International Journal of Applied Power Engineering (IJAPE)
Vol. 13, No. 3, September 2024, pp. 583~593
ISSN: 2252-8792, DOI: 10.11591/ijape.v13.i3.pp583-593

Transformation and future trends of smart grid using machine and deep learning: a state-of-the-art review

Khairul Eahsun Fahim[1], Md. Rakibul Islam[2], Nahid Ahmed Shihab[2], Maria Rahman Olvi[2], Khondaker Labib Al Jonayed[2], Adri Shankar Das[2]
[1]ZNRF University of Management Sciences, Dhaka, Bangladesh
[2]Department of Electrical and Electronics Engineering, BRAC University, Dhaka, Bangladesh

Article Info

Article history:

Received Jun 17, 2023
Revised Feb 22, 2024
Accepted Mar 15, 2024

Keywords:

Deep learning
Electricity market
Energy dispatch
Machine learning
Power generation
Smart grid
Smart grid security

ABSTRACT

A smart grid is a cutting-edge energy system designed to take over old-fashioned energy infrastructure in the twenty-first century. With comprehensive communication and computation capabilities, its primary objective is to increase energy distribution's dependability and efficiency while minimizing unfavorable effects. A number of approaches are needed for effective analysis and well-informed decision-making due to the massive infrastructure and integrated network of communications of the smart grid. In this study, we examine the architectural elements of the smart grid as well as the uses and methods using machine learning (ML) and deep learning (DL) with regard to the smart grid. We also clarify present research limitations and propose future directions for machine learning-driven data analytics. In order to improve the stability, reliability, security, efficiency, and responsiveness of the smart grid, this paper examines the implementation of several machine learning methodologies. This paper also covers some of the difficulties in putting machine learning solutions for smart grids into practice.

Corresponding Author:

Khairul Eahsun Fahim
ZNRF University of Management Sciences
Pragati Sarani, Dhaka 1212, Bangladesh
Email: fahim.iitbombay@gmail.com

1. INTRODUCTION

Notwithstanding the necessity for modernization and the electrical power grid's inability to adequately fulfill 21st-century needs, the fundamental structure hasn't altered over time. The grid has been further pressured by rising population and electrical usage, rendering its outmoded infrastructure unable to serve the demands of the present [1]. The United States demand for and use of electricity have both increased at a yearly average of 2.5% during the previous 20 years, according to the U.S. Government's Department of Energy [2]–[4]. The old way of distributing power is unable to keep up with the rising demand and is riddled with flaws, such as sluggish reaction times, an absence of real-time analytic tools, and poor situational awareness. Inadequacies like this are to blame for recent blackout occurrences.

A brand-new idea called the "smart grid" has arisen to address the problems caused by the outmoded electrical power system. The smart grid, also known as the smart grid or intelli grid, symbolizes an advanced electrical power network for distribution that utilizes dual direction flows of electrical power as well as data to create a computerized and centralized system for providing energy [5]. The traditional power grid supplied electricity to a big client base from centralized sources. With its interconnected and distributed supply of energy network that combines bidirectional flows of power and information, the smart grid (SG), in contrast, marks a paradigm change. The internet of things (IoT), which serves as a key enabler for its functioning, is largely dependent on the smart grid's operation [6]. Furthermore, cyber-physical systems (CPS) are essential to the smart grid because they make it easier to collect, share, and manage data and activities [7]. CPS are crucial elements of the contemporary smart grid, revolutionizing energy distribution, and are distinguished by their unique combination of computer and physical features.

The smart grid (SG) is a general term for an extensive electrical network that includes cutting-edge technology including self-healing mechanisms, intelligent communication, and real-time monitoring. Its main goal is to provide a steady and secure power supply while giving prosumers, who use and generate electricity, and various alternatives. Due to its elaborate design and seamless integration of both physical and computational components, the smart grid is regarded as a complex computerized physical system (CPS). The smart grid follows a centralized strategy in contrast with conventional power systems, where a small number of centrally located stations transmit energy to a wide variety of users [7]. Energy management and distribution have undergone radical change as smart grids and CPS have replaced conventional power systems over time.

There is no doubt that electricity is essential to human existence. Therefore, a crucial necessity for a smart grid (SG) is to provide high dependability. The smart grid’s reliability and stability are essential since many countries’ economies rely substantially on it [8]. Four basic pieces or components make up the functional division of the current smart grid.

- Generation: There are several ways to generate electricity, including burning fossil fuels, capturing sun and wind energy, and using nuclear reactors.
- Transmission: Electricity can be transferred over great distances from power plants to distribution facilities thanks to a high-voltage electronic infrastructure.
- Distribution: The transmission of power from distribution hubs to companies, residences, and other locations is the task of the distribution phase.
- Consumption: Electricity is used by end users, including businesses, households, and different sectors, for a variety of tasks including running machinery, lighting, and home appliances.

Consumer reports are typically used in the conventional grid to identify outages [8]. Due to the absence of precise methods for anticipating demand and demand reduction, forecasting and properly matching subsequent generations with demand is a challenging challenge for utilities. In order to satisfy peak demand, utilities frequently resort to over-generating energy, which raises prices and contributes to an increase in greenhouse gas emissions. As a result of their intermittent nature, intermittent generating sources like wind and solar electricity present extra hurdles when trying to be integrated into the grid architecture.

Smart grid technology (SG) has a number of benefits. By using intelligent communications, it makes it possible to effectively control peak demand by using load shedding techniques, which eliminates the need for extra generation facilities. Predictive analysis is possible using machine learning (ML) along with deep learning (DL), even in situations when solar and wind power provide less energy. This enables utilities to keep the supply of power balanced. The SG's capacity for intelligent demand prediction is further improved by the inclusion of cutting-edge utility-scale storage technology. Customers may also receive and react to price signals thanks to the SG, giving them control over their energy bills and assisting utilities in avoiding building more generation facilities. Overall, these approaches lead to a significant reduction in costs for both power generation and consumption within the smart grid [8]. Because there isn't much sunshine at night, solar PV has a low factor of capacity of 10-20%. As a result, more developed photovoltaic (PV) capacity is required to generate the same quantity of power as other energy sources [9]. In the ASEAN region, where numerous nations have abundant wind turbines and are striving to broaden their energy sources, wind energy encounters a lot of potential. The speed of the wind and the dimension of any prospective wind turbines determine how much wind can be produced at a certain location [9]. Rest of the paper is outlined as follows: i) section 2 talks about the different methods used in this process, ii) section 3 talks about the advancement is smart grid, iii) section 4 talks about emerging machine and deep learning technologies in the smart grid, iv) section 5 sheds light on the limitations of machine and deep learning applications in smart grid, and v) section 6 concludes the paper.

