize electrical network computational models, which now contain user data and energy provider prices. The IoT can optimize computational models. Corrections might increase latency and network noise. This article includes customer/supplier and smart meter data. The authors investigated the complexity, subtleties, speed, and correctness of statistical amalgamation [34]. First, this paper looks at the issues caused by corrupted data disseminated across the network as a direct result of transmission, quantification, and even basic consumption measurement errors.

The bandwidth requirements of SG are satisfied by BPLC. PLC. simulation coverage is excellent in NS-3. To repeat prior actions, this system examines several factors. A line's capacity for power and data is shown via NS-3 simulations. With the aid of UDP/IP, we could match substation output for an application-layer transmission rate. Coupling, climate, and cable age cannot be simulated. PLC. technology allows sophisticated simulation tools for end devices [35].

Green-RPL is a low-energy, loss-routing protocol for the CR-AMI network [36]. Estimated EVD influences the priority of packet routing. The least expensive technique is possible because the most energy-efficient node is transferred. While doing all this, the utility needs of SG and secondary consumers are met. An overview of the SG communication infrastructure is presented in Figure 3. Intelligent data collection devices and data communication techniques in SG are shown in Table 2, and the types of networks and their functions are shown in Table 3.

Table 2. Intelligent data collection devices and data communication techniques in SGs [37].

Intelligent Device	Technology	Application
Advanced metering infrastructure (AMI)	Customers and the utilities that provide them may develop two-way communication via data management systems, communication networks, and smart meters.	Power quality monitoring, on-site management, and remote meter setup
Phasor measurement unit (PMU)	A single-time reference is used to synchronize the findings of many distant sites taking real-time measurements at a pace of 30 to 60 samples per second.	The measurement of electrical waves using the power grid
Comprehensive area monitoring system (WAMS)	An application server processes the data that PMUs acquire.	Grid stability under dynamic load
Supervisory control and data acquisition (SCADA)	Both manually and automatically, respectively	Monitoring of the system, processing of events, and alarming
An intelligent electronic device (IED)	Monitoring and documenting the substation and its incoming and outgoing feeds for any signs of wear and tear	The combination of many different types of relay protection with the recording and monitoring of measurements

Table 3. Types of networks and their functions.

Type of Network	Function	Characteristic
H.A.N.	Integrating smart appliances with smart home and office devices to control local energy	Use only at home or in businesses; prolonged data transfer rate (less than 1 Kbps)
NAN	Data about energy usage are gathered and stored at the load data center, which is made up of many HANS (LDC)	Up to 2 Kbps per second is installed within a few kilometers
WAN	Facilitating communication between components of the intelligent grid	Designed for usage over short distances of tens of kilometers or less, and when employed under such conditions, capable of data transfer at many gigabits per second.

Machines may communicate without human involvement using IoT technologies. IoT devices are frequently connected by networks. Because it uses protocols across many network layers, the IoT is successful. A popular choice for network layer routing protocols is the Routing Protocol for Low-Power and Lossy Networks. The proper operation of RPL depends on the existence of the flowing timer mechanism. The setting of the algorithm is directly responsible for the delay in receiving control signals. The trickling algorithm's nodes periodically do nothing but listen. Due to delay and uneven load distribution among the nodes, by allowing the trickling timer mechanism to vary based on the number of hops, the Elastic Hop Count Trickle Timer Algorithm was proposed and offered a novel solution to the problems with the existing method. Experimental simulations were performed in a virtual environment using the Contiki Cooja 3.0 simulator to understand better how RPL with a dynamic trickle timer technique function in the real world. The proposed trickling approach uses less energy, converges more quickly, and sends more packets than the traditional trickling method, the dynamic algorithm, and the e-trickle algorithm [38]. Types of networks and their functions are shown in Table 3.

2.1.7. Short-Term Memory Network

Smart home technologies need more adaptive energy billing and invoicing techniques. The network must expand to meet user problems and adapt to changing situations. The work invented Grid-to-Go to extend S methods. New algorithms face new challenges, especially regarding network data privacy and security [39]. The P4G2Go algorithm is a natural evolution of current systems; it ensures users' and providers' data privacy. This strategy safeguards end-user data by banning connections using anonymous credentials. MASKER and FIDO2 are incorporated to boost the algorithm's security since they do not need sophisticated authentication or a password. They are excellent candidates for the algorithm. It is monitoring that alternative energy development aids communication and information processing. Green energy requires better Wi-Fi. Wi-Fi networks should be star-shaped. All children have one parent. Since secondary nodes need more power, constant connections are insecure, which are constraints on utilizing Blockchain to develop smart wireless networks. Distributed ledgers govern consumer behavior. Web-visibility Blockchain doubles transaction efficiency [40].

2.1.8. Energy Storage and Power Electronics Technologies

Due to inconsistencies in addressing integration criteria (such as standardization, reaction speed, and security) of power substations to SGs, standard communication protocols between grid devices may be challenging to integrate. Integrating these protocols may be challenging due to incompatibilities. Every upgrade necessitates an expensive review of integration needs. The use of a ZigBee sink node as a protocol link is suggested by [41]. The sensor node of each electrical device runs middleware. With the help of this middleware, SG devices may use PSCC data. Interoperability testing is accelerated and secured by power meters (SG elements) linked to sensor nodes. Experiments demonstrate the rapid setup of every new sensor.

Singapore needs microgrids. Nature may damage renewable energy sources. An SG needs microgrids. Molina stores and conditions energy to control it. This ensures the SG power, storage capacity, cost, applications, environmental effect, and longevity are graded for mechanical, electrical, electro-chemical, chemical, and thermal power systems. Alternatives can be considered. Each application must be assessed since none of these technologies meets the SG's needs. Companies may save money by minimizing remodeling expenses, integrating renewable energy sources into the system, reducing emissions, enhancing energy security, reducing import dependence, and avoiding power outages. Upgrade expenses are reduced [42].

