

Application of Machine and Deep Learning Models in Smart Grid Functionalities: A Survey

Abdulaziz Salihu Aliero¹, Neha Malhotra²

^{1,2}School of Computer Applications, Lovely Professional University, Punjab, India

Abstract - These days, one of the necessities for humankind is electricity. The idea of smart grids was developed to solve problems and difficulties in the traditional grid's ability to transmit electricity. The survey looks at relevant literature on machine learning (ML) and deep learning (DL) for smart grid applications, with a focus on works published in the last three years. A variety of databases, including Web of Science, Scopus, IEEE Xplore, Science Direct, and Google Scholar, were used to gather research publications. The research on machine learning (ML) and deep learning (DL) approaches used for load forecasting, grid stability, load optimisation, and anomaly detection in smart grids is systematically reviewed in this survey. Additionally, it offers more research problems for using DL and ML technology to make genuinely intelligent grids a reality. The survey will assist the industry and researcher in their future study and analysis of the latest advancements in smart grid technology.

Key Words: Smart Grid, Machine Learning, Deep Learning, Models

1. INTRODUCTION

A smart grid is an interconnected power system that uses automation and digital communication technologies to increase the long-term viability, dependability, and effectiveness of the production, dispersion, and use of electricity. It makes it possible for the Electricity Company and customers to communicate in both directions, which permits real-time monitoring and management of electricity consumption. Smart grids collect data on electrical supply and demand using sensors, meters, and other devices. This allows for improved resource management and grid stability through energy optimization, distribution, and reducing transmission defeats. Smart grids can contribute to energy efficiency and savings on costs for consumers and utilities. In addition to facilitating demand-side management and load balancing, the deployment of smart grids allows demand response programs, in which users can modify their electricity consumption according to price indications or system circumstances. Overall, smart grids are essential in modernizing the electrical sector and addressing the challenges of climate change, rising energy prices, and the need for a more sustainable and resilient electricity infrastructure [1]. The smart grid provides various services in real life that enable demand management, allowing clients and proprietors to control

energy use and lower demand during peak hours, thus avoiding power overload [2].

Machine learning (ML) is the prediction and ongoing learning from available data. ML is composed of various algorithms that evaluate the data and generate conclusions or forecasts about the current situation. Deep Learning is a machine learning subfield that focuses on artificial neural network techniques modeled after the brain's architecture and operations [3]. The integration of ML and DL has various applications in the context of smart grids. These applications include load forecasting, grid stability, energy optimization analysis, anomaly detection, and ensuring the stability of the Smart Grid [4]. Furthermore, deep learning and machine learning are utilized in energy forecasting to evaluate vast volumes of data and produce precise forecasts. These methods are capable of handling substantial volumes of data and extracting important traits to increase predicting accuracy [5]. Hossain et al. carried out a thorough investigation of the use of machine learning in smart grids, highlighting its potential in load forecasting, data acquisition, and stability assessment [6]. They emphasized the need for advanced techniques to handle the massive data volume generated by smart grids. Where by Massaoudi et al. reviewed the advancements and prospects of deep learning in smart grids, discussing its applications in energy forecasting, fault detection, and cybersecurity awareness [7]. Deep learning, in particular, involves stacking and connecting different learning layers that accurately map the link between input data and output [8].

This paper primarily focuses on understanding the opportunities for using the application of machine and deep learning models in smart grids. This will involve a detailed discussion of the various techniques, algorithms, and models used in machine deep learning for the smart grid. The paper will also enumerate the different data sources that were used in machine and deep learning for understanding how the smart grid works, like communication networks, intelligent meters, detectors, grid management networks, solar and wind turbines, grid storage systems, and data management. In addition, the paper will discuss why smart grid are important, and the architecture of smart grid. Finally, this survey comes to a close with a discussion of where research in this area will go in the future. As part of this, it will be necessary to identify research areas that need additional study, such as the creation of deep learning algorithms that are more accurate

and efficient, as well as the requirement for larger and more varied data sets.

