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Application of Smart Technology in Improving the Performance of Electrical Power Systems and Predicting Electrical Loads

Fhaid Fahad Alrashidi

ABSTRACT
Electric power systems have witnessed significant development in recent years due to technological advancements. There is an urgent need to improve the performance of these systems to ensure their efficiency and save energy consumption, especially with the increasing demand for electricity and the complexity of its distribution. The use of smart technology contributes to improving the response of electrical networks and enhancing the ability of electrical load prediction systems. Smart technology in electrical power systems includes the use of smart sensors, big data analysis, automated control tools, and artificial intelligence, which enhances the network's ability to react to changes in demand and distribute energy more efficiently. The aim of this research was to identify the effectiveness of applying smart technology in improving the performance of electrical power systems and predicting electrical loads. To achieve the objectives of the study, the research relied on the descriptive approach by studying the literature, books, and academic articles related to modern smart technologies and analyzing their effectiveness in improving performance and predicting loads. The results of the research showed that the application of smart technology in improving the performance of electrical power systems and predicting electrical loads is an important step towards achieving greater efficiency in energy distribution and reducing losses. With the increasing use of artificial intelligence and big data, it has become possible to predict future loads more accurately, which contributes to the sustainability and improvement of the performance of electrical networks.

Keywords: Smart technology, electrical power systems, predicting electrical loads, artificial intelligence, machine learning, forecasting, algorithms

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I. INTRODUCTION

Electrical power systems are witnessing a remarkable development with the advancement of modern technology, as it has become necessary to use smart technologies to improve their performance and meet the needs of population and industrial growth. The problem of predicting electrical loads is one of the main challenges in operating and managing electrical networks effectively. Therefore, developments in information technology, artificial intelligence, and smart systems have improved the ability to predict electrical loads, which helps improve network performance, reduce losses, and increase operational efficiency. The demand for advanced research and technology has been steadily increasing in the power grid sector [1]. Over time, in response to the development needs, automation and intelligent technologies have gained widespread application [2].

To maintain the stability, efficiency and sustainability of the grid, advanced prediction and optimization methods must be developed and put into practice due to the rapid development of power systems resulting from the integration of renewable energy sources (RESs) and the increasing complexity of grid operations. The importance of intelligent prediction and optimization in power grids will increase in a more powerful and sustainable energy future. As a result, intelligent prediction and optimization methods have become crucial for the efficient operation and maintenance of power grids [3]. These advanced computational techniques, based on data science and artificial intelligence, of which machine learning (ML) is a fundamental part, allow us to navigate the complexity of contemporary power systems more accurately and efficiently [4]. While machine learning is an important subset of AI that focuses on algorithms that can learn and improve from data without explicit programming, AI itself encompasses a broad range of computational techniques that seek to emulate human intelligence. A wide range of predictive methods are used in intelligent power system forecasting to anticipate different system states and properties [5].

Maintaining system stability [6], optimally allocating resources [7], and enhancing overall efficiency [8] all rely on the idea of forecasting. For example, load forecasting has long been an essential part of power system management and planning. Traditional approaches are mostly based on historical data and basic statistical models. However, this topic efficiency and reliability, modern energy management systems use real-time data, forecasts, and optimization algorithms [22].

Based on renewable generation forecasts and energy pricing, smart energy management systems can maximize the use of local generation [23], energy storage systems [24], and variable loads [25] in MG operations, ensuring reliable and economical operation. Furthermore, these advanced approaches aid demand response systems, which motivate customers to adjust their energy usage in response to grid conditions [26]. In addition, machine learning algorithms can predict customer behavior and optimize incentive schemes [27], and smart optimization technology applications can identify the most effective load shifting and peak reduction tactics [28].

A. Research Problem and Questions

Electricity worldwide faces increasing challenges related to increasing demand, low efficiency, changing consumption patterns, increasing population and economic growth, lack of necessary data and analysis, weak and obsolete infrastructure, and more. These challenges have been more acute in emerging market countries, where low efficiency is a particular problem. The energy sector in developed countries has already begun to adopt artificial intelligence and use related technologies that allow communication between components of smart grids, such as Internet of Things devices, as these technologies can help improve energy management, increase efficiency, and increase the use of renewable energy sources. The use of artificial intelligence in the electric power sector is reaching emerging markets, to have a decisive impact in addressing most of the challenges in the electric power sector, because artificial intelligence simply has the ability to reduce electricity waste and reduce its costs, facilitate the use of renewable energy sources in electric grids, and accelerate them to provide distinctive functions, such as prediction, monitoring, verification, estimation, etc. Artificial intelligence can also improve the planning, operation, protection, and control of electric power systems.

Predicting the occurrence and locations of faults is one of the main applications of smart technology in the electric power sector, along with maintenance and determining their scheduling and appropriate times. Failure of electrical equipment, such as generating units, networks, transformers, cables, substations, etc., is a common occurrence that can have serious consequences. Therefore, the application of smart technology and artificial intelligence, along with appropriate sensors, can be useful in monitoring equipment and detecting faults before they occur, thus protecting lives and saving has undergone a revolution with the introduction of artificial intelligence and machine learning (ML) [9]. Complex nonlinear relationships in data can be captured by sophisticated algorithms such as artificial neural networks (ANNs) [10], support vector machines (SVMs) [11], and more recently, deep learning (DL) models [12]. This allows for more accurate forecasts of electricity demand over a range of time horizons, from the short term (hours to days ahead) [13] to the long term (years ahead) [14].

Similarly, with the proliferation of wind [15] and solar [16], renewable energy forecasting has become increasingly important. To forecast electricity production from renewable energy sources, these forecasting models often combine machine learning (ML) methods with numerical weather prediction (NWP) data. To capture the inherent uncertainty of renewable energy, for example, ensemble approaches that combine multiple forecasting models have shown encouraging results [17].