2. METHODS

The methodological approach used in this study takes into account several aspects of IoT integration in smart grid technologies, the structure of a smart grid, and the use of machine learning and deep learning. while the network layer creates communication linkages and the application layer analyzes data to create intelligent services, data gathering for IoT integration requires sensors and devices capturing variables like voltage, current, temperature, and system status. Data kinds, communication connectivity, and overall efficacy are all included in measurements. Component identification, interconnectivity evaluation, data and information flow analysis, and security measure inquiry are steps in studying the anatomy of a smart grid, with measurements emphasizing interoperability, real-time data flow, and security effectiveness. The methodology for the machine learning and deep learning investigation includes a literature review, data collection, algorithm selection, model training, performance evaluation, and discussion of future research directions. Measurements include algorithm performance metrics, data sets, and requirements for future research. The extent of the investigation is finally affected by constraints and limitations, such as data accessibility and processing capacity. Key discoveries and contributions are summed up in the section's conclusion.

2.1. Using IoT to advance smart grid technology

The internet of things (IoT) ongoing development has made it possible to solve the changing smart grid's difficulties with solutions. The development of intelligent services that have become necessary for the operation of the smart grid is made possible by IoT-enabled technologies. The capabilities of the smart grid have been greatly improved, and progress has been made as a result of the integration of IoT.

The smart grid's IoT design unifies various layers, making it possible for effective data collecting, communication, and analysis. This improves the grid's functionality and effectiveness [10]–[12].

- Perception layer: It collects data from sensors and devices present in the smart grid.
- Network layer: This layer enables communication and connectivity between different devices and components of the smart grid.
- Application layer: It utilizes the collected data to provide intelligent services and applications.

IoT technologies, which provide a variety of applications, are now essential to the operation of the smart grid. They are used for deploying smart patrols, managing g electric cars, supporting smart homes, and monitoring power transmission lines. IoT technologies are also essential for the smart grid's network architecture, management of network security, maintenance and operation, data gathering, surveillance of security, measurement, and user engagement. IoT applications have a huge potential and may be used for all aspects of the electrical power system, particularly energy production, transmission, conversion, distribution, and use [13].

2.2. Anatomy of a smart grid, components, and connectivity

The modern smart grid is built with computerized regulatory systems, cutting-edge energy management techniques, advanced communications infrastructure, power converters, monitoring and measuring technologies, and the structural support needed to ensure reliable and efficient energy transmission. It is significant to highlight that this current smart grid architecture differs noticeably from the traditional grid and is far more complex. Figure 1 shows how the contemporary smart grid, which replaced the conventional grid, has communication capabilities, sophisticated controls, and a decentralized distribution system.

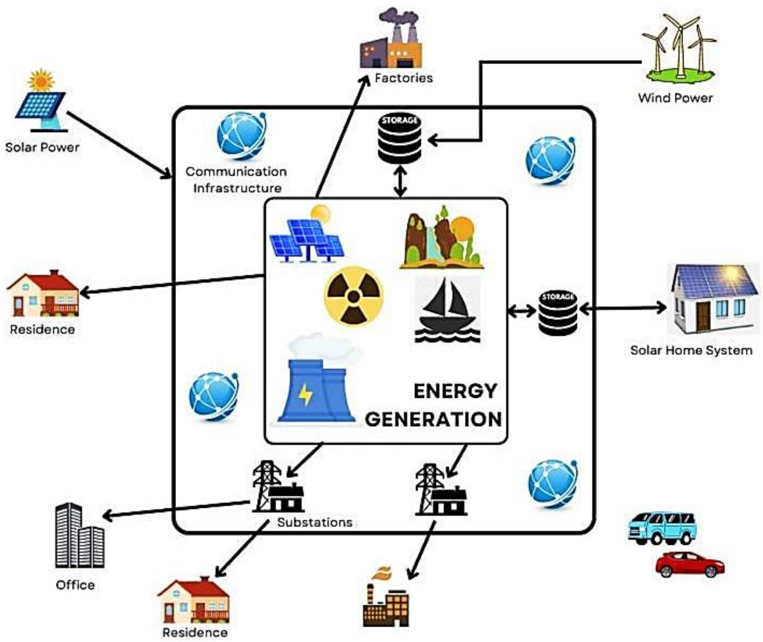

Figure 1. Anatomy of a smart grid

The grid system's many parts are connected to one another utilizing detecting nodes and communication paths to promote interoperability, as shown in Figure 1. Real-time data and information analytics are essential in the framework of the SG in order to guarantee a continuous and dependable energy distribution from power producing sources to users. In the case of equipment failures, natural catastrophes, or power outages, the SG system provides protection via real-time condition tracking, diagnostics, and outage monitoring. The SG system's real-time condition tracking and diagnostics quickly identify problems, allowing for immediate intervention. Its monitoring capabilities enable rapid response during outages or disasters, ensuring minimal disruptions and efficient restoration efforts [14]. For safe information transfer and storage, which is necessary for billing purposes, automated control mechanisms must exist inside the SG framework. The internet of things (IoT) is a large network made up of an increasing number of internet-connected devices, making it essential to create strong security measures to thwart unwanted cyberattacks.

The following part of this paper explores a comprehensive investigation of the application of machine learning along with deep learning uses in the context of the SG. We next move our attention to talking about the potential future directions for this field's progress. We also offer a thorough review of the constraints imposed by the ongoing research projects. Finally, we summarize the results and provide a comprehensive summary of the study to wrap up our work.