1.1 Motivation and contribution

Over the next few decades, it is anticipated that energy consumption will rise very high as a result of the world's growing population, industrialization, and expanding global economy. With this increase in electricity demand the traditional grid cannot handle it, consumer data can be combined with smart grid technology to create an effective electricity distribution network. The motivation behind smart grids is to address the limitations and challenges of traditional power grids. The power system is becoming more complicated, and traditional grids are not resilient or scalable enough to handle it, such as the integration of renewable energy sources and the growing scale of the grid [9] [10]. Furthermore, finding patterns and standards in the production process and extracting knowledge from aggregated data are the driving forces behind machine learning and deep learning. In the industrial sector, these methods are crucial, especially for smart manufacturing and the smart grid paradigm. ML and DL can increase output, find product flaws, and forecast how long machinery will last with the help of diagnostic, descriptive, prescriptive, and predictive analytics. Applications for ML and DL technologies can also be found in smart grids, secure IoT architectures, transportation, logistics and supply chains, and electric machine condition monitoring. The use of ML and DL technologies is becoming more widespread and promising, with advantages including increased general quality, dependability, and safety in a variety of domains [11] [12] [7]. However, smart grids aim to improve energy efficiency, interaction, security, and stability analysis in the power system [13]. They are designed to be self-healing, adaptable, and capable of integrating various systems, such as information systems, thermal energy systems, and transportation systems [2]. Smart grids enable customers to send information to the grid station and improve communication between the grid station and customers, allowing for real-time information exchange and demand management [12]. Additionally, smart grids facilitate the incorporation of renewable energy sources and assist in the growth of the electrical market more effective, reliable, and persistent energy network.

In light of the above, the primary contributions of this survey can be summed up as follows: An overview of ML, DL, and SG has been explored to get in-depth knowledge behind them and review the applications of ML and DL in SG systems, which include load forecasting, grid stability, load optimization, and anomaly detection.

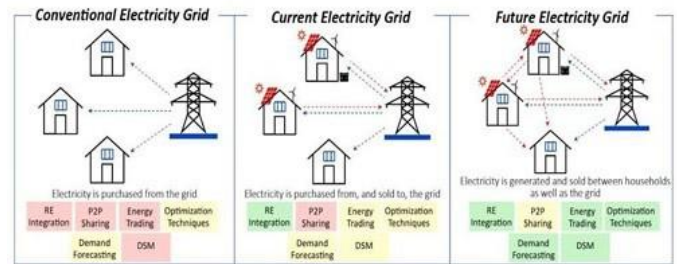


Fig -1: An illustration of a standard, modern, and prospective electrical grid [15]

1.2 Paper organization

The paper's organization is delineated as follows: Section I comprises the introduction, succeeded by an examination of smart grids in Section II, applications of the machine and deep learning in Smart Grids in Section III, a comprehensive review and discussion of existing literature in Section IV, exploration of challenges and future prospects in Section V, and a succinct recapitulation of the conclusions in Section VI.

2. SMART GRIDS

The smart grid is a modern electric power grid in which electricity flows from the supplier to the customer in a smart way. It represents two-way communication by distributing power and optimizing consumption. The system that allows bidirectional energy and information flow is fundamentally referred to as a smart grid, where data travels in both directions from the devices to the central server and from the server to the smart devices, making the information flow bidirectional [14]. As mentioned on [2], Smart Grid is a modernized electricity network designed to improve the efficiency and stability of power supply through the integration of nine machine learning algorithms. Unlike the conventional grid where electricity is purchased from the grid to the customers. Likewise in the current smart electricity grid, the electricity is obtained from the grid and also sold to the grid, and in the future smart grid Electricity is generated from the grid and sold between customers as well as the grid [15] as illustrated in Figure1. There are several types of smart grid which include: Advanced metering infrastructure, Distribution Automation, Renewable energy integration, Demand response, Energy storage integration, Electric vehicles, and micro grids. The smart grid is well poised to fundamentally change our lives with the help of machine learning and deep learning models. Smart grid has several uses for deep learning and machine learning. They can be applied to evaluate and extract useful information from the vast amounts of data generated in an Internet of Things-based grid system [6]. To efficiently analyze the data and make the right judgments to operate the grid, ML methods are made possible [16]. These methods can be applied to anomaly detection, adaptive control, sizing,

consumption, price, power generation, future optimal schedule, and detecting network intrusions in the event of a data leak [17]. In the future, deep learning and big data may be essential tools for resolving issues with the smart grid. It can improve the smart grid's responsiveness, efficiency, security, stability, and dependability.