However, there are many different and challenging optimization applications in power systems. However, more sophisticated optimization algorithms and applications of intelligent technology are needed as power systems become more complex due to the integration of renewable energy sources and the consideration of multiple objectives (e.g. maximizing reliability, minimizing cost, and reducing emissions pollution) [18]. When it comes to tackling complex, nonlinear, and sometimes non-convex optimization problems, intelligent technology applications have proven remarkably successful. Even in very limited settings, these nature-inspired algorithms are able to efficiently search through large solution spaces to identify nearly optimal answers. Furthermore, the field of reinforcement learning (RL) in machine learning is becoming increasingly popular in power system optimization. Power systems are ideally suited for reinforcement learning algorithms, which learn optimal solutions by interacting with the environment [19].

In the context of power systems, it is particularly useful to use prediction and optimization techniques. For example, stochastic optimization techniques that take into account uncertainty in prediction may result in more flexible decision making [20]. Demand response programs and energy storage management are just two of the power system issues increasingly addressed by model-based predictive control (MPC) frameworks, which use predictions to optimize system performance over a renewable time horizon [21]. The creation of advanced energy management systems (EMSs) is aided by the application of smart technology. In order to make proactive choices and improve system describing technologies in general terms without providing specific examples of their application in real-world settings. On the other hand, this article presents case studies and real-world implementations of intelligent forecasting and optimization methods in areas including demand response, energy storage management, and electricity price forecasting. In doing so, it provides insights for practitioners and scientists who are trying to use these methods in practical contexts. Therefore, the problem of the current research lies in answering the following main research question: **How effective is the application of smart technology in improving the performance of electrical power systems and predicting electrical loads?**

The main question is divided into the following sub-questions:

1. How can the application of smart technology contribute to improving the performance of electrical power systems and predicting electrical loads more accurately and effectively?
2. What are the different applications of smart technology in improving electrical power systems?
3. How to use artificial intelligence and machine learning in predicting electrical loads?
4. What are the challenges and opportunities related to adopting the application of smart technology to contribute to improving the performance of electrical power systems and predicting electrical loads?

B. *Research Objectives*

The main objective of this study is: **"To identify the effectiveness of applying smart technology in improving the performance of electrical power systems and predicting electrical loads."**

This main objective is subdivided into the following sub-objectives:

1. To highlight the ways in which the application of smart technology can improve the performance of electrical power systems and increase the accuracy of load forecasting.
2. To study the various applications of smart technology in improving electrical power systems.
3. To understand how artificial intelligence and machine learning are used in predicting electrical loads.
4. To identify the challenges and opportunities related to adopting the application of smart technology to contribute to improving the performance of electrical power systems and predicting electrical loads.

resources, effort and time. The electric power sector has a promising future with the advent of smart grids that can be managed intelligently and competently by artificial intelligence. Because smart electricity grids allow communication in two different directions, i.e. between utilities and consumers, they include an information layer that allows communication between its various components so that it can better respond to rapid changes in electricity demand. The information layer is created by installing smart meters and sensors that allow data to be collected and then analyzed later. With the presence of data analysis through the application of smart technology and artificial intelligence, smart grids help improve the reliability, safety and efficiency of electricity transmission and distribution.

AI can also help predict renewable energy production due to its ability to improve the reliability of solar and wind energy, by analyzing huge amounts of meteorological data and making predictions and decisions about when to collect, store and distribute wind and solar energy. AI is used to help balance the electrical grid, where its components are analyzed by processing intermittent units and helping to decongest the grid, which is really useful for the grid operator. In the field of improving energy efficiency, AI monitors electricity consumption in buildings and factories in order to control evaluate and manage their consumption. Accordingly, AI has the ability to control electricity use during peak hours, and even identify and flag sources of high consumption by detecting building equipment failures before they occur.

The need for this research is due to a number of reasons. First, predictions and optimizations have undergone significant changes in recent years due to the rapid development of artificial intelligence and machine learning. These days, methods such as deep learning (DL), reinforcement learning (RL), and hybrid models are used to address highly complex power system issues. These techniques can analyze massive amounts of data, handle nonlinear interactions, and adapt to the dynamic nature of contemporary grids, especially when renewable energy is integrated. Even if they are still useful, older statistical methods and classical optimization techniques have often been the subject of previous evaluations. These methods are not fully capable of managing the complexity of today's power systems. Therefore, to provide researchers and engineers with the latest information on these advanced methods, a new review is needed that includes the application of contemporary smart technology.

By providing insights into practical smart technology applications, this research goes beyond academic arguments. Many of the evaluations available now tend to be theoretical in nature, to improved performance and accurate load prediction.

II. METHODOLOGY

The methodology used in this study is based on the descriptive analytical approach, which is mainly used to understand and analyze current phenomena related to the application of smart technology in electrical power systems, specifically in predicting electrical loads. This approach allows for the interpretation and study of the tools and techniques used in this field based on the data available from previous studies and practical experiences, and aims to provide an accurate description of the phenomena and analyze their relationships and effects.

The applications of smart technology in electrical power systems will be described, with a focus on how to use artificial intelligence, machine learning, and modern technologies such as smart grids and smart meters to improve electrical load prediction. The literature on modern smart technologies will be studied and their effectiveness in improving performance and predicting loads will be analyzed. This will include books and academic articles.

III. LITERATURE REVIEW

A. Smart technology in electrical power systems

Smart grids have received significant attention in a number of technical fields, including academia and business, in recent times [29]. For legacy power systems, they are seen as a wise alternative [30]. As they integrate a variety of technologies, including cloud computing (CC), big data (BD), Internet of Things (IoT), etc., they have tremendous potential to provide smart services [31]. In order to improve the security, efficiency, flexibility, and reliability of electric power systems to increase electric power generation using the latest communication technologies, smart grids are described as a revolutionary digital electric power network that provides two-way communication [32]. It is a two-way power distribution and transmission system that gives customers the ability to reduce energy costs by taking energy-related actions [33]. When natural disasters and other human attacks occur, smart grids enhance the security measures in place [34]. Conversely, they reduce the possibility of harming people and other physical infrastructure necessary for routine grid-related operations. In terms of setup, solar power systems modernize the transportation field and include electric vehicles. In the context of global warming concerns and energy efficiency requirements, solar energy systems reduce energy waste and environmental pollution caused by greenhouse gas emissions.