3. SMART GRID ADVANCEMENTS

ML and DL are establishing themselves as revolutionary technologies for analyzing the big data created by the underlying IoT devices, critical infrastructure, and enormous communications system in order to accurately understand and make timely decisions to manage the SG. The phrase "big data" refers to the vast amount of statistical data that needs to be gathered, handled, managed, and evaluated utilizing increasingly advanced techniques [15]. The term "machine learning" refers to suggestions based on readily available information and continuous learning. It is composed of a variety of algorithms that examine data before applying a set of rules to make judgements or predictions about the current state of affairs. Artificial neural networks, a type of algorithm used in deep learning, are inspired by the architecture and functioning of the brain [15]–[17]. In the domain of SG, ML, and DL functions include forecasting regarding.

- Sustainable electrical power generation: algorithms using machine learning and deep learning forecast demand patterns, the production of renewable energy sources, and grid stability to optimize energy generation.
- Value forecasting the future: To anticipate energy prices, ML and DL models examine past information and market variables. This enables efficient pricing schemes and demand response initiatives.
- Consumption of electricity analysis: To find potential for energy savings, to improve load balancing, and to make demand forecasting easier, algorithms using machine learning, and deep learning examine consumption trends.
- Anticipatory fault identification: Self-restoring capabilities on grid failure [18], and machine learning and deep learning models identify anomalies and structures in grid data to identify errors or malfunctions in the electrical infrastructure [19], enabling preventative repairs and minimizing downtime.
- Optimization of constituent sizing: Based on system requirements and load requirements, ML and DL approaches help determine the best size for grid components like transformers and capacitors.
- Initial identification of network abnormalities: ML and DL algorithms keep an eye on network data for anomalies like aberrant power flows or voltage changes, allowing for the early identification of possible problems.
- Illegal behavior identification: ML and DL models spot anomalous patterns of consumption or meter manipulation, assisting in the identification and prevention of energy theft and other fraudulent activities [20].
- Cybersecurity breach recognition: To identify and stop cybersecurity risks, ML and DL algorithms analyze network data to find suspicious activity. ML and DL algorithms act as vigilant watchdogs, analyzing network data in real-time to quickly identify and mitigate potential cybersecurity threats in the smart grid system. Their ability to detect anomalies ensures proactive detection and immediate response, protecting the grid from evolving cyber risks [21].
- Optimal schedule optimization: To maximize efficiency and cost-effectiveness, ML and DL algorithms optimize the scheduling of energy resources by taking into account variables including generation capacity, demand, and market circumstances.
- Improving the dependability of the smart grid: To guarantee the stability and dependable functioning of the smart grid, ML and DL approaches monitor system parameters, forecast possible stability concerns, and optimize control measures.

In the subsections that follow, we'll go deeper into the primary ML and DL application sectors within the context of the smart grid. These fields cover energy security and planning, along with smart grid security. We will next go over the other ML and DL fields of application within the context of the smart grid.

Figure 2 represents the numerous applications of machine learning (ML) in smart grids. It depicts how ML and deep learning (DL) technologies are used in a variety of applications, including sustainable power generation prediction, energy consumption analysis, fault detection, cybersecurity breach detection, and scheduling optimization. This visual aid provides a comprehensive overview of how machine learning and deep learning algorithms contribute to improved grid efficiency, reliability, and security by leveraging data analytics and predictive capabilities to manage and optimize smart grid operations.

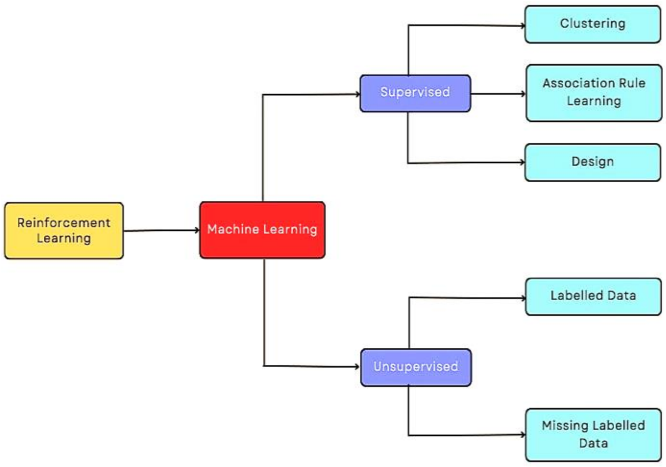

Figure 2. Applications of machine learning (ML) in smart grids

3.1. Improving energy forecasting through ML and DL techniques

An important renewable energy source, solar energy has challenged such topographical variances, seasonal fluctuations, and weather conditions. To gather exact information on energy generation, accurate forecasting is crucial. Similar difficulties are encountered with electricity generation and transmission by wind power, an energy source that is expanding quickly, including varying wind speeds that cause output swings. The smart grid may become unstable as a result of such causes, emphasizing the importance of precise forecasting. These issues are addressed with forecasting models that use ML along with DL. The ML and DL algorithms created for energy prediction in the smart grid are listed in Table 1 as an overview.

Table 1. Improving energy forecasting through ML and DL techniques

Ref.	Year	DL/ML technique	Application	Contribution
[22]	2006	Neuro-adaptive fuzzy inference	Wind forecasting for electricity generation	Advancements in wind forecasting using neuro-adaptive fuzzy inference
[23]	2006	Neural networks with recurrence	Predicting perpetual wind power and velocity	Improved prediction of perpetual wind power and velocity
[24]	2012	Fuzzy computational modeling	Short-term power production forecasting	Development of a short-term wind farm power production model
[25]	2008	Simulated neural systems assist	Investigation and forecasting of wind energy	Enhanced methods for wind energy production investigation and forecasting
[26]	2013	k-nearest neighbors (k-NN)	Very temporary wind speed prediction	Prediction techniques for very short-term wind speed
[27]	2013	Support vector algorithm (SVM), multi-layer perceptron (MLP), and least median square (LMS)	Conventional power forecast enhancement	Improved precision in conventional power forecasting
[28]	2014	Unconventional training algorithm	Regional solar radiation levels forecast	Innovative approaches for regional solar radiation forecasting
[29]	2016	Support vector regression (SVR) and artificial neural networks (ANN)	Photovoltaic system power prediction	Enhanced prediction of electricity generation from solar PV systems
[30]	2017	Asymmetric improving, random forest and regression tree algorithms	Sun radiation forecast	Improved forecasting of solar radiation
[31]	2016	Support vector regression (SVR), gradient boosted regression (GBR), and random forest regression (RFR)	Ultraviolet radiation prediction	Advanced techniques for forecasting ultraviolet radiation parameters
[32]	2010	Fuzzy logical frameworks and neural networks	Worldwide sun irradiance parameters	Development of models to estimate global sun irradiance parameters