In their blueprint for a smart city, the hierarchy of control for a grid of micro grids, the installation of artificial dynamic limits based on self-adequacy criteria, and the existing arrangement of power-producing features. According to the authors, these developments will boost renewable and sustainable energy sources; raise power quality, system security, stability, and resilience; combine many energy providers into energy hubs; and lower end users' energy expenditures [43] According to the hypothesis of the authors, the integration of a self-healing SG in contemporary and future urban settings is now feasible.

Six challenges to the transition to the SG are examined They then call for further study to create safe, effective SGs. This helps in resolving the problems with the energy market [44].

3. Methods and Techniques

3.1. Integration of IoT with Machine Learning to Create Smart Grid

In the subsections that follow, the most popular machine learning algorithms that, when paired with IoT, may make SG as energy-efficient as feasible are detailed. Integrating IoT Technology and machine learning into SG increases energy efficiency, which is presented in Figure 4.

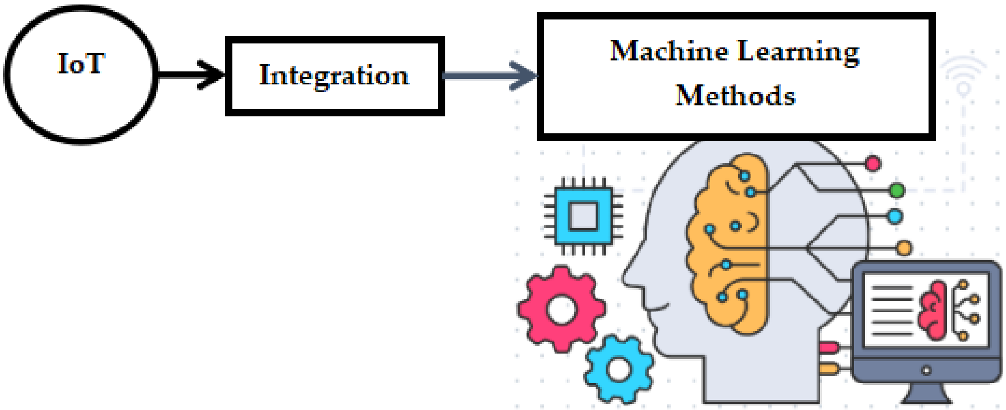

Figure 4. Integrating IoT technology and machine learning into SG increases energy efficiency [45].

3.2. Exclusion and Inclusion

A keyword-based string comprising machine learning approaches and IoT was used to search the papers in various databases, including IEEE, Springer, Scopus, Google Scholar, A.C.M., Science Direct, and Wiley. Those selected papers discussed machine learning classification, SG security, and integration with IoT, and are published in the journals above. After the initial selection of papers, those papers were reviewed. The papers focused on machine learning-based approaches were then identified and included in this research to learn the foundation of machine learning and its SG security. All other papers taken from the initial search were excluded. We included only selective papers in the review selection as the aim was to obtain the baseline of machine learning approaches and research gaps to continue the study. All other papers were excluded from the review.

Research Question

The research questions are given below:

1. What machine learning methods are used in SG?
2. What is the role of the machine learning methods in SG (critical analysis)?
3. What are the challenges in IoT-enabled SGs?

3.3. AI-Based Approaches in Smart Grids

If a structure has automated control systems that utilize data to improve the design's efficiency and the degree of comfort its occupants feel, it is said to be "smart." The levels of resident enjoyment, operational efficiency, and asset utilization may significantly increase due to the integration of AI into structures and devices linked to the IoT [46]. It allows the autonomous integration of surplus data from the IoT sensors and occupant behavior into building systems to produce information, optimize operations, and improve environmental efficiency. These objectives may be achieved by increasing environmental effectiveness, streamlining processes, and discovering new information.

3.4. Machine Learning in Smart Grid

Non-technical losses can be estimated, and smart meter data can be transformed into graphics with fewer mistakes or missing data. This confirms the data. Image analysis employs a neural network design for computer vision. The semi-supervised picture application of this approach facilitates the detection and classification of anomalies. This exposes SG's power abnormalities. This concept uses NTL detection to gather electrical magnitudes, technical characteristics, measurement quality, and GIS. data from SGs [47].

A previous study suggested employing a spectrum-aggregation-based MAC approach to boost CRSN throughput to alleviate the poor wireless conditions in SG The SACRB-MAC moniker was assigned to this protocol (Aggregation Cognitive Receiver-Based MAC). Additionally, SACRB-MAC contributes to enhancing the dependability of CRSNs using the broadcast capabilities of the wireless medium. The simulations and analyses show that SACRB-MAC has a significant capacity and reliable performance, making it an appealing option for CRSNs to pursue to meet the SGs' goal [48].

A real-time online control method was devised for distributed ES energy management [49]. By sharing and redistributing the capabilities of physical ESs, users can administer their own virtual ESs (VESs) without knowing how PESs carry out their duties. This proposal uses the optimization framework to make choices solely based on the recognition of the existing conditions of the system rather than attempting to anticipate the future of energy price, user load, and renewable production [50]. This is done rather than trying to foresee the end (uncertain system states). The authors updated the offline parameter selection to maintain user privacy while transmitting data to anybody, allowing users to control their VESs locally. This was done to enable local VES administration for users. The authors advise that more work on developing the price control for the ES sharing service should be performed soon [51].

For the smart phase to succeed, the DSM, where users report app energy use, is essential. The key is electrical efficiency. SG&HAN supplied safety demand-side management (process). The DSM-focused SG of the smart phase employs HAN SGs that can adjust to changing energy requirements. Residential energy usage is managed through HANs. The smart meters of visitors are controlled and network activity is tracked. New concepts include the HAN, the housing market, and the "Smart Home." Demand-side operations increased HAN connections amongst SG vendors. High-powered gadgets are cleared quickly depending on the load and cost. Figure 4 depicts the system model for DSM. There is no business plan. An IoT-enabled DSM was established DSM receivers may encrypt messages. Human input is used in the SG. HAN uses the final findings. Analysis of trends enables foresight. A diagrammatic presentation of the DSM system is presented in Figure 5.