C. *Research Significance*

The importance of this study stems from the importance of applying smart technology in electrical power systems, which represents a global issue and an important research field. Studies that have addressed the application of smart technology in improving the performance of electrical power systems and predicting electrical loads are rare. Therefore, it is expected that conducting such research on this topic will have high positive repercussions and importance that can be summarized as follows:

1) The importance of the study comes from the importance of applying smart technology, as the use of advanced technology contributes to enhancing the efficiency of electrical networks, reducing costs, and improving sustainability.
2) Applying smart technology to improve the performance of electrical power systems and predict electrical loads is a fundamental step towards enhancing the efficiency of electrical grids and increasing their sustainability. Through accurate load forecasting and the use of technologies such as artificial intelligence and smart grids, energy management can be improved and costs reduced. As technology advances, more achievements are expected in this field, contributing to enhancing sustainability and achieving energy security.
3) The application of smart technology in improving the performance of electric power systems and predicting electrical loads is an important dimension towards improving energy efficiency and ensuring the sustainability of electric grids in the future. This research will provide a useful tool for understanding the future impacts of these technologies and the challenges they may face, which will contribute to improving planning and implementation in the energy sector.
4) This study will provide new literature in the field of smart technology in electrical power, which will enhance academic knowledge on how these technologies can be used to improve the performance of electrical networks and predict loads. This literature will be a valuable reference for researchers in this field who study artificial intelligence, smart grids, and energy management.
5) This research will provide a useful tool for understanding the future impacts of smart technology applications in electrical power systems, as researchers will be able to identify the challenges that these technologies may face in the future, such as integration problems with legacy infrastructure or challenges related to cybersecurity in smart grids.
6) Smart technology will contribute to achieving a complete digital transformation in the energy sector, so that electrical systems become smarter and more adaptable to future needs, leading

load forecasting has increased in more sophisticated power grids, such as those in Europe.

According to Escalabez et al., the computational load on forecasting systems in Europe has increased significantly as they now have to operate on a quarter-hour basis. In order to reduce computing resources while maintaining or even increasing accuracy, this circumstance has led to the emergence of new techniques in load forecasting, such as algorithms that selectively update forecasts [44]. The study by Stamatellos and Stamatellos [45] showed that a basic feed-forward artificial neural network (ANN) could provide hourly power load forecasts 24 hours in advance with accuracy comparable to that of a Greek system operator using public domain electrical load data and regular weather data. These uses demonstrate the adaptability of load forecasting methods in many power system scenarios. Load forecasting is a key component of contemporary power system management, enabling everything from the integration of renewable energy and smart grids to optimization of day-to-day operations and long-term planning.

1) Generation Strategy Development

Load forecasting is essential for optimizing power generation, as it provides insights into the anticipated demand for electricity. This allows power producers to enhance their operations and maintain a reliable and cost-effective energy supply. In terms of generation planning, accurate predictions of future load trends enable power generators to choose the most effective mix of thermal, hydroelectric, nuclear, and renewable energy sources. Such precise forecasting reduces operational costs, increases the efficiency of generation assets, and helps avoid both surplus and deficits in production. Economical distribution is also improved through AI algorithms that optimize how output from different units is allocated based on forecasted demand and unit characteristics. This approach not only lowers total production expenses but also ensures that the most efficient resources are utilized effectively. While incorporating variable renewable sources like solar or wind into the grid, precise load forecasts are vital for smooth integration. By predicting backup or balancing resource requirements during peak renewable production periods accurately, power generators can minimize reliance on traditional plants while facilitating seamless incorporation of renewables.

2) Power Grid Energy Distribution

Accurate load forecasting is pivotal in ensuring effective energy distribution within power grids by aiding operators in managing and optimizing their networks. With reliable forecasts regarding load

Solar energy systems provide a number of smart solutions for all electricity-related tasks. Real-time energy consumption monitoring, dynamic pricing, faster and more efficient energy restoration after power outages, home electrical displays, adjusting electricity consumption during the day based on pricing signals and consumption rates, enabling the consumer to act as an energy producer, and monitoring energy consumption online through smart applications such as web pages and mobile applications are all features they offer [35,36].

Load forecasting (LF), which is often required for many applications to enhance the performance of power generation units, has received a great deal of attention. These applications include energy management, energy cost optimization, microgrids, smart meter misreading detection, and electricity theft detection [37]. Moreover, load forecasting - especially the efficient energy process of grid-interactive buildings - is a distinct area of study in power generation units. In order to provide efficient energy to buildings, load forecasting is an essential component of complex management and operation planning.

LF is important in the construction of grid groups such as demand response and load management [38]. It is the key player to improve the communication between the demand part and SGs, which is important for the coordination of power system charging, power system reliability, and economic power deployment and distribution [39]. Finally, LF contributes greatly to the initial stage of power parameter construction and performance evaluation of SGs. Meanwhile, it is a regression-based problem, thus many machines learning (ML) models have been overused in this field [40].

B. The importance of Predicting electrical loads (Load Forecasting)

In electric power systems, load forecasting is a crucial use of smart forecasting techniques that support the transition to a more efficient and sustainable energy infrastructure [41]. According to Ibrahim et al. [42], load forecasting is particularly important in the context of smart grids, where the security and reliability of the power system are critical considerations. Accurate load forecasting is now more important and challenging than ever before due to the liberalization of the energy sectors and the inclusion of renewable energy sources (RESs), which have increased the complexity of contemporary power grids. Many operational and planning tasks in power systems can benefit from the use of load forecasting. For example, Giap et al. emphasize that accurate load forecasting is essential to ensure adequate power supply and avoid financial losses due to overcapacity or power shortages [43]. The need for particularly good at using data to learn and gradually increase the accuracy of forecasting. This method produces more accurate forecasts [1].

By utilizing resources and managing energy storage, smart forecasting can be used for both power systems and solar photovoltaic systems. The proliferation of solar photovoltaic systems and the increasing integration of renewable energy sources are increasing the importance of this field. Among the methods used in this field are advanced artificial intelligence algorithms and traditional statistical techniques. Research in intelligent forecasting must continue as power systems change in order to improve system reliability and efficiency. This paper discusses all the different methods used in predictive analytics, from traditional statistical models to advanced artificial intelligence and machine learning algorithms, because intelligent forecasting is essential to ensure efficient and reliable operation of large and small power systems [41].