2.1 Why Smart Grid Are Important

The current electricity grid infrastructure was established over a century ago, primarily to meet the relatively straightforward electricity needs of that era. This grid system comprised power lines and substations, facilitating the transmission of electricity from coal and fossil fuel-powered plants to residential and commercial properties. The power generation process was localized, with power plants strategically located within communities to cater to modest energy demands. Consequently, the grid was designed to deliver electricity from utilities to individual customer premises.

The contemporary energy landscape presents challenges that the traditional grid structure struggles to address. The grid's inherent limitation lies in its one-way directional flow, which impedes its ability to adapt to the dynamic energy demands characteristic of the 21st century. For instance, disruptions such as power line failures can lead to inadequate energy supply from power plants precisely when demand peaks. Moreover, the current grid predominantly relies on a singular power source, lacks granularity in usage data, and consequently, poses challenges in effective energy management.

To remedy these shortcomings, historical approaches involved the construction of additional power plants.

Within this context,) machine learning (ML) and Deep Learning (DL) models have emerged as compelling tools for addressing challenges across various sectors within smart grids [18]. The adoption of machine learning methods within smart grids has gained significant traction, especially in areas that include load balancing, fault detection, energy management, and cybersecurity. Researchers have leveraged algorithms such as support vector machines (SVM), decision trees, and ensemble methods to predict energy demand patterns. Additionally, clustering algorithms have been employed to group consumers with similar energy consumption profiles, aiding in personalized energy management strategies [19]. For demand forecasting, deep learning models such as long short-term memory networks (LSTMs) and recurrent neural networks (RNNs) have demonstrated superior capabilities in capturing complex temporal relationships. These models have been successfully applied to predict short-term and long-term energy consumption patterns, enabling utilities to optimize resource allocation and grid operations.

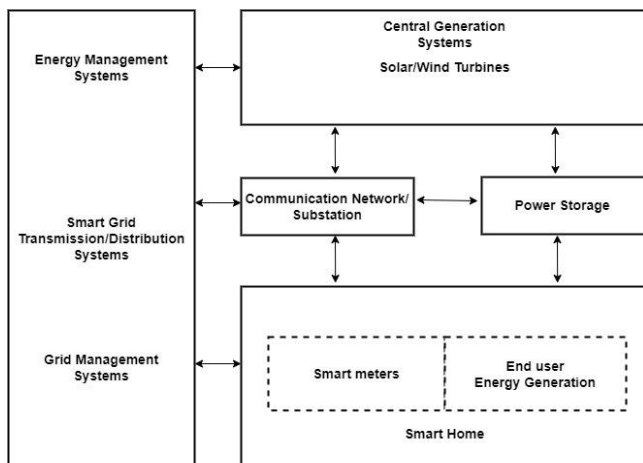
2.2 Smart Grid Architecture

A smart grid is a computerized electrical system that improves the sustainability, efficiency, and consistency of energy delivery through the use of digital technologies to provide a more intelligent and responsive energy infrastructure [3]. Traditional grids are not capable of two-way communication, but the infrastructure of the new smart grid, as shown in Figure 2, has distributed delivery systems and sophisticated controls. A smart grid's architecture combines several different parts and technologies as follows:

