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AI Techniques for Smart Grid Load Forecasting: An Overview with Focus on External Factors

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***Abstract*— Accurate load forecasting is essential for managing smart grids effectively. It helps grid operators anticipate demand changes, optimize resources, and prevent overloads. However, achieving high accuracy is challenging because energy use can change a lot, and renewable energy adds more uncertainty. Traditional methods often fall short in addressing these issues, so better tools are needed. This study explores how Artificial Intelligence improves load forecasting in smart grids. Unlike most reviews that focus only on short-term forecasting, this paper covers short-term, mid-term, and long-term horizons. Each type needs different kinds of data, accuracy, and computational efficiency, which AI is well-suited to handle. The paper highlights recent advancements and trends in building reliable and sustainable energy systems. It focuses on studies that adapt to real-time conditions like weather forecasts, social events, and economic indicators. The findings show that AI methods can predict energy demand more accurately, especially when uncontrollable factors are incorporated. This study also shows that hybrid models can make forecasts more reliable. Finally, it points out areas where more research is needed to solve challenges in managing smart grids using AI.**

***Index Terms*— Load Forecasting - Smart Grids - Artificial Intelligence - Short-Term Forecasting - Energy Consumption**

I. INTRODUCTION

As global demand for electricity grows because of the rise of electric vehicles [1], digital technologies [2], and the growth of urban populations, traditional power grids are struggling to meet today's complex energy demands. This has led to the development of smart grids. They allow two-way communication between energy providers and consumers, which improve the security and efficiency of electricity market [3]. They also facilitate the integration of renewable energy sources, reducing harm to the environment [4].

In this evolving energy system, ensuring security, efficiency, and cost-effective management is crucial for the success of smart grids [5]. Artificial Intelligence (AI) plays a key role in achieving these goals by improving Load Forecasting (LF) [6], [7], maintaining grid stability and optimization [8], [9], detecting faults and predicting equipment failures [10], [11], [12], managing Distributed Energy Resources (DERs) [13], [14], strengthening the security by detecting cyber threats [15], [16], and adapting to demand response [17], [18], [19]. These abilities make smart grids more adaptable to modern challenges.

Load forecasting is a key part of smart grids. It predicts how much energy will be needed in the future to ensure a steady supply for consumers. Accurate load forecasting is essential for stable power supply [20], integration of renewable energy sources [21], cost optimization for both providers and consumer s [22], and efficient resource allocation [23]. With advanced tools, energy providers can predict demand and improve grid operations, making the energy system more sustainable and reliable [24].

Generally, load forecasting methods are categorized into three main levels based on timeframes [25]:

- Short-Term Load Forecasting (STLF): Predicts demand over minutes to hours or days. It is critical for real-time grid operations like unit commitment, demand response, and optimal load flow [26], [27].
- Mid-Term Load Forecasting (MTLF): Covers hours to weeks or months and supports tasks such as fuel management, energy trading, and system maintenance [28].
- Long-Term Load Forecasting (LTLF): Focuses on yearly trends, helping with strategic planning and network development [29].

By understanding and addressing the unique needs of these timeframes, AI can greatly improve forecasting in all these areas, ensuring smart grids meet current and future energy demands.

It is important to evaluate the methods used to predict energy demand. Traditional statistical approaches, such as regression [30] and time series analysis [31] are simple and widely used [32]. They include models like Autoregressive (AR), Moving Average (MA), Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), and the Kalman Filtering (KF) algorithm [33], [34], [35]. These methods rely on historical data and statistical patterns to make predictions. However, they have limitations with complex, non-linear datasets. This makes them less effective for modern grids, especially with the unpredictability of renewable energy sources [36], [37], [38].

AI techniques, on the other hand, are better at handling large datasets and adjusting to changes. Therefore, they are highly effective in dynamic environments like smart grids [39], [40]. In energy systems, AI is used to automate and optimize processes and integrate renewable energy by forecasting supply and demand [41]. Fig. 1 shows how AI, Machine Learning (ML), Artificial Neural Networks (ANN), and Deep Learning (DL) are related.