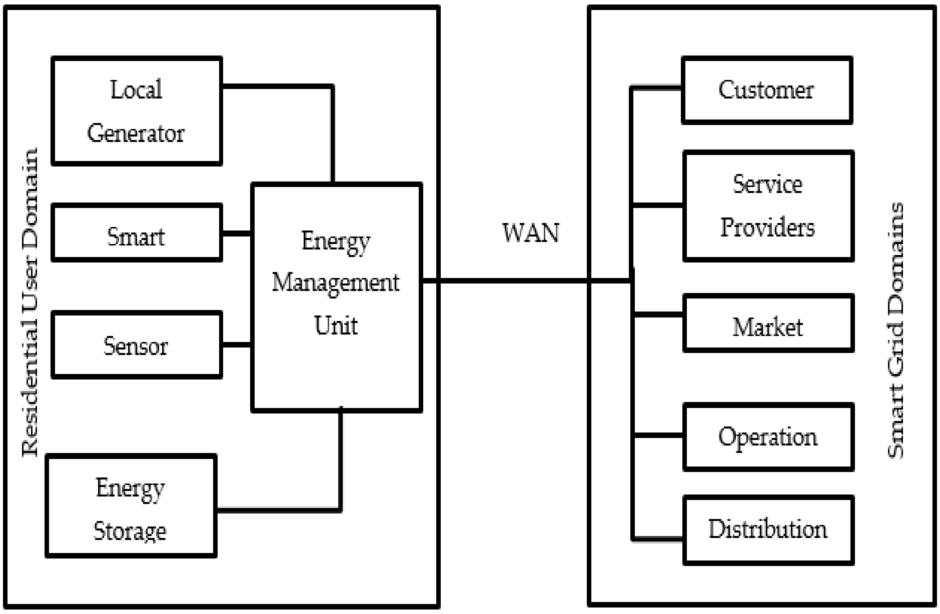

Figure 5. Diagrammatic presentation of the DSM system [52].

3.5. Data Mining in Smart Grids

High-tech sensors are being used more often for measurement purposes due to the extensive development of related infrastructure. It is a requirement for companies that sell electricity to analyze their customers' usage habits using data science technologies such as data mining [53] Grouping consumption loads has led to the development of methods for forecasting the data distribution and, therefore, all the elements that make up the network load. This is being undertaken to advance consumer-friendly energy-saving technologies that may be used in SGs. This is being done to develop unique techniques that might be used in SGs to benefit all stakeholders involved in the energy industry. This article may help with load grouping in SGs since it discusses the basic ideas that form its foundation. These many concepts are organized under the charge classification. The electric charge may be divided into five distinct levels, with eight of the most crucial validity estimators present in each group, depending on the grouping method employed [54].

The creation of novel new services for connecting with people who reside in buildings is made possible by the capacity of the IoT and AI systems to learn new things. These technologies may contribute to cost savings by automating tasks that often require a large amount of human labor [55]. AI technology may be used in SGs to enhance automation, control, and consistency while lowering energy usage. It is possible to examine how various machine learning techniques are applied in SGs, comparing, and contrasting each. Many facilities are using energy management systems powered by AI. Energy equipment found in smart grids includes diesel generators, wind turbines, solar panels, thermal energy storage systems, electric energy storage systems, lighting systems, HVAC systems, window management systems, blind systems, electric vehicles, electric heaters, gas boilers, and washing machines (WMs) [56]. It is imperative to be simultaneously ready for such machinery because of its significant effects on society, the environment, and the economy [57]. Data mining in SGs is presented in Figure 6.

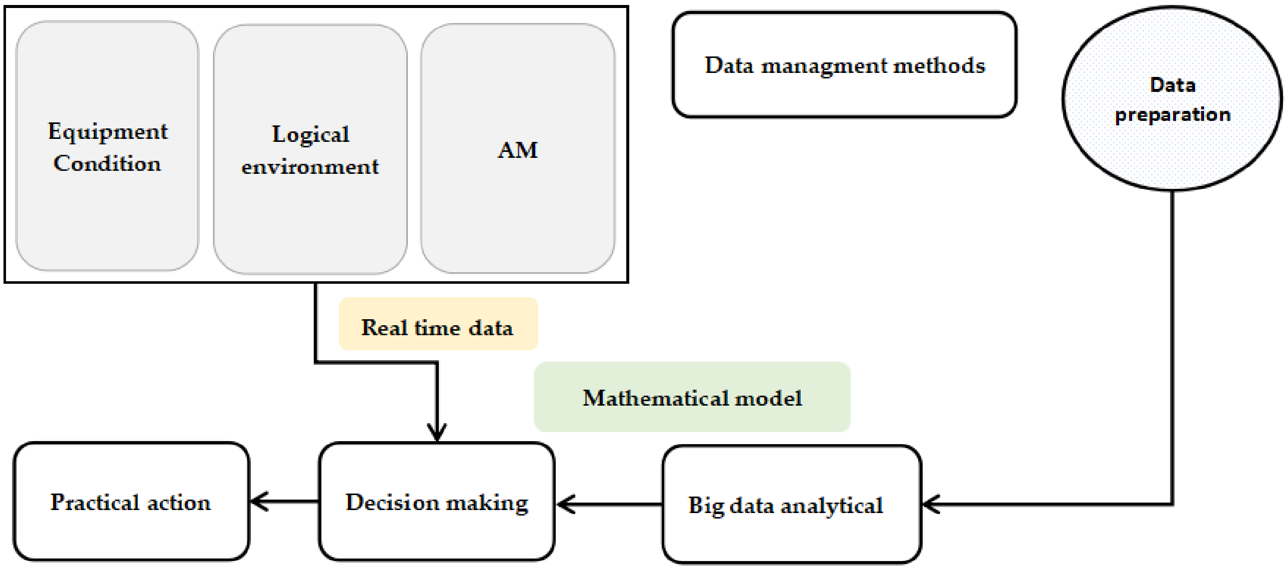

Figure 6. Data mining in smart grids [58].