1) Traditional Load Forecasting Techniques

Traditional load forecasting (LF) techniques encompass a variety of strategies and algorithms aimed at predicting future electricity usage. For many years, electric utility firms and power system managers have relied on these methods to organize and oversee their power generation as well as distribution systems. A set of five sliding window-based forecasting methodologies was introduced by Alberg et al. [50] specifically for projecting electricity demand in smart meters (SMs). These tools merge seasonal with non-seasonal time series models utilizing an advanced learning method called online information network (OLIN). The construction of models via these algorithms differs, adapting accordingly to seasonal fluctuations. The data were organized beforehand through the researchers' utilization of SM technology. The findings indicated that the SWDP2A algorithm surpassed others in performance, revealing that using daily consumption figures paired with hourly transactions during model input could yield precise hourly forecasts for electricity demands.

Employing a time-sensitive data-driven approach, Kaneriya et al. [51] estimated energy requirements through a weather-oriented LF model. Their findings demonstrated accurate predictions for both residential and commercial electrical consumption within the model employed. Zhang et al. [52] introduced an innovative hybrid framework combining three distinct models: wavelet neural network (WNN), fine-tuned with the fruit fly optimization algorithm (FOA), improved empirical mode decomposition (IEMD), and ARIMA components. This newly crafted hybrid model growth, operators can pinpoint regions requiring additional substations or infrastructure enhancements to accommodate rising demand efficiently. This foresight aids in preventing congestion issues and voltage fluctuations by confirming that the network can adequately support expected loads through proactive planning. For balancing loads across distribution networks effectively, operators rely heavily on data derived from load forecasting techniques [29]. By precisely anticipating demand patterns, they can allocate resources appropriately while adjusting network design for balanced distributions—thereby improving voltage profiles and maintaining high-quality power across all areas while minimizing losses and wasteful consumption of energy reserves.

Moreover, this capacity to foresee emergencies allows operators to bolster network resilience against potential overload conditions or stability challenges presented via accurate predictions informed by existing literature [47]. One notable proposal involves a hybrid machine learning algorithm (SaDE-LSTM), aimed at enhancing short-term load prediction abilities utilizing differential adaptive evolution strategies alongside memory-based algorithms driven by system demands for accuracy benchmarks.

Additionally referenced literature [48] merges user-load data from JH City with weather information employing deep random forest methodology producing optimal predictions followed closely by results from support vector regression methods; overall performances indicate relative rankings among several tested algorithms such as Bayesian ridge regression coupled with various structures leveraging multidimensional neural nets characterized under four assessment criteria [49].

C. Existing Applied Load Forecasting Techniques

Intelligent forecasting in power systems uses advanced computing techniques, including artificial intelligence and machine learning, to predict energy production and demand. In complex power grids, this forecasting is essential to maintaining grid security and stability. By predicting the factors that affect energy supply and demand, the method helps utilities make informed decisions about energy storage management, hybrid energy optimization, and system security. Accurate forecasting generates financial benefits in competitive markets by providing unambiguous price signals. This method uses artificial intelligence techniques, particularly machine learning algorithms, to examine large data sets. These advanced computational techniques are able to detect complex patterns that traditional techniques might typically miss. As a branch of artificial intelligence, machine learning is evolving grid conditions fosters a stronger and more flexible power supply framework. The utilization of AI in fault detection is transformative; it not only identifies disturbances instantly but also plays an essential role in addressing these proactively. Such foresight helps avert possible power outages while reducing the repercussions of disruptions, ensuring an uninterrupted and smooth electricity supply.

For load forecasting (LF), techniques powered by AI—including support vector regression (SVR) and artificial neural networks (ANN)—are increasingly being adopted. These methods can be trained to replicate the intricate nonlinear relationships between various input factors and electricity demand—an output variable that traditional statistical or economic approaches often struggle to articulate. This section highlights several existing methodologies showcasing advanced AI models, particularly focusing on machine learning and deep learning frameworks applied within LF tasks. A decision tree strategy for energy modeling was introduced in previous research; experimental findings revealed that the C4.5 model could accurately classify building energy requirements with 93% accuracy based on training data and 92% accuracy with test data—employing intensity levels automatically during the identification process of critical building energy parameters while providing key characteristics along with threshold values pertinent to predicting superior building energy performance.

To assess buildings' energy performance effectively, various data mining strategies have been reviewed previously, including artificial neural networks, classification trees, chi-square automatic interaction detectors (CHAID), generalized linear regression models, combined inference models, SVR among others. Comparisons indicate that SVR excelled at predicting cooling loads while a combined approach using both SVR and ANN worked best for heating loads—with mean absolute percentage error (MAPE) below 4%. Notably, this joint model achieved reductions in root mean square error (RMSE) by at least 39% for cooling load predictions compared to earlier studies.

Furthermore, Sha et al., proposed a more straightforward LF method suited for engineering applications utilizing just three features as inputs into their model—which included transforming daily average dry bulb temperature into degrees per day as an input feature improving performance considerably. Additionally proposed was a technique determining equilibrium point temperature through representations based on type-of-day/month capitalizes on each constituent's strengths to enhance reliability and efficiency in LF for electricity needs, showcasing exceptional accuracy and stability through experimental results [29].

2) AI-Based Load Forecasting Techniques

Artificial intelligence enhances predictive maintenance—a vital function that anticipates equipment failures to prevent unexpected breakdowns—by analyzing data gathered from various sensors and systems across power grids to forecast necessary maintenance intervals, thereby prolonging equipment lifespan while minimizing downtime. AI is fundamental in managing demand forecasting within electrical networks; it utilizes sophisticated machine learning techniques capable of accurately estimating electricity consumption patterns influenced by historical data, weather conditions, and other critical factors relevant to demand prediction efforts. Such predictive capabilities are essential since they afford grid operators real-time adjustments in electricity supply management—this flexibility helps avert potential overloads or outages particularly during peak utilization times [1].