- **Smart Metering:** Smart meters, facilitating bidirectional communication between utilities and customers, are ubiquitous within smart grid infrastructures. With the utilization of these meters, energy usage can be monitored in real time, improving demand responsiveness, billing accuracy, and outage management.
- **Communication Networks:** Powerful communication networks are necessary for information sharing amongst the various smart grid components. This covers both conventional and wireless communication technologies, including cellular networks, WiFi, and fiber optics.
- **Sensors:** The grid is equipped with sensors that gather information on voltage, current, and temperature, among other characteristics. By enabling utilities to promptly detect and resolve problems.
- **Grid Management Systems:** The smart grid is monitored and controlled by sophisticated software and control systems. Utilities can use these systems to detect and address defects, optimize the distribution of energy, and instantly balance supply and demand.
- **Solar panels and wind turbines:** The advent of the smart grid heralds a paradigm shift in the utilization of renewable energy sources. Power generation is now diversified across multiple sources, resulting in a more robust and efficient system. Renewable resources like wind and solar energy, being sustainable and increase prevalent, play a pivotal role in modern electric power generation. However, the intermittency inherent in these renewable sources introduces complexities to conventional grid operations. The smart grid infrastructure facilitates the integration of renewable energy sources by providing essential data and automation capabilities. This enables solar panels and wind farms to contribute energy to the grid and optimize its utilization. The grid's capacity for communication and electricity management enhances its intelligence, paving the way for reduced reliance on fossil fuels in the future.
- **Cybersecurity Measures:** Considering smart grids primarily rely on digital technology and communication

networks, strong cybersecurity defenses are essential to thwarting cyberattacks and guaranteeing the confidentiality and integrity of grid data.

- **Electric Vehicles Integration:** Smart grids are made to facilitate the integration of electric vehicle charging infrastructure in response to the growing popularity of electric vehicles. To effectively handle the increased load, there's a need for intelligent charging stations and grid control technologies.
- **Grid Storage Systems:** Batteries and other energy storage devices are essential for balancing changes in supply and demand. They store extra energy at times of low demand and release it during moments of high need.
- **Analytics and Data Management:** Through advanced analytics, the vast quantities of data produced by smart grid components undergo processing and analysis. Utilities can forecast system behavior, maximize grid performance, and make well-informed decisions with the aid of this data-driven strategy.



3. APPLICATIONS OF MACHINE AND DEEP LEARNING IN SMART GRIDS

Machine learning algorithms can be categorized into two main types: supervised and unsupervised learning. In supervised learning, the dataset comprises attributes, with each data instance being assigned a class label or target class. Deep learning which uses a deep neural network (DNN) most effectively is an expanded version of artificial neural networks (ANNs) to determine the network's depth, artificial neural networks (ANNs) with a larger number of significant layers are employed. Deep learning algorithms typically utilize the dataset to learn the entire probability distribution, either through indirect means (such as synthesis) or directly through density approximation [20]. Machine learning and deep learning have various applications in the electric grid. These applications are used for power forecasting, which is very important in facilitating the dependable transition of power systems [9]. They have

been employed to enhance the stability, reliability, security, efficiency, and responsiveness of smart grids [13]. Machine learning models, including K-Nearest Neighbor (KNN) and Gaussian Process Regression, have been employed to analyze the impact of customer schedulable loads and forecasted daily electricity price profiles on aggregator profits [2]. Deep learning models, including Deep Neural Networks (DNN) and Long Short-Term Memory (LSTM), have been applied for load forecasting at the transformer level within extensive electrical distribution networks [12]. These models have demonstrated encouraging outcomes regarding accuracy and scalability, thereby contributing to effective demand response management, generation scheduling, and loss reduction [21]. Overall, machine learning and deep learning applications hold the promise of enhancing the efficiency and reliability of smart grids. Figure3 illustrates the diverse applications of Machine Learning.