3.2. Enhancing security in the smart grid with ML and DL applications

Before using ML and DL to defend the SG, it is essential to understand the security objectives and requirements which any SG should meet. By fulfilling these objectives and requirements, the SG can offer an energy distribution system that is dependable and secure. Ahead to implement ML and DL for SG defense, it is critical to define the security objectives and requirements that ensure the resilience of the SG. These goals include ensuring the security, integrity, and availability of critical grid infrastructure. By meeting these requirements, the SG can build a strong energy distribution system that ensures reliable operations and protects against potential cyber threats, ensuring uninterrupted energy supply and protecting against vulnerabilities in the grid's ecosystem. Understanding and aligning with these security goals is the foundation for deploying ML and DL to fortify the SG against evolving cyber security risks.

3.2.1. Objectives of smart grid security measures

As discussed in [33], a smart grid should strive to meet the following three main security objectives:

- Confidentiality: Restricting unauthorized access to and disclosure of private data and information exchanged throughout the smart grid.
- Transparency: Preventing unauthorized tampering or adjustments to guarantee the reliability and accuracy of the data and information contained in the smart grid.
- Accessibility: Ensuring that, despite disruptions or attacks, the intelligent grid infrastructure, and its constituent parts continue to function constantly and are available to provide uninterrupted energy distribution.

Meeting all three of these critical security requirements is critical to assuring timely and dependable energy delivery.

3.2.2. Requirements for ensuring smart grid

Security prerequisites for ensuring the security of the smart grid further to the aforementioned sophisticated safety objectives, the following safety specifications that cover a significant number of the elements of physical, network, and cyber security that are associated with SG, including the development and operation of massive network infrastructure required for energy delivery, must be met [4], [33].

- Verification and authentication: To ensure security access to vital resources, all devices and individuals inside the SG network's structure must be verified and authenticated.
- Access protection: Use of strong security measures to limit access to authorized employees only.
- Highly encrypted communication protocols: Acceptance of dependable and safe methods of communication to protect the privacy and integrity of passed on information.
- Threat recognition: With the enormous network of communications spanning a wide region, thorough techniques for filtering, evaluating, and keeping track of network traffic are necessary to find and recognize any discrepancies or prospective attacks.
- Self- repair abilities: The SG system and other crucial components should be able to independently recover and go on running in the case of a malicious attack, including a distributed denial of service (DoS) assault.

The infrastructure of the smart grid will be enhanced with the defenses required to successfully stop cyberattacks and mitigate their consequences by meeting these safety objectives and requirements. By implementing security measures including identification and authorization, control over access, secure communication protocols, surveillance and mitigation, and self-healing systems, the smart grid will become more secure overall. These processes ensure data integrity, protect the privacy of extremely sensitive data, and keep vital resources accessible. With the aid of these safety precautions, the smart grid can operate with resilience and successfully fend off cyberattacks.

3.2.3. Enhancing smart grid security through ML and DL applications

For the smart grid to operate at its best, there must be consistent and reliable network connectivity. But continued network connectivity also reveals potential holes that dishonest parties can take advantage of. To address these security issues, several ML and DL programmed have been developed and put into use to enhance the safety of the smart grid. These programs employ highly developed approaches and algorithms to identify and get rid of any cyber threats. Table 2 lists the ML and DL applications developed specifically to safeguard the smart grid.

3.3. Expanding the spectrum of ML and DL applications in smart grids

This section looks at the various fields other than predicting for security and energy production where ML alongside DL methodologies have been successfully applied. We highlight the several fields where in ML and DL are now being actively used by looking at the literature that is currently accessible. We also look at the connections that ML and DL may make with other complementary technologies like big data, blockchain technology, fog computing, cloud-based computing, and edge computing [34]–[37]. A brief description of major ML and DL implementations across many fields is provided in Table 3.

Table 2. Securing smart grids: machine learning applications

Ref.	Year	DL/ML technique	Application
[34]	2019	Support vector machine alongside k-nearest neighbors	Finding sneaky exploits using fraudulent information dumping
[35]	2014	Support-vector machines, random forest models, and naive bayes principles	Identifying numerous types involving electricity system interruptions and breaches
[36]	2019	Remote forest	Monitoring SG network communications for discrete malicious data attacks
[37]	2018	SVM or support vector machine	Using data gathered through the SG connecting system, identifying sophisticated cyber manipulation attacks
[38]	2017	Artificial neural networks, machine learning, support vector machines, random forest machines, reasoning trees, and naive bayes categorization	Identification of attacks on intrusion using data acquired from synchro phasor devices
[39]	2019	Recurring neuronal systems	identifying fraudulent activity in a renewable energy system built on blockchain technology and preventing hacking attempts
[40]	2017	Model of a Gaussian mixture	For identifying bogus malware injections, researchers use quantitative detection of anomalies
[41]	2018	Perpetual neural network training	Find vulnerabilities using fraudulent information injection (FDI) against SG's
[42]	2019	Strategies for autonomous machine learning	A scalable anomaly detection engine that is suitable differentiating cyber-attacks
[43]	2014	System supporting vectors	Identifying and detecting stealthy attacks
[44]	2014	Artificial neural network	To document energy theft and study statistics on usage of energy.
[45]	2017	Convoluted neural systems with an extensive variety of nodes	Processing data aimed at screening for power theft
[46]	2018	Auto-encoder	protection of the ac power systems from sporadic cyberattacks using periodic condition measurement