4. Results

4.1. Artificial Neural Networks (ANNs)

The key objectives of smart grid projects are to reduce overall energy consumption and to boost both the contentment and comfort levels of building occupants. Smart sensors and software analyze exterior and internal parameters to provide a straightforward method for monitoring comfort and safety while simultaneously regulating energy use. It is possible to teach Artificial Neural Networks (ANN), to recognize and rank the importance of basic data patterns in a context with several dimensions. Solar energy has been used with ANNs to estimate the required heating amount [59].The applications of ANN are not limited to just refrigerators; solar energy, air conditioning, modeling, controlling power production, load forecasting, and ventilation systems all use the same technology. Refrigerators are one example of an appliance that can benefit from the applications of ANN. The random forest model was used to estimate the energy used in houses. The Bayesian regularized neural network (BRNN) technique was used to anticipate the energy required by various structures in the future. Real-time monitoring is made possible, for instance, using an ANN to forecast and foresee the temperature of a specific place inside the building [60]. Energy

Plus is software for simulating energy systems. Its numerous potential simulations provide a plethora of data that may be used to train an ANN model and calculate energy usage [61]. Energy Plus is a piece of software that can be downloaded here [https://energyplus.net/ accessed on 1 December 2022]. The neural network-based optimization approach in SGs is shown in Figure 7.

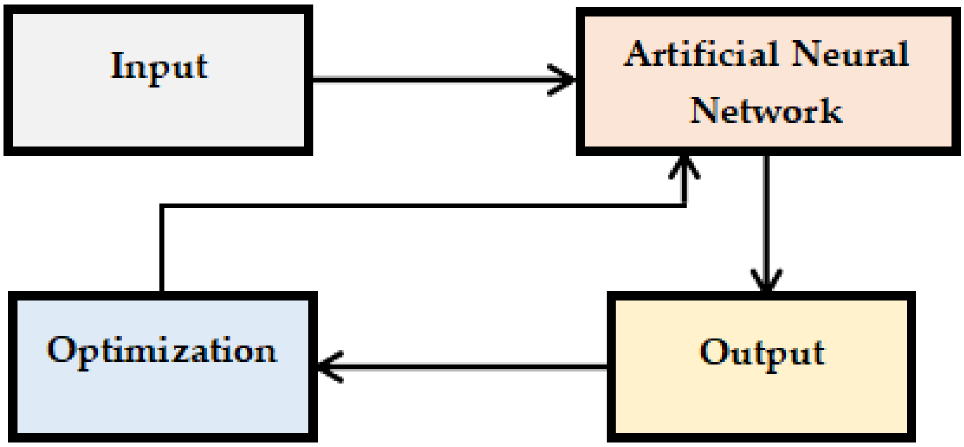

Figure 7. Neural network-based optimization approach in SGs [62].

It takes a significant amount of training to acquire the same output from a neural network, and even if the input is the same, the production can still be different [63]. The signal includes all the procedures that must be undertaken to analyze the input signal and produce an estimate of the energy contained within it. Using energy estimates derived from input signals to guide the following stages in installing hardware- and software-based SG features is standard practice [64]. A user may dictate voice orders into a mobile phone, which are then sent to the building's energy management system through Bluetooth and Wi-Fi [65] Intelligent buildings may also use mobile phones to receive speech instructions for managing electrical appliances.

Many protections have been put into place as security risks rise. The best security tool for finding and following hackers across various network domains is an IDS. The effectiveness of intrusion detection systems has improved with the use of machine learning classifiers to identify threats. This work proposes an investigative model for intrusion detection systems that makes use of a support vector machine-based kernel classifier and feature selection based on principal component analysis. It examines how support vector machines are affected by linear, polynomial, and Gaussian radial basis functions, and Sigmoid kernel functions [66]. The detection accuracy, True Positive, True Negative, Precision, Sensitivity, and F-measure of the inquiry model are assessed in order to choose an appropriate kernel function for the SVM. Utilizing information from the KDD Cup'99 and UNSWNB15, the research model was tested and assessed. For both sets of data, the Gaussian radial basis function kernel outperformed the linear kernel, the polynomial kernel, and the sigmoid kernel. The UNSW-NB15 dataset's accuracy varied from 93.94 and 93.23 to 94.44% [67].

4.1.1. Wavelet Neural Network

The ability to accurately predict a building's energy requirements is fundamental for efficient energy management and pollution prevention. Issues with VAV temperature, flow, and pressure sensors may be uncovered using a wavelet neural network. This technique is used in wavelet transforms and neural networks. Time-series analysis has the potential to shorten charging times for batteries and save system costs. This is made more accessible by micro grid dependency prediction. Integrating the two approaches improves accuracy [68].

The authors] promote using a wavelet neural network as a technology to improve the effectiveness of PID controllers. A PID controller executes both integral and derivative functions [69]. A cutting-edge control system was constructed by on top of an existing neural network, having PID as its main component. The system portion responsible for delivering the required value is the control strategy management component, sometimes called the "brain" of a closed-loop control system [70]. An intelligent strategic control approach is necessary to create control logic for SG technologies that can adapt to the most current environmental circumstances that is, the capacity of SG technology to save energy and lessen its adverse effects on the environment [71]. The most popular control techniques include the on/off control, the proportional control, the proportional integral derivative control, and the proportional/integral control (PI). Frequently, all that is needed to take control of the building's lighting and window treatments is to turn on or off a switch. PI/PID model controllers are often used in HVAC systems to manage temperature and humidity [72]. This is done for the system to maintain the proper temperature or humidity level. A neural network PID offers advantageous traits, including self-learning capability and decoupled dynamic control [73].