The application of AI in demand forecasting is transformative. It enables grid operators to make informed decisions by providing insights into expected electricity consumption patterns, facilitating more effective load management strategies. The ability to accurately predict demand allows for proactive adjustments in electricity supply, ensuring a balance between supply and demand. This not only enhances grid stability, but also contributes to optimizing energy resources. The proactive nature of AI-based demand forecasting is the cornerstone of the smooth operation of power grids, enhancing reliable and efficient electricity supply to consumers. AI can optimize electricity distribution, ensuring that the right amount of power reaches the right places at the right time. This not only enhances efficiency, but also facilitates the integration of renewable energy sources, which are often intermittent and difficult to predict, effectively leveraging AI in power grids to improve resource management.

Artificial intelligence (AI) has become a significant asset for improving grid resilience and identifying faults in power systems. Its capability to swiftly detect issues or disruptions enhances the stability and dependability of power grids. By employing sophisticated machine learning algorithms, AI acts as a proactive tool in spotting irregularities and anomalies across the grid. It effectively pinpoints potential concerns, isolates them promptly, and dynamically reallocates power to alleviate disturbances, thus boosting overall grid reliability. This capacity for rapid adaptation to response mechanisms is a cornerstone in the quest for a more resilient power grid. Its adaptive capabilities not only strengthen the grid against disturbances, but also contribute to maintaining a reliable and stable power supply that is essential for our modern-day needs [60].

Applications of Intelligent Forecasting

Optimizing the energy mix, managing energy storage, and coordinating hydrothermal processes are just a few of the many smart approaches used in power systems. These approaches also facilitate efficient and reliable power system performance by making electricity demand more predictable and providing advance informed conditions for renewable energy development. They are also expected to improve market competitiveness and reduce costs.

1) Electricity Price Prediction

Forecasting electricity prices has become an essential application of advanced predictive techniques in today's energy market. As power systems grow more intricate and variable, precise price forecasts are crucial for market players, system managers, and consumers to make well-informed choices and enhance their strategies [1].

The fluctuation and uncertainty of electricity pricing—affected by elements such as consumption trends, climatic conditions, outages, geographical factors, and economic indicators—highlight the need for sophisticated forecasting approaches. Koribeau et al. emphasize this complexity, noting that the ability to anticipate these prices provides significant advantages for both consumers and utility providers [61]. Their findings showcase the success of computational intelligence and neural networks in evaluating historical electricity pricing data to forecast future rates with remarkable accuracy; they achieved a root mean square error (RMSE) of 0.476 along with a mean absolute percentage error (MAPE) of 3.61%.

In relation to smart grids and demand response initiatives, predicting electricity prices is vital for minimizing investment needs as well as operating expenses. Rezaei et al. introduced a novel technique utilizing gated recurrent units (GRUs) for forecast modeling [62]. This method incorporates electrical load usage as an input factor while also employing an adaptive noise reducer to optimize model performance. Such innovation enhances the efficiency of demand response efforts while equipping producers with essential tools for making knowledgeable decisions within the energy market leading potentially to considerable cost reduction through optimal resource management.

The significance of long-term electricity price predictions is underscored by Ortiz et al., who reflecting usage characteristics of buildings; they tested three machine-learning frameworks: ANN targeting superiority over multivariate linear regression alongside enhanced performances seen within both SVR against MLR particularly highlighted discrepancies between heating/cooling prediction effectiveness underscoring significance regarding training dataset size adopted influencing predictive successes overall.

In exploring ways to forecast energy consumption more accurately Fan et al., introduced an improved prediction model termed DEMD-SVR-AR which demonstrated advancement over original SVR especially effective when facing challenges inclusive complex systems/imbalanced datasets—their statistical framework extends improved predictive capabilities towards novel inputs maintaining accurate representation derived from established training sets itself yielding notable superiority across metrics surrounding prediction precision interpretability generalizability predictiveness against alternatives utilized preceding theirs.Moreover, Fan et al. [56] discussed the potential use of DL in LF cooling from two perspectives, including developing prediction models and extracting important features. The results showed that nonlinear prediction methods performed better than linear methods. Compared to previous methods, the extreme gradient boosting (XGB) strategy performed better. The greatest prediction results are obtained when XGB models are adapted using features learned by unsupervised DL models, including deep autoencoders.

In [57], a novel multi-directional long short-term memory (MLSTM) model was used to predict the stability of SGs. In terms of accuracy (3% higher), precision, loss, and ROC curve metrics, the proposed model performed better than traditional ML models, including LSTM, gated recurrent unit (GRU), and RNN. Data obtained from a small payload, roughly equivalent to one transformer, were examined by Marinescu et al. [58]. Data from ANN, fuzzy logic, autoregressive, autoregressive moving average, autoregressive integrated moving average, and WNN were analyzed using six distinct methods. They found that the different methods produced comparable and approximately equal results.

Bader et al. [59] proposed a cryptographic energy prediction technique to preserve privacy of net metering systems based on federated learning (FL).They devised an efficient data aggregation strategy as well as a hybrid deep learning-based energy prediction model. To protect user privacy, they used functional encryption (FE) to encrypt their model parameters during federated learning training. In short, integrating AI into fault detection and energy and their effects on grid reliability. By merging consumption patterns with renewable energy forecasts, innovative approaches to resource management can arise. Vinagre et al. investigated the relationship between solar radiation and electricity usage trends to improve forecasts concerning energy consumption. Their research at the Polytechnic University of Porto utilized various forecasting methodologies such as support vector regression, multilayer artificial neural networks, and linear regression [67]. This study showcases how better load management can be achieved through both load prediction and renewable energy forecasts within the broader framework of managing the energy system effectively. The adoption of artificial intelligence algorithms for renewable energy forecasting is rapidly increasing, particularly highlighted in Szczepaniuk's thorough review on AI applications in the electric sector, focusing specifically on renewables. Their results indicate that AI technologies could significantly enhance operations related to generation, distribution, storage, consumption, and trading of electricity. These algorithms provide improved capabilities for navigating complex nonlinear relationships tied to weather-dependent power sources concerning renewable forecasting [68]. In addition, Kleuev et al. point out that integrating more renewable sources into power systems heightens the urgency to balance production against demand even further. Their analysis of different forecasting methods emphasizes considering forecast horizons—a critical aspect due to the variability linked with various time frames relevant to renewable energies [65].