Table 3. Expanding the spectrum of ML and DL applications in smart grids

Ref.	Year	Application
[41]	2020	To forecast the stability of the smart grid network, our ground-breaking multidirectional long short-term memory (MLSTM) method applies gated recurrent units (GRU), long short-term memory (LSTM), and recurrent neural networks (RNN) machine learning models. Accuracy and performance are improved because it captures temporal dependencies. Our study aids in the smart grid's dependable network functioning.
[45]	2019	SG's can identify network threats and fraudulent transactions using a revolutionary deep learning and blockchain-based energy architecture that uses recurrent neural networks.
[46]	2013	Customizable and quick predictions of demand are made possible by the smart electricity system CPS structure, which makes use of cloud technologies. To precisely forecast patterns of power usage, it uses models based on machine learning that have been trained on big datasets.
[47]	2020	Our system uses machine learning, smart meter readings, sensor processing, and blockchain-based methods to quickly and precisely identify irregularities in power use. These technologies can be combined to improve detection capabilities and maintain system integrity
[48]	2020	A unique combination artificial intelligence identification approach was recently created to analyses the power consumption behavior profile of electrical vehicles (EVs) by combining cloud-based technology and fog computing technologies. This technique makes it possible to precisely identify target EVS depending on how they charge.
[49]	2020	In smart grids, cloud computing is used to provide IoT big data analytics enabling home energy regulation. This connection enables effective analysis and processing of massive amounts of data gathered from internet of things (IoT) devices, which improves domestic energy efficiency.
[50]	2019	To handle and analyze smart grid information at the network edge, edge computing and analytics and data management tools are used. This method reduces latency and enables real-time insights by moving data processing capability closer to the data source. Edge computing can help the smart grid analyze data more quickly, be more effective, and make better decisions for managing and operating the grid.

4. EMERGING PATHS FOR ML AND DL APPLICATIONS

In smart grids ML is still a helpful tool for the interpretation of enormous volumes of statistical information in the power sector. It boosts forecasting accuracy, making it easy to identify patterns in demand and production, and facilitates the adoption of effective management strategies. Researchers are continually examining cutting-edge ML strategies to increase both effectiveness and accuracy in these fields. There is a great deal of promise for utilizing data-driven insights to enhance power systems and boost efficiency as algorithms and methods for ML continue to advance. To effectively deploy and analyze big data in the smart grid, research and development efforts are required to enhance the interconnection between devices, data analytics tools, and data repositories.

- Utilizing diverse data sources: To utilize multiple sources of big data, sophisticated apps need to be developed. This will make it possible to analyze thoroughly how dependent vital infrastructure is on power networks and to find useful data.
- Forecasting algorithmic improvements: DL and ML are two examples of artificial intelligence techniques that need to be further optimized if we want to reduce our reliance on human input in decision-making processes. The flexibility of ML models will be more crucial as the quantity of data generated through the smart grid rises [51].
- Interaction with facilitating technological advances: To improve efficiency, dependability, safety, cost savings, and performance, data analysis algorithms must be readily integrated with cutting-edge technologies like cloud computing, the blockchain technology, fog computing, and edge computing.
- Incorporation of real-time administration and operations: Analytics in real time must be integrated into smart grid systems to enable proactive grid management and ongoing scenario monitoring. Future research should prioritize the simple integration of statistical evaluation into instantaneous procedures.

5. LIMITATIONS OF ML AND DL APPLICATIONS IN SMART GRIDS

Exploring the information that underlies them is the only way to discover significant information as well as discovering novel answers to many challenging problems that cannot be handled using conventional methods. However, because of their extensive infrastructure and labor-intensive nature, ML and DL-based systems may run into problems including learning from imbalanced data, comprehension concerns, and transfer learning issues, among others.

The electric power grid's safety is a very active area for study and development. Security must come first when designing and building the smart grid since it will be connected with energy systems. The smart grid is made up of a complex communications architectural network with a range of devices and standards that are all connected to the greater internet.

In order to ensure security and scalability within a distributed energy system, specialized safety measures that are expressly designed for the unique network applications within the smart grid are required. Studies on cybersecurity are essential in this situation since the smart grid's infrastructure requires robust protection against cyberattacks and vulnerabilities. The interconnection of the smart grid's components and its reliance on outside networks necessitate sophisticated safety measures [52]. To effectively address the security concerns particular to smart grids, the research and development of encrypted methods of communication, protocols, and infrastructures is the key focus. Making sure the smart grid design is dependable, safe, and trustworthy is part of this. Making a safe smart grid requires taking an anticipatory approach and factoring security considerations in right from the start. By building a comprehensive design with security as the main premise, the electrical grid of the future may be better equipped to handle the security requirements of its crucial infrastructure.

The requirement for comprehensive security measures to prevent cyberattacks and vulnerabilities is one of the major issues facing smart grids. The creation and application of sophisticated cybersecurity measures especially designed for smart grids is a potential remedy for this problem. To successfully detect and address security threats, this includes designing intrusion detection systems, anomaly detection techniques, and real-time monitoring solutions [53]. Additionally, ongoing research into secure communication protocols and encryption techniques can improve the security of critical data within the smart grid network. Smart grids can considerably increase their resilience and reliability in the face of evolving cybersecurity threats by adopting a proactive security approach from the early design phase and including these cutting-edge security features.

Research and development in the area of smart grid security are underway. Specialized security procedures and protocols are required to meet the unique challenges given by the communications network of the smart grid. Cybersecurity is crucial to defending the smart grid from potential threats. An attempt is being made to enhance security protocols in order to maintain a robust and reliable smart grid construction.

6. DISCUSSION

Future implications of the adoption of ML and DL techniques in smart grids include improved energy forecasting accuracy, grid resilience against cyber threats, seamless integration with emerging technologies like blockchain and edge computing, improved data utilization from a variety of sources, and a potential shift away from human reliance in decision-making processes. In order to optimize energy use and protect grid dependability, improved forecasting and real-time security measures are becoming increasingly important. More effective energy management is made possible by the synergy of developing technologies, and overcoming current obstacles will be essential to maximizing the promise of ML and DL and improving the adaptability of smart grids to the needs of a changing energy landscape.

7. CONCLUSION

The power grid is moving to an IoT-based, connected smart grid, and with the benefits of such a system come risks that were previously unheard of. For proper management and data extraction, the smart grid's massive data necessitates modern analysis approaches such as machine learning algorithms. The linked devices and data they generate are also highlighting the severe need for effective protection, as they are being targeted to attacks of varied magnitudes, highlighting the lack of proper counter-measures in place. In this research, we reviewed and synthesized machine learning and deep learning-based applications that have been developed and introduced in relation to the smart grid. The smart grid's networked system and the data they produce lead to a critical need for accurate analysis and the value it holds.