Low-power and lossy networks must adopt effective protocols that use few resources due to the nature of their operation. Multiple low-processing, low-storage, or low-power devices are linked together by low-power, wide-area networks [74]. Traditional routing protocols such as Open Shortest Path First do not work well with LLNs because of their constrained capabilities. The IPv6 Routing Protocol for Low-Power and Lossy Networks was created to solve these problems. However, it soon became clear that relying on a single metric for the OF was insufficient to account for the wide range of use scenarios [75]. Based on the research's conclusions, OFRRT-FUZZY was proposed as an upgrade to OF. This new and enhanced version makes full use of measurements and fuzzy logic. Both connection metrics and node metrics are used by OFRRT-FUZZY [76]. By doing this, the problems caused by using a single measure are avoided. The Received Signal Strength Indicator (RSSI), Remaining Energy (RE), and throughput are three relevant measurements (TH). To identify which OF is preferable to OF0 and MHROF, the proposed OFRRT-FUZZY approach was implemented in the Cooja simulator, and the results were compared [77].

4.1.2. Machine Learning Algorithms

Machine learning techniques such as unsupervised or semi-supervised feature extraction and hierarchical feature extraction show promise. RNN, CNN, DBM, SAM, and DBN are some of the most well-known machine learning approaches [78]. Convolutions and drop-out algorithms are used in deep understanding to rapidly learn from massive dataset. More data are needed for machine learning than conventional methods. Unsupervised or semi-supervised feature extraction is an effective machine learning technique [79]. These approaches include the decision tree, KNN, random forest, SVM, and SVD. Convolutions and drop-out algorithms are used in machine learning to quickly analyze big datasets. More data are needed for deep understanding than usual. Machine learning algorithms are presented in Figure 8.

4.1.3. Time Series Analysis

It is crucial that machine learning places a strong focus on time series prediction. Dimensionality is a common issue in time series data sets. The non-data-adaptive depiction, model-based depiction, and data-adaptive depiction are three distinct methods of representation that all aim to reduce the dimensionality of time series [81]. The authors in developed a time series-based framework for SGs to determine temporal principles from the measurable machine and human activities [82]. To create a reliable electric load forecast model, a support vector machine (SVM) was employed in conjunction with fuzzy time series and universal harmonic search approaches [83]. Building data-driven energy consumption measurement techniques was examined in [84]. Their research revealed that retrofitting, energy consumption profiles, and load forecasts are part of data-driven solutions. The most well-known alternative for many applications, such as energy estimates and retrofitting solutions, is the ANN model. Because SVM models may be adjusted during training, they have often been employed for extensive building energy evaluations [85].

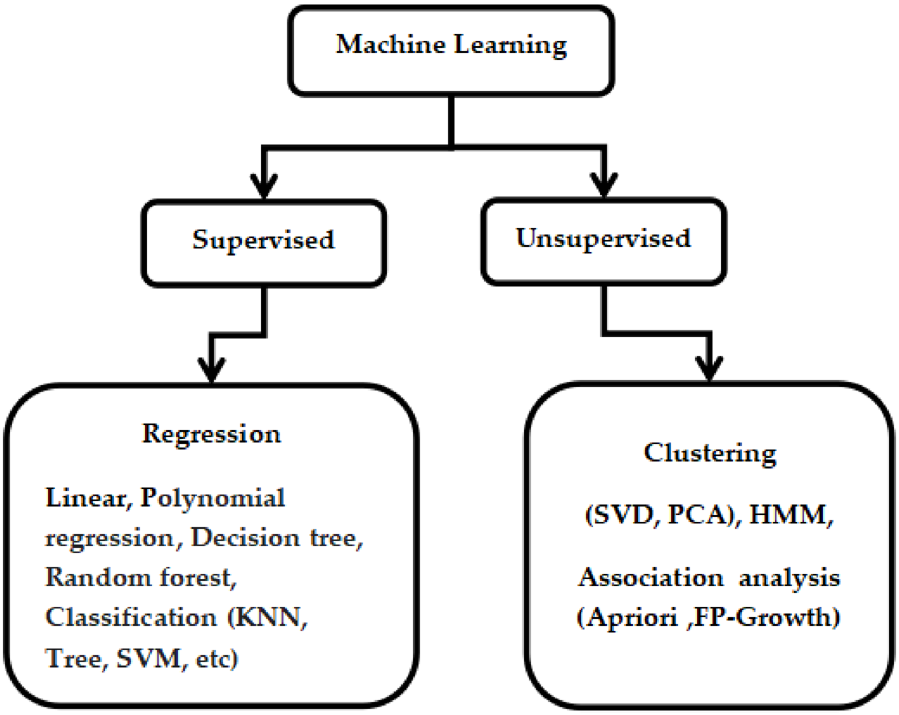

Figure 8. Machine learning algorithms [80].

4.1.4. Regression

Finding the desired function using the gathered data is the aim of a regression problem. It describes the correlation between variables often assessed regarding the accuracy of the model's predictions [86]. The three most common types of regression analysis are linear regression, ordinary least squares regression, and regression analysis. The authors employed the orthogonal matching pursuit algorithm's regression technique to identify the environmental and physical factors that affect the energy efficiency of SGs [87]. This research sought to determine and assess the effectiveness of regression models in predicting the energy consumption of commercial buildings. They used data gathered from actual structures to make empirical comparisons between various models easier. The researchers found that the regression models performed adequately compared to other, more complicated ML models [88].

4.1.5. Deep Learning Methods

Because it addresses the problem of making thoughtful judgments in uncertainty, reinforcement learning is a popular topic in machine learning [89]. Artificial artifacts may use reinforcement learning to learn from their activities and make accurate predictions. The trial-and-error approach teaches this. Existing methods struggle with real-time building energy optimization in huge areas. Traditional energy management systems are less versatile due to deployment limits. Thanks to IoT and computer capacity, AI is now a fundamental tool for management and optimization [90]. Deep reinforcement learning (DRL) improves SGs energy efficiency [91]. Deep reinforcement learning is presented in Figure 9.