D. Practical applications of smart technology in improving the performance of power systems

Many applications, such as OPF, use optimization techniques to help determine the most efficient operating conditions for power distribution and generation. In order to schedule power plants to meet demand as efficiently as possible, these algorithms are also used in unit commitment. Furthermore, economic load distribution, which seeks to minimize the total cost of generation while meeting all operational constraints, relies heavily on optimization techniques. They are also used in demand response management, which aims to increase grid stability by regulating customer demand to match supply conditions. Additionally, by controlling the unpredictability and uncertainty associated with these resources, optimizations methods help integrate renewable energy sources. In order to provide a reliable and economic power supply, they are essential for planning and operation tasks including maintenance scheduling and expansion of transmission networks [1].

put forth two methodologies tailored specifically for the Spanish energy sector [63]. Their analysis used actual data to highlight the necessity of price forecasting across all participants in the marketplace. Long-range forecasts hold particular value in strategic planning processes, investment considerations, and policy formulation within the energy industry.

Advances in DL techniques have enhanced the accuracy and reliability of electricity price forecasting. Pourdaryaei et al. presented a new framework that combines multi-head self-attention techniques and CNNs. Their approach, which includes feature selection method using mutual information and neural networks, demonstrated superior performance across different seasons. The proposed model achieved the lowest average MAPE of 1.75% and RMSE of 0.0085, outperforming other DL models and setting a new standard in forecast accuracy [64]. The application of electricity price forecasting goes beyond mere forecasting. As Kleev et al. highlighted in their literature review, various forecasting methods, including regression, autoregressive models, probabilistic forecasting techniques, and deep machine learning algorithms, can be applied to electricity price forecasting. The choice of method often depends on the specific forecast horizon and the unique characteristics of the electricity market in question [65].

1) Renewable Energy Generation Forecasting

As power grids evolve, the significance of renewable energy generation forecasts continues to rise. Precise forecasting is essential for ensuring grid stability, enhancing energy management, and supporting the shift toward sustainable energy systems amid increasing integration of renewables into power networks. The Smart4RES project exemplifies leading advancements in this field, as outlined by Camal et al. in [66]. This initiative seeks to enhance the effectiveness of short-term forecasting models related to renewable energy sources and their associated weather predictions while informing decisions within power systems and electricity markets. Given the fluctuating nature of renewable resources, this initiative particularly targets distribution networks, tackling issues like grid congestion, voltage fluctuations, and challenges pertaining to power quality.

The daily functions of wind and solar farms are significantly dependent on forecasting renewable energy. Consequently, Camal et al. emphasize the importance of creating accurate forecasting systems that are vital for energy traders and grid operators. They further demonstrate how these predictions help maintain a stable power supply by examining methods to forecast short-term variations in wind bidding processes. Their model utilizes a virtual power plant (VPP) configuration to demonstrate that renewable energy systems can achieve more favorable market bids and enhance production efficiency while accounting for technological limitations related to new energy units and storage [73]. Oriza et al. devised a two-tier optimization model aimed at facilitating optimal energy trading between electricity providers and distribution companies (Discos), incorporating elements like demand management alongside renewable resources. Utilizing their PSO-based method, they identified the best solutions for both consumption and trading of energy [74]. In addressing nonlinear dynamics in battery inverters, Carreras and Kirchsteger proposed an improved strategy to tackle nonlinear optimization challenges within home energy management systems. Their iterative linear optimization approach yielded the most effective charging and discharging methods, resulting in reduced emissions as well as cost savings [75].

4) Demand Response and Load Management

In order to pinpoint the most efficient pricing strategies and improve the timing of flexible loads, optimization methods play an essential role in designing and implementing successful demand response programs and load management tactics. For residential clients, Priolkar and Sriraj advocated for initiating a demand response program that employs direct load control (DLC), coupled with optimizing load scheduling amidst dynamic pricing. Their initiatives resulted in significant savings on energy costs as well as an enhanced peak-to-average ratio (PAR), achieved by reducing expenses and PAR using binary Particle Swarm Optimization alongside discrete elephant herd optimization algorithms [76]. In a similar vein, Fan et al. developed an optimization strategy focused on boosting the adaptive responsiveness of power systems under financial constraints. This method aimed to decrease operational expenses by integrating a bidding mechanism based on monthly price estimates while accounting for factors dampening demand response and ensuring feature point reliability across various situations [77]. Additionally, Dwijendra et al. proposed an ideal approach for managing power demand within electricity distribution networks through interval optimization techniques blended with incentive-driven modeling of demand response programs that included reserve scheduling components. Their ε-constraining technique produced positive results even amid uncertainties [78].

5) MG Operation and Control

1) Generation Dispatch and Unit Commitment

Two fundamental optimization issues in power system operations are generation distribution and unit commitment. In order to meet expected demand while minimizing operating costs and meeting a number of system constraints, these applications focus on finding the best scheduling and production levels for generation units. To address the optimal active power distribution (OAPD) problem, Naderi et al. proposed a hybrid fuzzy-based PSO-DE method for global reinforcement learning. Their method, which takes into account the unified power flow controller (UPFC) device, shows significant cost reductions in simulations performed over a 365-day period on an IEEE 30-bus system [69]. Borges et al. presented a multi-objective PSO model for energy resource management in systems with a high penetration rate of distributed generators and electric vehicles. Their strategy, implemented on a real Spanish electrical grid in Zaragoza with 1300 electric vehicles and 70% penetration of distributed generators, sought to maximize profit while reducing CO_2 emissions [70].

2) Optimal Power Flow (OPF)

OPF refers to a problem in power systems optimization that seeks to determine the most efficient operating levels of power plants while predicting system loads at the minimal cost, all while ensuring system security. To enhance the efficiency of power distribution systems, Saadnan introduced a scalable distributed optimal power flow (D-OPF) method grounded in equivalent network approximation (ENApp). This strategy is particularly resilient against specific failures and tackles the computational challenges associated with centralized optimization methods [71]. In addition, leveraging smart energy management solutions, Foruzandeh et al. proposed an innovative business model aimed at smart buildings. They formulated a mixed binary optimization challenge to ascertain the optimal contractual power capacity along with charging and discharging schedules for electric vehicles and battery storage. Their simulation results indicated an impressive 47% decrease in electricity expenses [72].