The information is primarily focused on the value of cybersecurity and specific safety measures in the context of smart grids, which are essential for maintaining the security, dependability, and protection of vital infrastructure. An intellectual contribution could include the development and implementation of new cybersecurity protocols and infrastructures specifically adapted to smart grids, emphasizing a proactive approach to security in smart grid system design and construction. This contribution could also include research into novel ways of communication encryption and rigorous security processes to protect the smart grid from potential cyber-attacks and weaknesses, thereby improving the electrical grid's resilience and reliability. In conclusion, the study's findings were presented, summarizing the major machine learning and deep learning-based applications based on the literature. We believe this will be helpful to other researchers working in this field.

REFERENCES

[1] J. B. Ekanayake, N. Jenkins, K. M. Liyanage, J. Wu, and A. Yokoyama, *Smart grid: technology and applications*. John Wiley & Sons, Inc., 2012.

[2] Y. Yan, Y. Qian, H. Sharif, and D. Tipper, "A survey on cyber security for smart grid communications," *IEEE Communications Surveys & Tutorials*, vol. 14, no. 4, pp. 998–1010, 2012, doi: 10.1109/SURV.2012.010912.00035.

[3] N. Komninos, E. Philippou, and A. Pitsillides, "Survey in smart grid and smart home security: issues, challenges and countermeasures," *IEEE Communications Surveys & Tutorials*, vol. 16, no. 4, pp. 1933–1954, 2014, doi: 10.1109/COMST.2014.2320093.

[4] W. Wang and Z. Lu, "Cyber security in the smart grid: survey and challenges," *Computer Networks*, vol. 57, no. 5, pp. 1344–1371, Apr. 2013, doi: 10.1016/j.comnet.2012.12.017.

[5] X. Fang, S. Misra, G. Xue, and D. Yang, "Smart grid — the new and improved power grid: a survey," *IEEE Communications Surveys & Tutorials*, vol. 14, no. 4, pp. 944–980, 2012, doi: 10.1109/SURV.2011.101911.00087.

[6] W. Chen, K. Zhou, S. Yang, and C. Wu, "Data quality of electricity consumption data in a smart grid environment," *Renewable and Sustainable Energy Reviews*, vol. 75, pp. 98–105, Aug. 2017, doi: 10.1016/j.rser.2016.10.054.

[7] G. N. Ericsson, "Cyber security and power system communication—essential parts of a smart grid infrastructure," *IEEE Transactions on Power Delivery*, vol. 25, no. 3, pp. 1501–1507, Jul. 2010, doi: 10.1109/TPWRD.2010.2046654.

[8] A. Anwar and A. N. Mahmood, "Cyber security of smart grid infrastructure," *Computer Science Cryptography and Security*, 2024, doi: https://doi.org/10.48550/arXiv.1401.3936.

[9] K. E. Fahim, L. C. De Silva, F. Hussain, S. A. Shezan, and H. Yassin, "An evaluation of ASEAN renewable energy path to carbon neutrality," *Sustainability*, vol. 15, no. 8, p. 6961, Apr. 2023, doi: 10.3390/su15086961.

[10] K. E. Fahim, S. M. Farabi, S. S. Farhan, I. J. Esha, and T. Muhtadi, "Overview of maximum power point tracking techniques for PV system," *The 7th International Conference on Renewable Energy Technologies (ICRET 2021)*, vol. 242, p. 01004, Mar. 2021, doi: 10.1051/e3sconf/202124201004.

[11] I. Chiuchisan, H.-N. Costin, and O. Geman, "Adopting the Internet of Things technologies in health care systems," in *2014 International Conference and Exposition on Electrical and Power Engineering (EPE)*, Oct. 2014, pp. 532–535. doi: 10.1109/ICEPE.2014.6969965.

[12] Y. Yang, L. Wu, G. Yin, L. Li, and H. Zhao, "A survey on security and privacy issues in Internet-of-Things," *IEEE Internet of Things Journal*, vol. 4, no. 5, pp. 1250–1258, Oct. 2017, doi: 10.1109/JIOT.2017.2694844.

[13] T. M. A. Khan, S. Rahman, M. K. Afgani, and K. E. Fahim, "Solar car," BRAC University, 2014. [Online]. Available: http://hdl.handle.net/10361/3228

[14] K. E. Fahim, "Off grid solar PV system sizing for a typical East African household," *TechRxiv*, 2023. https://www.techrxiv.org/doi/full/10.36227/techrxiv.22722511.v1

[15] N. Talpur, S. J. Abdulkadir, H. Alhussian, M. H. Hasan, N. Aziz, and A. Bamhdi, "A comprehensive review of deep neuro-fuzzy system architectures and their optimization methods," *Neural Computing and Applications*, vol. 34, no. 3, pp. 1837–1875, Feb. 2022, doi: 10.1007/s00521-021-06807-9.

[16] R. B, K. M, and S. V, "A novel speech emotion recognition model using mean update of particle swarm and whale optimization-based deep belief network," *Data Technologies and Applications*, vol. 54, no. 3, pp. 297–322, Apr. 2020, doi: 10.1108/DTA-07-2019-0120.

[17] Z. Li, S. Rahman, R. Vega, and B. Dong, "A hierarchical approach using machine learning methods in solar photovoltaic energy production forecasting," *Energies*, vol. 9, no. 1, p. 55, Jan. 2016, doi: 10.3390/en9010055.

[18] H. Farhangi, "The path of the smart grid," *IEEE Power and Energy Magazine*, vol. 8, no. 1, pp. 18–28, Jan. 2010, doi: 10.1109/MPE.2009.934876.

[19] S. A. Foroutan and F. R. Salmasi, "Detection of false data injection attacks against state estimation in smart grids based on a mixture Gaussian distribution learning method," *IET Cyber-Physical Systems: Theory & Applications*, vol. 2, no. 4, pp. 161–171, Dec. 2017, doi: 10.1049/iet-cps.2017.0013.

[20] J. Momoh, *Smart grid: fundamentals of design and analysis*. John Wiley & Sons, Inc., 2012.

[21] X. Yu and Y. Xue, "Smart grids: a cyber–physical systems perspective," *Proceedings of the IEEE*, vol. 104, no. 5, pp. 1058–1070, May 2016, doi: 10.1109/JPROC.2015.2503119.