4.1.6. Decision Tree Classification Algorithm

It helps to choose the machine learning algorithm best suited for the dataset being used and the issue being addressed since many machine learning algorithms can be used to build a model. The simplicity of decision trees' construction may be part of their growing popularity [93]. Regression and data classification may both be performed with the use of decision trees and non-parametric supervised learning. With the help of prediction models such as decision trees, it may be possible to map many different paths to the desired outcome. There are many nodes of various types included in the decision trees that are built. The decision tree's root node or starting node represents the whole dataset in machine learning [94]. The junctions at the very tip of the branches are known as leaf nodes. Creating additional components at the highest level of the decision tree's leaf node is impossible. The leaf node of a decision tree is used to represent the conclusion in machine learning, whereas the inner nodes represent the data qualities]. Decision tree models have a broad range of uses in smart energy buildings including predicting the likelihood of an outage and storing data on energy management and consumption [95].

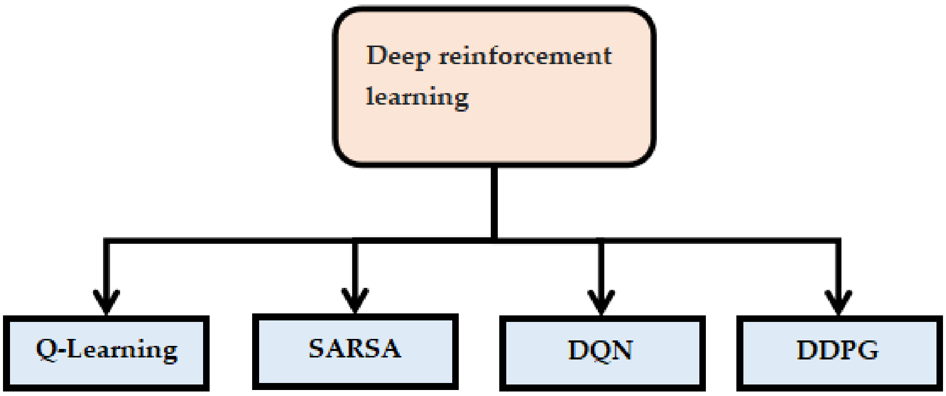

Figure 9. Deep reinforcement learning [92].

4.1.7. Genetic Algorithms and Their Use-Cases in Machine Learning

A genetic algorithm (GA) may help in many optimization problems. GAs, or geographic information systems, may accurately identify large and complex locations. When creating GAs, a heuristic search method is used [96]. To address issues with search and optimization, a GA is employed. Evolutionary algorithms, of which this specific one is a subtype, are used to solve this problem using a computer. Genetic algorithms use the concepts of evolution and natural selection to solve issues and provide answers. Binary strings, or arrays of bits or characters, are sometimes used in genetic algorithms to represent chromosomes [97]. This enables the algorithm to use its calculations. Each string represents a different approach, and the genetic process keeps enhancing the chromosomes with the best chances of succeeding. The automated machine learning method tree-based pipeline optimization (TPOT) is used to optimize ML pipelines. Genetic algorithms are used in this procedure. The authors developed a power management system based on predictive analytics to lower energy consumption and increase user comfort in residential buildings. To maximize customer happiness and boost the overall effectiveness of energy consumption reduction, researchers employed a genetic algorithm in combination with data smoothing during the whole optimization process [98]. The application of genetic algorithms in machine learning is presented in Figure 10.

4.1.8. Support Vector Machines (SVMs)

Support vector machines, or SVMs, are a kind of technology that fits within the supervised learning category. The purpose of developing an occupancy rate projection is to foresee the facility's current management position, resident satisfaction, and overall security and safety [100]. SVM algorithms hunt for the hyperplane that offers the most significant distinction between the two kinds to divide data into two groups, both occupied and vacant [101]. Non-differentiable pair data may be classified using non-linear kernel functions, such as essential radial functions. By expanding the data dimensions, SVMs categorize almost all data nowadays. These approaches find an objective function for all training data. Sunlight, temperature, and humidity are also important. Table 4 describes the various machine learning algorithms, their objectives, and potential uses in IoT applications to improve energy efficiency in intelligent grids. In response to the rise in security breaches, researchers are using support vector machines and other classifiers in intrusion detection systems. Prior to anything else, a basic understanding is required of how security attacks, IDSs, and SVM classifiers work. The SVM-based intrusion detection strategies show how researchers have altered SVM classifiers to detect a range of security threats. They also cover the main conclusion schemes and show how algorithms and techniques were used to raise the detection rate and precision of the SVM [102].

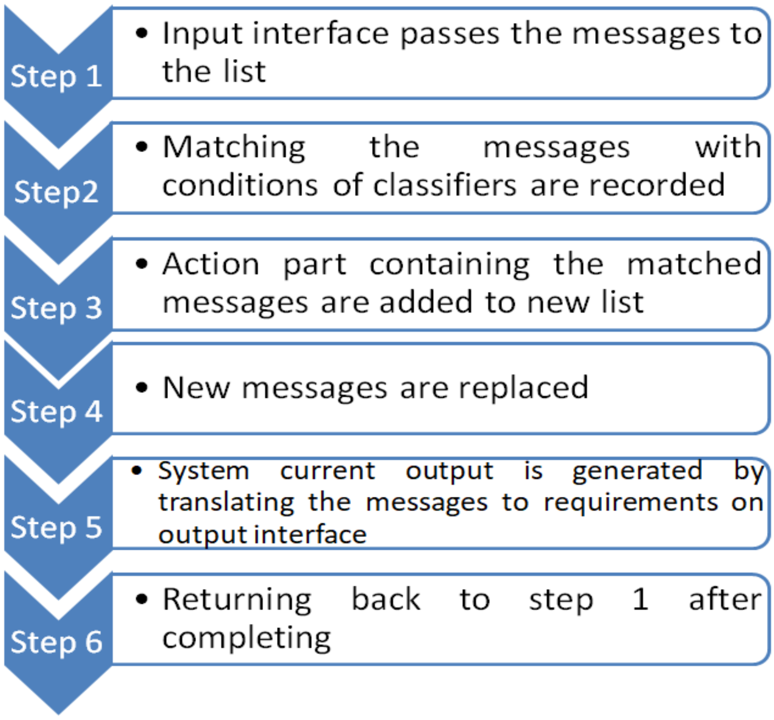

Figure 10. Application of genetic algorithms in machine learning [99].