3) Renewable Energy Integration

As the integration of renewable energy sources into power grids increases, optimization becomes vital to manage the unpredictability and uncertainty associated with these sources. Khan et al. introduced an optimal decision-making framework for the electric power market that incorporates various factors such as loads, energy storage systems, renewable energy units, and the involvement of electric vehicles along with new energy in market to rise—leading to the establishment of multi-source models encompassing heterogeneous big data—the application of AI within power systems presents both new opportunities and complexities. Technologies such as expert systems, pattern recognition tools, genetic algorithms, and neural networks are among those categorized under artificial intelligence [41].

AI has the potential to improve the efficiency of electrical automation management, reduce the risk of accidents, and ensure the long-term reliable performance of the power system when integrated into power system control automation. According to the relevant study, machine learning (ML) has also been widely used in the creation of new materials and in the prediction of the properties of rechargeable battery materials, namely electrolyte and electrode materials. With the development of machine learning technology and the emergence of new and distinct problems in the study of rechargeable battery materials, the scope of machine learning applications will gradually expand [9]. Although machine learning has shown great promise in modeling complex systems, its practical application poses new difficulties. Before machine learning can be widely used, several issues must be resolved, such as the difficulty of obtaining reliable and relevant data sets and the need to correct inaccurate model predictions. Strong evidence of the effectiveness of machine learning across a variety of fields, including manufacturing processes, power generation, storage, and management, is essential for its widespread use. In addition, it is crucial to have trained personnel with specialized knowledge in the relevant fields and commercially available software [81].

Machine learning has been instrumental in developing data-driven models that accurately link material properties, such as activity, selectivity, and stability, to catalytic performance. However, applying current machine learning algorithms to accurately predict catalyst performance or come up with plans to create high-performance catalysts remains a challenge [82]. Recognizing the need for and availability of autonomous systems now and in the future, successful applications of machine learning in short-term hydrothermal scheduling will improve the link between actual processes and problem formulation and prepare the hydropower industry for autonomy. A survey of the latest developments in machine learning applications for the hydropower industry is presented in this study [83]. Especially in smart homes, digital technologies have a significant impact on the safety of occupants and energy users as well as energy market services. Decarbonizing heating and cooling systems, promoting responsible electric vehicle charging, utilizing local renewable energy sources, and

Due to their flexibility, reliability, and robustness, generators are becoming a viable option for future power generation and distribution systems. In order to integrate renewable energy sources, address energy balance, and economic concerns, generator operations must be optimized. De Somma et al. used MATLAB's MILP to present an optimization method for a residential generator. With cost reductions ranging from two to four times and primary energy use reductions ranging from two to five times throughout the winter season for both the heating and electricity sectors, their approach produced significant savings in both costs and primary energy use when compared to standard scenarios [79]. Zhang et al. used the enhanced Remora optimization (PRO) method to provide an optimal approach for generators. Due to their flexibility, reliability, and robustness, generators are becoming a viable option for future power generation and distribution systems. In order to integrate renewable energy sources, address energy balance, and economic concerns, generator operations must be optimized. De Somma et al. used MATLAB's MILP to present an optimization method for residential MG units. With cost reductions ranging from two to four times and primary energy use reductions ranging from two to five times throughout the winter season for both the heating and electricity sectors, their approach produced significant savings in both costs and primary energy use when compared to standard scenarios [29]. Zhang et al. used the enhanced Remora optimization (PRO) method to provide an optimal approach for MG units.

E. Challenges and opportunities for applying smart technology

The incorporation of intelligent prediction and optimization into power systems holds great promise, yet it also encounters numerous challenges and hurdles. Recent research has outlined these obstacles, setting the stage for improved efficiency in power system operations. Traditional approaches to addressing power system issues often rely on practical numerical optimization methods; however, due to the nonlinear nature of many optimization problems combined with various constraints, these methods can be slow and complicated. Consequently, a range of AI strategies is explored here to tackle numerous optimization challenges while reducing computational time. Ongoing research is dedicated to applying AI algorithms within power plants [80]. Nonetheless, traditional AI techniques frequently suffer from prolonged cycle times, intricate calculations, and difficulties in learning processes. With the ongoing advancement of AI algorithms over recent years, operational efficiency has seen significant enhancements. As data volumes continue

• Managing rising uncertainty and fluctuations in power production linked to renewable energy sources.

F. Related Work

It is essential to recognize the body of literature that has made significant contributions to the fields of power system prediction and optimization. Over the years, a number of surveys have been produced that focus on specific aspects of these topics. For example, some reviews have only addressed optimization algorithms used in power systems, which include both contemporary heuristics such as PSO, GA, and ACO, as well as traditional methods such as linear programming. Other studies have focused on prediction methods, examining the transition from sophisticated machine learning-based models such as ANN and SVMs to more traditional statistical models such as ARIMA (Autoregressive Integrated Moving Average) [41].

In SG applications, artificial intelligence (AI), especially machine learning (ML) and deep learning (DL) models, have shown excellent results in terms of increasing accuracy, stability, reliability, and efficiency, especially in the field of LF. Analyzing and evaluating different machine learning and deep learning models is crucial to determining the most suitable model for use with machine learning approaches in decision sets. We present a number of survey publications that examined machine learning and deep learning-based machine learning approaches in this field. A comparative analysis including the latest machine learning algorithms working in machine learning approaches for decision sets is presented in [93]. The decision tree model outperformed other machine learning approaches, such as logistic regression, support vector machines (SVM), K-nearest neighbors (KNN) algorithms, neural networks (NN), and naive Bayes algorithm, according to the results of the study. The accuracy rate of the decision tree was 99.96%, its recall rate was close to 100%, its F1 score was 100%, and its accuracy rate was flawless.

Current machine learning strategies were examined in [94] to determine the most appropriate approach for a given situation. Time frame, input, output, scale, data sample size, error type, and value were the applicable criteria used to evaluate these different methods. The two most commonly used methods for LTLF were regression and multiple regressions. Machine learning-based methods, including artificial neural networks, SVM, and time series analysis using autoregressive integrated moving average (ARIMA) and autoregressive moving average (ARMA), were used for STLF and VSTLF applications.

increasing energy efficiency are all possible with sustainable smart home networks [84].