[22] R. Qi, C. Rasband, J. Zheng, and R. Longoria, "Detecting cyber attacks in smart grids using semi-supervised anomaly detection and deep representation learning," *Information*, vol. 12, no. 8, p. 328, Aug. 2021, doi: 10.3390/info12080328.

[23] K. Bitirgen and Ü. B. Filik, "A hybrid deep learning model for discrimination of physical disturbance and cyber-attack detection in smart grid," *International Journal of Critical Infrastructure Protection*, vol. 40, p. 100582, Mar. 2023, doi: 10.1016/j.ijcip.2022.100582.
[24] K. Sadaf and J. Sultana, "Intrusion detection based on autoencoder and isolation forest in fog computing," *IEEE Access*, vol. 8, pp. 167059–167068, 2020, doi: 10.1109/ACCESS.2020.3022855.
[25] M. Alazab, S. Khan, S. S. R. Krishnan, Q.-V. Pham, M. P. K. Reddy, and T. R. Gadekallu, "A multidirectional LSTM model for predicting the stability of a smart grid," *IEEE Access*, vol. 8, pp. 85454–85463, 2020, doi: 10.1109/ACCESS.2020.2991067.
[26] N. Javaid *et al.*, "A hybrid genetic wind driven heuristic optimization algorithm for demand side management in smart grid," *Energies*, vol. 10, no. 3, p. 319, Mar. 2017, doi: 10.3390/en10030319.
[27] M. Abushwereb, M. Alkasassbeh, M. Almseidin, and M. Mustafa, "An accurate IoT intrusion detection framework using apache spark," *Computer Science Cryptography and Security*, 2022, doi: https://doi.org/10.48550/arXiv.2203.04347.
[28] H. Fan, Y. Liu, and Z. Zeng, "Decentralized privacy-preserving data aggregation scheme for smart grid based on blockchain," *Sensors*, vol. 20, no. 18, p. 5282, Sep. 2020, doi: 10.3390/s20185282.
[29] N. Javaid, N. Jan, and M. U. Javed, "An adaptive synthesis to handle imbalanced big data with deep siamese network for electricity theft detection in smart grids," *Journal of Parallel and Distributed Computing*, vol. 153, pp. 44–52, Jul. 2021, doi: 10.1016/j.jpdc.2021.03.002.
[30] H. Karimipour, S. Geris, A. Dehghantanha, and H. Leung, "Intelligent anomaly detection for large-scale smart grids," in *2019 IEEE Canadian Conference of Electrical and Computer Engineering (CCECE)*, May 2019, pp. 1–4. doi: 10.1109/CCECE.2019.8861995.
[31] M. Esmalifalak, L. Liu, N. Nguyen, R. Zheng, and Z. Han, "Detecting stealthy false data injection using machine learning in smart grid," *IEEE Systems Journal*, vol. 11, no. 3, pp. 1644–1652, Sep. 2017, doi: 10.1109/JSYST.2014.2341597.
[32] J. Xu, F. Wang, C. Lv, Q. Huang, and H. Xie, "Economic-environmental equilibrium based optimal scheduling strategy towards wind-solar-thermal power generation system under limited resources," *Applied Energy*, vol. 231, pp. 355–371, Dec. 2018, doi: 10.1016/j.apenergy.2018.09.113.
[33] A. Gopstein, C. Nguyen, C. O'Fallon, N. Hastings, and D. Wollman, *NIST framework and roadmap for smart grid interoperability standards, release 4.0*. NIST National Institute of Standards and Technology, 2020. [Online]. Available: https://www.nist.gov/system/files/documents/2020/07/24/Smart Grid Draft Framework.pdf
[34] C. Potter, M. Ringrose, and M. Negnevitsky, "Short-term wind forecasting techniques for power generation," in *Australasian Universities Power Engineering Conference (AUPEC 2004)*, 2004, pp. 1–6.
[35] T. G. Barbounis and J. B. Theocharis, "Locally recurrent neural networks for long-term wind speed and power prediction," *Neurocomputing*, vol. 69, no. 4–6, pp. 466–496, Jan. 2006, doi: 10.1016/j.neucom.2005.02.003.
[36] I. G. Damousis, M. C. Alexiadis, J. B. Theocharis, and P. S. Dokopoulos, "A fuzzy model for wind speed prediction and power generation in wind parks using spatial correlation," *IEEE Transactions on Energy Conversion*, vol. 19, no. 2, pp. 352–361, Jun. 2004, doi: 10.1109/TEC.2003.821865.
[37] G. Nazaré, R. Castro, and L. R. A. Gabriel Filho, "Wind power forecast using neural networks: Tuning with optimization techniques and error analysis," *Wind Energy*, vol. 23, no. 3, pp. 810–824, Mar. 2020, doi: 10.1002/we.2460.
[38] R. Mahaseth, N. Kumar, A. Aggarwal, A. Tayal, A. Kumar, and R. Gupta, "Short term wind power forecasting using k-nearest neighbour (KNN)," *Journal of Information and Optimization Sciences*, vol. 43, no. 1, pp. 251–259, Jan. 2022, doi: 10.1080/02522667.2022.2042093.
[39] R. Hossain, A. M. T. Oo, and A. B. M. S. Ali, "The combined effect of applying feature selection and parameter optimization on machine learning techniques for solar power prediction," *American Journal of Energy Research*, vol. 1, no. 1, pp. 7–16, Feb. 2013, doi: 10.12691/ajer-1-1-2.
[40] A. Aybar-Ruiz *et al.*, "A novel grouping genetic algorithm–extreme learning machine approach for global solar radiation prediction from numerical weather models inputs," *Solar Energy*, vol. 132, pp. 129–142, Jul. 2016, doi: 10.1016/j.solener.2016.03.015.
[41] H. Wang, D. Wang, and Z. Peng, "Neural network based adaptive dynamic surface control for cooperative path following of marine surface vehicles via state and output feedback," *Neurocomputing*, vol. 133, pp. 170–178, Jun. 2014, doi: 10.1016/j.neucom.2013.11.019.
[42] P. Kumari and D. Toshniwal, "Deep learning models for solar irradiance forecasting: A comprehensive review," *Journal of Cleaner Production*, vol. 318, p. 128566, Oct. 2021, doi: 10.1016/j.jclepro.2021.128566.
[43] Y. Gala, Á. Fernández, J. Díaz, and J. R. Dorronsoro, "Hybrid machine learning forecasting of solar radiation values," *Neurocomputing*, vol. 176, pp. 48–59, Feb. 2016, doi: 10.1016/j.neucom.2015.02.078.
[44] M. Ashrafuzzaman, S. Das, Y. Chakhchoukh, S. Shiva, and F. T. Sheldon, "Detecting stealthy false data injection attacks in the smart grid using ensemble-based machine learning," *Computers & Security*, vol. 97, p. 101994, Oct. 2020, doi: 10.1016/j.cose.2020.101994.
[45] Z. Wang, M. Ogbodo, H. Huang, C. Qiu, M. Hisada, and A. Ben Abdallah, "AEBIS: AI-enabled blockchain-based electric vehicle integration system for power management in smart grid platform," *IEEE Access*, vol. 8, pp. 226409–226421, 2020, doi: 10.1109/ACCESS.2020.3044612.
[46] A. A. Munshi and Y. A. I. Mohamed, "Cloud-based visual analytics for smart grids big data," in *2016 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT)*, Sep. 2016, pp. 1–5. doi: 10.1109/ISGT.2016.7781163.
[47] S. Shukla, S. Thakur, and J. G. Breslin, "Anomaly detection in smart grid network using FC-based blockchain model and linear SVM," in *Machine Learning, Optimization, and Data Science*, 2022, pp. 157–171. doi: 10.1007/978-3-030-95467-3_13.
[48] D. Sun *et al.*, "Integrated human-machine intelligence for EV charging prediction in 5G smart grid," *EURASIP Journal on Wireless Communications and Networking*, vol. 2020, no. 1, p. 139, Dec. 2020, doi: 10.1186/s13638-020-01752-y.
[49] S. A. Hashmi, C. F. Ali, and S. Zafar, "Internet of things and cloud computing-based energy management system for demand side management in smart grid," *International Journal of Energy Research*, vol. 45, no. 1, pp. 1007–1022, Jan. 2021, doi: 10.1002/er.6141.
[50] M. Y. Mehmood *et al.*, "Edge computing for IoT-enabled smart grid," *Security and Communication Networks*, vol. 2021, pp. 1–16, Jul. 2021, doi: 10.1155/2021/5524025.
[51] M. N. Q. Macedo, J. J. M. Galo, L. A. L. de Almeida, and A. C. de C. Lima, "Demand side management using artificial neural networks in a smart grid environment," *Renewable and Sustainable Energy Reviews*, vol. 41, pp. 128–133, Jan. 2015, doi: 10.1016/j.rser.2014.08.035.
[52] M. E. Merza, S. H. Hussein, and Q. I. Ali, "Identification scheme of false data injection attack based on deep learning algorithms for smart grids," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 30, no. 1, pp. 219–228, Apr. 2023, doi: 10.11591/ijeecs.v30.i1.pp219-228.
[53] N. M. Ibrahim, S. T. F. Al-Janabi, and B. Al-Khateeb, "Electricity-theft detection in smart grids based on deep learning," *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 4, pp. 2285–2292, Aug. 2021, doi: 10.11591/eei.v10i4.2875.