Table 4. The objectives of IoT technologies, the domain of machine learning algorithms, and the context of smart grid applications.

Sr. #	Machine Learning Models/Algorithms	Objectives in IoT Technologies	Smart Grids Applications Domain	Advantages	Disadvantages
1	ANNs	Making predictions and models	Intelligent sensors may help to cut energy use	Excellent accuracy and comfortable monitoring	Complex
2	WNN.	Making predictions based on historical facts	Useful for architectural lights and window coverings	Excellent consistency	Low speed
3	Deep learning	Both data predictions and pattern modeling benefit from it	Helpful for modeling and planning energy-saving solutions	High precision and acceptable speed	Very complicated
4	Time series analysis	High dimensionality	Produces accurate findings for energy use forecasting in buildings.	Predict the future	The observationsare not independent of one another
5	Regression	Predictions based on behavior	Learn more about the physical and environmental factors affecting Smart Grids' energy efficiency.	Rapid speed	Unreliable precision
6	Deep reinforcement learning	They are systematically making decisions	It may help solve the problem of energy waste in intelligent structures.	Solve complicatedtasks	Very complicated

Table 4. *Cont.*

Sr. #	Machine Learning Models/Algorithms	Objectives in IoT Technologies	Smart Grids Applications Domain	Advantages	Disadvantages
7	Decision treeclassification	Presents many available options	Indicates the probability of an outage and manages the building's energy supply and use.	Simple to understand	Relative inaccurate
8	Genetic algorithms	Troubles are optimized	Optimal load management and improved energy efficiency.	Excellent accuracy	Low speed
9	Support vector data and the machines	Methods for ensuring its safety in the IoT environment.	Estimation of future construction energy consumption.	Excellent accuracy	It is complex, and the speed is low

4.2. Challenges in IoT-Enabled Smart Grids

The term "Industry 4.0" is often used to refer to a specific industrial infrastructure that utilizes the IoT to link embedded software, the real world, and cyber-physical technologies [103]. This paradigm encourages cooperation throughout the manufacturing process due to the employment of ML and AI. Healthcare, home automation, entertainment, commerce, education, and the workplace are just a few areas where the IoT may be applied [104]. The ability to remotely manage and monitor a variety of appliances and other equipment in smart grids may make tenants feel safer and at peace. Despite the potential advantages of intelligent buildings, many issues must be resolved before they can be extensively used. The degree of safety in smart grids may be significantly raised by paying close attention to the building's administration, design, and rules [105].

Residents may feel more secure and comfortable in buildings that integrate AI, and the IoT-enabled smart grids employ the data collected from various sensors to lower their energy usage and improve operational efficiency [69]. Smart grids can better manage their energy usage since they are outfitted with the IoT devices [106]. Smart grids may use less energy due to IoT monitoring of environmental characteristics, including humidity, temperature, and pressure. In smart grids, sensors linked to the IoT automatically switch lights. Networked devices connected through the Internet may improve emergency management and response. The IoT has profoundly changed our knowledge of how safety mechanisms work since it allows the connection of sensors and the transmission of real-time data to those in control of the situation and those at risk [107]. Figure 4 illustrates a few advantages that may be attained by incorporating these new ideas and cutting-edge technology into the design of intelligent buildings. This sort of application may contribute to the development of structured smart features and provide users with greater ease. The essential IoT-enabled factors need to be integrated with AI for smart grids to become more energy efficient. Challenges in IoT-enabled smart grids are presented in Table 5.

Table 5. Challenges in IoT-enabled smart grids.

Sr. #	Challenges	Function, Role in IoT and Smart Grids	Descriptions
1	Big data analytics	Critical data volumes are produced every second in smart grids	Vast amounts of varied, high-resolution data are being produced by the IoT, which may be put to various uses—applied to gathering massive amounts of data for analytical purposes, given the situation [108].
2	Availability of services and networks	Intelligent buildings manage a complex network	For intelligent buildings, coordinating the operations of several linked building systems is a big task [109].
3	Cyber security	Take care of the building operations' growing complexity	Increased demands on building operations need to incorporate IP cameras into building automation systems (BASs). These changes put individuals in harm's way and opened up new attack vectors [110].

Table 5. *Cont.*

Sr. #	Challenges	Function, Role in IoT and Smart Grids	Descriptions
4	Control and legislation of how much energy a structure uses	The system is in place to manage a building's energy use	It is impossible to manage energy effectively without this system implemented in the facility. Energy cost inspection, energy use anomaly detection, and automated demand response offer significant challenges [111].
5	Boost visibility	To find improper settings, visibility is crucial	Monitoring the data flow into and out of the network is critical when there is a connection. Only if there is visibility into them may misconfigurations, errors, or anomalies that might result in a security vulnerability be detected [112].
6	Connectivity, programmability, and manageability	Offers users high-level services while minimizing the number of resources used	Intelligent building management using the IoT could improve user experience and resource efficiency. The main concerns include control, connection, and programmability [113].
7	Sensors' range	To convey data, smart grids need sensors	Costs may quickly increase, particularly for "smart" buildings, when the range of sensors is restricted [114].
8	Smart grids reduce energy usage	It offers data analytics on the energy consumption of intelligent structures	Finding the most pertinent elements to the issue at hand is the first step in increasing energy efficiency; with this information, appropriate algorithms may then be designed for processing the data and information acquired [115].
9	Information gathering, handling, and storage	The system should concurrently gather several sorts of data	Thanks to the IoT, data may be gathered from a building's interior, exterior, and infrastructure. For the system to provide accurate results, it must be able to concurrently collect many kinds of data [116].
10	Recognizing and attempting to anticipate the behavior of locals	The precision needed for safe navigation inside contemporary constructions is nonexistent in existing GPS systems.	Deciphering resident behavior is complex, and finding those who have concealed themselves within structures is much more difficult. The precision of current GPS systems is insufficient for usage in enclosed spaces; instead of assisting with navigation, they are intended to track geo-fences and other location-based applications [108].