Decarbonizing buildings is a big issue, and the next 10 years are critical to reaching aggressive global CO_2 reduction targets. Resilient housing and water-efficient construction are crucial to mitigating the effects of climate change. In light of climate change, research into energy efficiency and sustainability is essential to raise living standards [85]. With regard to the present and future of smart homes, a number of important points were emphasized [86]. It was recognized that there are still significant challenges that researchers need to overcome in order to gain global acceptance, even if smart homes are becoming more common and people are becoming more comfortable with them [87]. The diversity of manufacturers and devices, each with different charging systems, frequencies and communication technologies, is one of the technological challenges mentioned [88]. This fragmentation may hinder the compatibility and interoperability of devices and systems. One of the main obstacles is the increased adoption of smart home technology. This assessment emphasizes the importance of convincing customers that these technologies are reliable and safe. A method has been proposed to create predictive models that can detect faults and malfunctions in power equipment [89], and these models have been shown to be successful in predicting how the degradation phenomenon will develop [90].

Predictive analysis in power systems, especially in the context of smart grids, shows great potential thanks to machine learning and data-driven methodologies. In a landscape increasingly focused on renewable energy, these technologies can efficiently analyze massive amounts of data collected from smart meters and other devices in real time, enabling optimal energy flow [91]. They have benefits including increased efficiency, reduced costs, and improved accuracy. However, there are several hurdles that need to be addressed, such as ensuring access to high-quality data and controlling the potential risk of information overload [92].

Additionally, as energy systems progress and enhance through the incorporation of renewable energy sources and smart grid innovations, a variety of new challenges are anticipated to arise. Upcoming research may need to tackle several of these issues, including:

• Creating models that can adjust to evolving system conditions and learn from new data instantly.
• Combining prediction and optimization across various time scales, ranging from immediate operations to long-term strategies.

classical methods, which are more suitable for the highly complex and nonlinear nature of modern power systems. In conclusion, load forecasting supports grid planning, load management, grid optimization, outage management, grid stability, and grid resilience, all of which are critical for efficient power distribution. Reliable load forecasting enables grid operators to make informed choices, optimally allocate resources, improve system reliability, and ensure efficient power supply to customers. A reliable, efficient, and robust power supply system is facilitated by load forecasting, which matches transmission and generation with the expected load.

AI systems can effectively predict energy consumption by examining historical data, weather trends, and other relevant variables. The application, algorithm models, computational stages, and complexity of many AI algorithms differ from each other. Accurate load prediction in real-world applications depends on the selection of appropriate AI algorithms according to the requirements. Moreover, new architectures have emerged that enhance the stability and efficiency of systems as a result of combining prediction and optimization.

Despite their advantages, smart energy management systems face some challenges. The initial cost of implementation can be high, and there may be compatibility issues with existing building infrastructure. Additionally, the complexity of these systems requires specialized knowledge to install and maintain. Looking ahead, advances in artificial intelligence and machine learning are expected to enhance the capabilities of smart energy management systems. As these technologies become more accessible, they are likely to play an increasingly important role in achieving energy efficiency and sustainability goals.

The implementation of intelligent technology to enhance the efficiency of electric power systems and forecast electrical loads boosts grid performance, opens avenues for cost savings, and promotes environmental sustainability. As the use of artificial intelligence, big data, and advanced storage increases, so does the capability to refine load forecasting and attain an optimal equilibrium between supply and demand. The field is anticipated to evolve further with advancements in technologies like reinforcement learning and quantum computing. These innovative strategies will be essential for creating effective, dependable, and eco-friendly energy systems at decentralized levels as the energy sector transitions toward sustainability. Future research should emphasize developing more computationally efficient and flexible approaches to tackle the evolving challenges posed by modern power grids while paving the way for a stronger, more sustainable energy future. Based on an analysis

Zhang et al. [95] presented an alternative literature survey. They examined the use of machine learning algorithms in generating LFs that complete task T using P in order to evaluate and analyze performance and reliance on knowledge gained from recognized experts. Task T demonstrated the use of machine learning techniques, the performance metric P evaluated the quality of task execution, and expertise E was collected from several sources, including feature extraction and preprocessing.

Another evaluation of building energy usage forecasting methods that incorporate both conventional and AI models can be found in [96]. The purpose of this survey was to examine each model separately and discuss the potential of combining the two concepts. Together, SVM and swarm intelligence (SI) have produced excellent results [97].

Khan et al. presented a survey of LF approaches based on dynamic pricing systems in SGs. They considered a few pricing strategies, including critical peak pricing (CPP), time of use (ToU), and real-time pricing (RTP). They integrated LF approaches into computational models that were based on mathematics and AI.

Nespoli et al. presented a comparison of several PLF techniques for estimating load demand for tanks and secondary substations in a distributed low-voltage network. The methods were analyzed using standard KPIs for probabilistic and deterministic forecasts. In addition, they evaluated how well a number of hierarchical techniques improved the performance of lower-level forecasters. Studies have found that using smart technology to improve the performance of electrical networks can enhance the sustainability of electrical systems by improving efficiency and predicting electrical loads [98].

IV. CONCLUSION AND RECOMMENDATIONS

In electric power systems, the foundation for reliable and efficient power supply is accurate forecasting and optimization. This research has emphasized the need for intelligent forecasting and optimization for modern electric power grids. However, these advanced methods are now essential for managing complex power grids due to the new configurations resulting from the integration of renewable energy sources and smart technologies. Forecasting techniques have greatly improved the predictions of load and renewable power generation. These techniques range from traditional statistical methods to intelligent technology models and machine learning. At the same time, new heuristic and hybrid optimization methods have replaced

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of existing literature regarding smart technology's role in enhancing electric power system performance and load prediction, this research suggests that upcoming studies should concentrate on these areas:
1. Creating sophisticated prediction and optimization models capable of addressing high variability and uncertainty within load data.
2. Exploring an increased application of neural networks that have yielded promising results in load forecasting recently.
3. Examining how renewable energy sources affect load forecasting within smart grids while formulating models that can accurately reflect their impact on the system.
4. Designing prediction and optimization frameworks tailored to accommodate various types of loads such as residential, commercial, or industrial categories.

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