BIOGRAPHIES OF AUTHORS

Khairul Eahsun Fahim is an assistant professor-Information Technology Management, ZNRF University of Management Sciences, Bangladesh and a Ph.D. researcher at the University Brunei Darussalam. He joined the East China University of Technology, Jiangxi, China as a lecturer in September 2018. He obtained his Master of Technology degree in Systems and Control Engineering from IIT Bombay, in 2018. Khairul also worked as a Research Scholar at the School of Control of IIT Bombay. His current research interest involves various aspects of renewable energy, power system modeling and optimization, machine, and deep learning. He can be contacted at email: fahim.iitbombay@gmail.com.

Md. Rakibul Islam is an undergraduate student, currently studying Electrical and Electronics Engineering at BRAC University, since July 2020. His research focus lies in the field of renewable energy, power electronics, wireless and mobile communication, food studies, artificial intelligence, machine learning, and deep learning. He can be contacted at email: md.rakibul.islam9@g.bracu.ac.bd.

Nahid Ahmed Shihab is a student of Electrical and Electronic engineering Department of BRAC University. He is highly motivated and passionate with a keen interest in power, renewable energy, power electronics, robotics, machine vision, Unity, Unreal Engine, and AR. He is a driven individual with a thirst for knowledge and a desire to make a real impact in his field of expertise. He has also excelled in several extracurricular activities, including 3D, robotics and machine vision. Also working with LaSSET (Laboratory of Space System Engineering and Technology) under BRAC University. He has developed and implemented cutting-edge technologies and models of the environment and game using Unity and Unreal Engine. He can be contacted at email: nahid.ahmed.shihab@g.bracu.ac.bd.

Maria Rahman Olvi currently pursuing her undergraduate studies in the subject of Electrical and Electronic Engineering. From her early age, she displayed a natural aptitude for science and mathematics. Fascinated by the intricate workings of electrical systems, she embarked on her undergraduate studies with a singular focus on honing her skills and expanding her knowledge in the field. She has a lot of interests for doing research in the sector of renewable energy, control and operation of electric power systems, IoT, control systems, artificial intelligence, telecommunications, microelectronics, and aerospace engineering. She can be contacted at email: maria.rahman3@g.bracu.ac.bd.

Khondaker Labib Al Jonayed pursuing his B.Sc. in Electrical and Electronic Engineering at BRAC University, with research interests in circuit theory, power systems, and signal processing. Passionate about renewable energy, embedded systems, and telecommunications for their innovation potential and sustainability impact. He can be contacted at email: khondaker.labib.al.jonayed@g.bracu.ac.bd.

Adri Shankar Das is a final-year student pursuing a B.Sc. in Electrical and Electronic Engineering (EEE) at BRAC University, at Bangladesh. With a strong passion for power systems, control systems, and renewable energy, Adri is dedicated to gaining knowledge and skills in the field. He can be contacted at email: adri.shankar.das@g.bracu.ac.bd.