The application of ML and DL in the profession of smart grid includes:

1. Load forecasting: The ability to predict the amount of electricity that will be consumed by the grid is known as load forecasting and it is essential to the power system's effective operation. Conventional techniques like exponential smoothing and AutoRegressive Moving Average (ARMA) are not as good at capturing the intricate nonlinear patterns found in load data. For this reason, models based on machine learning have become more and more common in load forecasting. These models can manage the nonlinear relationships between input and output variables and uncover hidden patterns in huge datasets. Examples of these models are Artificial Neural Networks (ANNs), Decision Tree Regression, Support Vector Regression (SVR), and Extreme learning machines (ELM) [2] [12] [21]. Load forecasting can be categorized into three categories based on the duration of predicted required: short-term LF (STLF), which forecasts the load from minutes to hours; mid-term LF (MTLF), which forecasts the load from hours to weeks; and long-term LF (LTLF), which forecasts the load over years. In addition, several additional variables can impact LF, including the type of consumer, the weather, the time of day, the season, and the academic calendar. In most cases, historical data on power consumption is used to model MTLF and LTLF predictions together with additional variables including consumers, weather, and demographic information. Research has shown that the majority of STLF has several applications, which include demand response, energy transfer scheduling, and real-time control. Future power plant planning and power system dynamics visualization can be accomplished by leveraging both MTLF and LTLF methodologies. Various techniques are proposed and applied for power system load forecasting, utilizing data obtained from smart meters [22].

3.1.1 ML and DL Approaches for Load Forecasting

ML Approaches: The most widely used machine learning methods that produce accurate load forecasts are random forest (RF), support vector regression (SVR), and extreme gradient boosting (XGBoost). However, the multilayer perceptron (MLP), a form of recurrent neural network (RNN), temporal convolutional network (Conv- 1D), long short-term memory (LSTM), and feed forward artificial neural networks (ANN) are applied to boost the resilience of the best AI modeling and forecasting methods for power consumption [23].

DL Approaches: There was a presentation of a new taxonomy and a representation of the main deep learning (DL) techniques for the smart grid. According to the study by [24], among the various deep learning techniques, RNN, CNN, and LSTM were the three main methods with the most applications for load forecasting. However, DL employs multiple layers of neurons of intricate structures to represent a high level of abstraction, also DL models are a good substitute for learning patterns. The process involves utilizing consumer data and forecasting demand over multiple forecasting periods, Long Short-Term Memory networks which are based on recurrent neural networks are among the frequently used artificial neural networks [25].

2. Grid Stability: Grid stability is the ability of an electrical power system to sustain a steady and dependable supply of electricity under a range of operating circumstances without any disruptions. Grid stability can benefit from machine learning and deep learning approaches in several ways, such as by predicting maintenance voltage control, demand response, and theft detection. The stability of grid is very important when implementing machine learning and deep learning methods, which are commonly used to analyze grid stability using datasets for simulation of result [10] [13]. Furthermore, Smart Grid stability evaluation is essential since the process is dynamically time-sensitive. This is because smart grid stability prediction enhances electrical supply consistency and reliability, analyses disruptions and variations in energy production or consumption, and aids in efficiency growth through grid optimisation [29].

3.1.2 ML and DL Approaches for Grid Stability

ML Approaches: To forecast the stability of the smart grid network, a study by Amjad et al. [30] employs a novel multi-layer Perceptron-Extreme Learning Machine technique (MLP-ELM) to anticipate the smart grid's sustainability. Karthikeyan et al. propose a model with four ML classifiers such as NB, Random forest Nu-SVM and Extreme GBM with four ML classifiers CS-SEM model was developed to predict the stability of the smart grid the result shows the CS-SEM has effectively predicted the accuracy of the smart grid with 98.57 accuracy [31].

DL Approaches: The application of deep learning algorithms in smart grid stability becomes essential to enhance the dependability of the smart grid and boost the effectiveness and uniformity of the power supply. In this paper [29]. A novel neural network methodology is proposed to predict smart grid stability in a four-node star network, considering both complete and missing input data variables. Similarly, employing full input data, the classic FFNN is designed for predicting the stability of a four-node star network smart grid system [29]. A study by [32] developed a new fusion model that combined ML SVM and DL artificial neural networks (ANN) these inputs were subsequently utilized by the primary neural network to generate stability predictions, yielding results with an accuracy of 98.92

3. Load Optimization: Load optimization is an essential piece of smart grid application that keeps contemporary society running smoothly. It makes sure that residences, companies, and industries always have access to a steady supply of power, which promotes economic expansion, advances technology, and enhances quality of life. Nevertheless, there are a lot of optimization techniques and procedures that entail analyzing several alternatives to determine an appropriate or ideal solution to a problem [15]. Today, numerous optimization algorithms are available to conserve energy, reduce costs, and address security issues across the production, transmission, and distribution sectors of energy in each domain. Similarly, the smart grid employs a diverse range of optimization techniques for achieving cost minimization, managing energy on the distribution side, implementing protection systems, and optimizing various aspects of the smart grid infrastructure [33].