A "smart grid" is an intelligent electrical grid that can grow and change in response to fluctuating power needs. It is crucial to prepare the power grid for the future. The term "smart grid" describes a system of electrical power distribution that controls energy generation, transmission, and consumption using state-of-the-art computerized systems. This is now possible due to the smart grid. In their design, cutting-edge communication, control, monitoring, and self-diagnosis technologies set these networks apart [117]. The main elements that affect how an intelligent grid is constructed are shown in Figure 3.

Energy distribution networks are more complex in nations with fewer renewable energy sources. Mexico has high-quality power. Poor resource management, improper integration of renewable energy, and subpar service are all problems. Renewable energy is valued in Mexico and Central America. By 2030, it is envisioned that big power plants will generate 50% of their energy from renewable resources such as the sun and wind [118]. The traditional sources will provide half of the power, with the other half coming from distributed and micro-generational sources such as household wind and solar. Innovative grid development is impacted by several important factors in Figure 11.

Any country that aspires to thrive sustainably must have an energy system that is efficient, adaptable, and intelligent. This enhances technology, economics, and environmental productivity in addition to energy supply. Smart grids bring a new era of reliability, availability, and efficiency to the electric power industry, which benefits the global economy and the environment. To guarantee that the benefits of smart grids are realized throughout the transition phase, it is essential to perform testing, implement technical developments, educate customers, set norms and laws, and disseminate information among electrical workers [120].

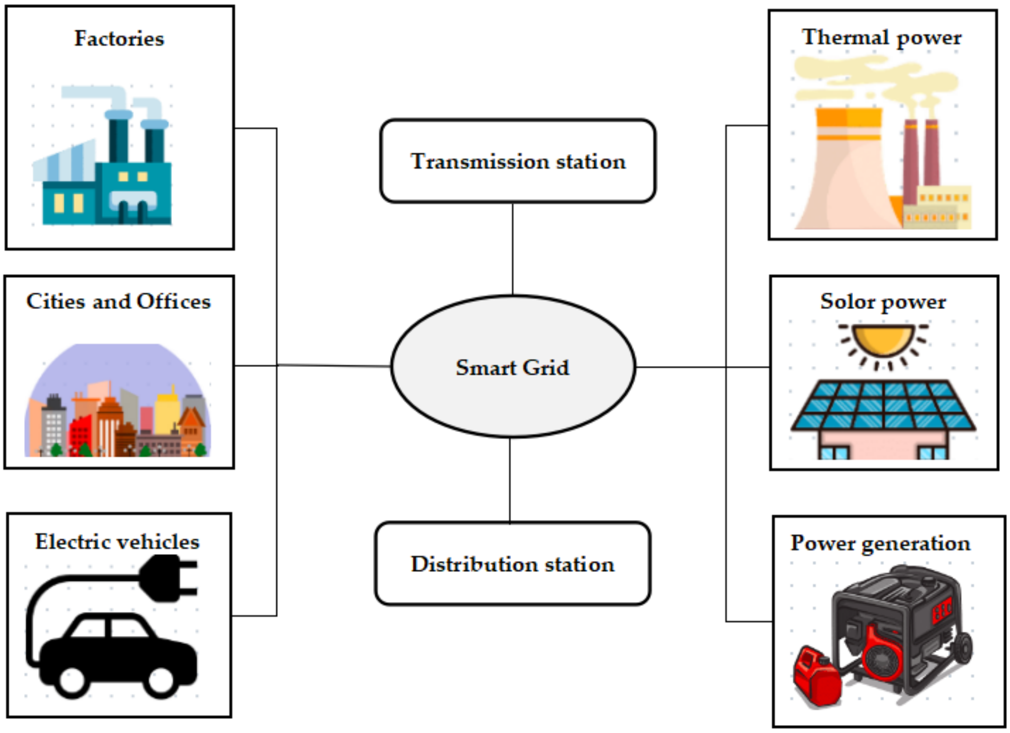

Figure 11. Innovative grid development is impacted by several important factors [119].

Before this shift, it is essential to make informed assumptions regarding the technologies' effects on energy providers, consumers, and other electrical sector actors. We looked at smart grids' advantages over alternative systems, their benefits for a functioning electricity grid, and the problems of implementing them. Our primary objective was to examine these technologies and learn how they affect different contexts [120]. This involves analyzing how they may improve the electrical system's safety, dependability, and general quality.

5. Conclusions

Machine learning techniques applied to physical data, according to this research, are used to detect cyber-physical threats and make testing easier by requiring less processing. Additionally, using ML and deep learning, systems that can distinguish between a genuine problem and a cyber intrusion are being developed. These engines will be used by massive SGs. Service providers are using machine learning-based techniques to collect energy resources from a variety of clients. This will reduce energy fluctuations and increase the dependability of SG. Deep learning is used to investigate Het Nets' energy efficiency and latency difficulties in order to convey SGs' data under different time constraints. Deep learning is used to safeguard SGs against cyberattacks. The models put blocks together using hashing and short signatures. Machine learning is used to analyze and improve the energy efficiency of SGs. Intelligent power grids work in this manner. This article aims to improve energy efficiency by connecting buildings to IoT-enabled smart grids, which have both advantages and disadvantages. This article discusses the use of IoT by advanced facilities. IoT devices can test smart grids. Machine learning and SGs have the potential to improve energy efficiency. Aspects and components of the SG are discussed. This article discusses how IoT and machine learning can improve SG's efficiency. AI and IoT devices have the potential to improve SGs. Because of recent advances in machine learning, SGs are now more accessible, although improving energy efficiency remains challenging. SG issues may aid in commercial and academic research.

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