3.1.3 ML and DL Approaches for Load Optimization

ML Approaches: This Study [33] investigates optimization techniques within the demand sector of the smart grid, encompassing heuristics and meta-heuristics algorithms aimed at energy conservation, cost reduction, and security enhancement across energy generation, transmission, and distribution. Additionally, machine learning algorithms can be leveraged to further energy generation and distribution by predicting the optimal output of energy sources.

DL Approaches: Deep learning can improve energy grid optimization by predicting energy demands, enhancing production and distribution, and preventing fraud. However, neural networks are a fundamental deep-learning technique widely utilized in energy grid optimization [15]. A study by [34] Integrated artificial neural networks ANN and HGAC optimization algorithms for demand-side management in smart grids with renewable energy resources and real-time price-based demand response programs to enhance consumer energy usage and reduce the costs, peak loads, carbon emissions, and user discomfort.

4. Anomaly Detection: An anomaly refers to an unexpected phenomenon that manifests within a dataset, often used for detecting data without a label, any occurrences or modifications in the smart grid data that deviate from the typical pattern are referred to as anomalies [36]. From the perspective of security and revenue protection, there are two problems in the adoption of smart grids. The first are anomalies that arise naturally, whereas the second, in which malicious individuals steal electricity, is tied to human circumstances [16]. The authors in [37] present a comprehensive survey of different detection algorithms for FDIA in smart grids, comparing their pros and cons, identifying challenges, and outlining criteria for future development.

3.1.4 ML and DL Approaches for Anomaly Detection

ML Approaches: The study [16] employs the Isolation Forest machine learning model to leverage historical data for forecasting future values of grid parameters, facilitating the identification of potential attack points with a precision of 98.74. Furthermore, it monitors grid activity to detect intrusions following successful penetrations or any other anomalies impacting grid parameters.

DL Approaches: Deep learning combined with reinforcement learning to have DRL models in power systems to identify and mitigate vulnerabilities in DRL models, enabling power grid operators to minimize security risks [38]. Anomaly detection algorithms analyze unlabeled data to detect deviations from normal patterns, providing early warnings for potential grid faults. This helps in proactive maintenance, reducing system failure risk. Anomaly detection techniques, combined with clustering provide a comprehensive understanding of the energy grid system, optimizing energy generation and distribution strategies [15].

4. DISCUSSION AND FUTURE RESEARCH

Having presented in the previous study the studies show that there is a considerable emphasis on enhancing the prediction of load forecasting, scalability, load optimization, anomaly detection and effectiveness of smart grid management in several areas such as complexities in data pre-processing, model accuracy in real-world scenarios, scalability for large networks, and validation using real data are among the main issues that have been discovered. By engaging with these challenges, researchers are poised to make substantial contributions to the development of predictive models, security mechanisms, and the holistic optimization of smart grid operations. The incorporation of advanced ML and DL methodologies demonstrates how smart grid technologies are always evolving to meet these issues. To assure dependable and useful grid management solutions, future research areas might focus on improving

model robustness and scalability, integrating real-time data streams, and testing models with substantial field data.

5. CONCLUSION

In this survey, we have explored the diverse applications of machine learning (ML) and deep learning (DL) models in enhancing smart grid functionalities. From load forecasting to optimizing grid operations. Through a comprehensive review of recent literature and advancements, we have highlighted the key contributions of ML and DL techniques in addressing various challenges that modern grid systems face. These include improving forecasting accuracy, enhancing predictive maintenance strategies, enabling real-time monitoring and control, and fostering the integration of renewable energy sources.

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