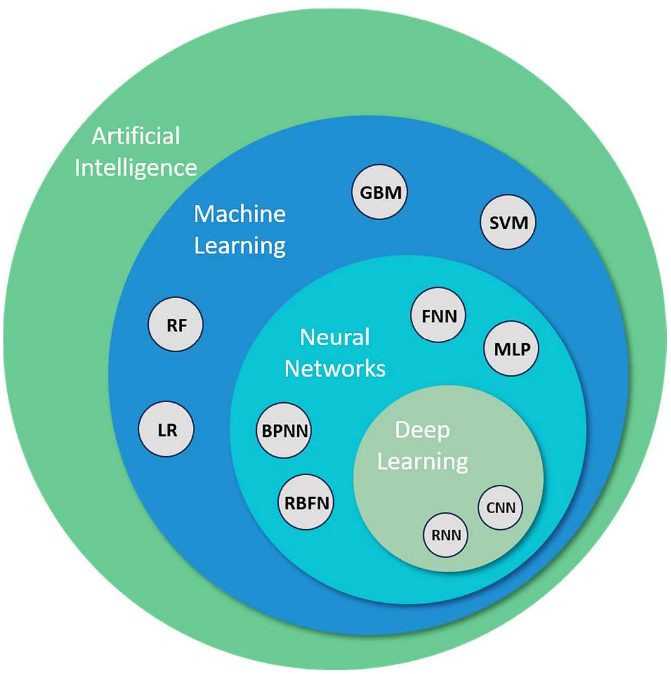

Figure 1. A hierarchical view of AI to DL

Machine learning, a branch of AI, has greatly improved load forecasting. It analyzes large amounts of historical data to find patterns and trends that traditional methods may miss [43]. Neural Networks (NNs) are particularly good at identifying patterns in past load data and adjusting to real-time changes. Reinforcement learning techniques can adapt to feedback and improve medium-term and long-term forecasting, even when conditions change [32]. Unlike traditional methods that need manual adjustments, AI models are self-learning. They get better as they process new data [42]. AI can consider multiple factors at once by analyzing high-dimensional data from different sources. This results in more detailed and accurate forecasts. It's worth noting that ML methods work well with the large data sets in smart grids, often performing better than DL models. Because of this, recent studies have focused on ML for load forecasting [44]. Advances in data collection and processing technologies have greatly improved forecasting accuracy [45]. For instance, the integration of Internet of Things (IoT) devices and smart grids allows for real-time data collection, which is especially useful for STLF. Similarly, high-resolution weather data and demographic information have improved accuracy for MTLF and LTLF. These advances make it easier to manage energy needs today and plan better for the future.

Many studies highlight AI's role in improving load forecasting. This paper focuses on progress in the past five years and how AI is helping create smarter energy systems.

II. AI Techniques for Load Forecasting

AI-based load forecasting methods can be grouped into three main categories: machine learning, deep learning, and hybrid models. Machine learning techniques, such as Support Vector Machines (SVM) and Linear Regression (LR), are effective at handling large datasets and finding complex patterns. On the other hand, deep learning methods such as Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) are particularly effective at understanding complex relationships and dependencies in time series data. Hybrid models combine different approaches, such as statistical methods with neural networks, to improve accuracy and reliability. These AI techniques have shown great success in improving load forecasting.

It's worth noting that while AI techniques offer great benefits for smart grids, several factors must be taken into account to ensure accurate prediction. As it's depicted in fig.2, these are key factors that can affect load forecasting models in smart grids:

- Weather conditions: Temperature, humidity, cloud covering, and solar radiation affect energy use patterns, particularly in short-term horizons. Considering these features is crucial with the increased use of renewable energy sources and heating or cooling systems [46].
- Time of day and seasonality: Energy usage changes daily and seasonally, requiring models to adjust to these patterns [47]. These features can influence short-term forecasting extensively.
- Economic activity [48]: Economic factors like changes in Gross Domestic Product (GDP), industrial activity, and electricity prices affect demand, especially in long-term horizons.
- Consumer behavior: Lifestyle changes, new appliances, and energy-saving habits lead to variations in energy usage patterns [49].
- Population growth and urbanization: Increasing population and urban development in long-term raise demand, especially in high-growth cities [50].

- Technological advancements: Energy-efficient technologies and electric vehicles change demand patterns in long-term view [51]. In addition, variability from renewable sources like wind and solar adds complexity.
- Grid infrastructure and energy losses [52]: Inefficient infrastructure and transmission losses can reduce the reliability of predictions.
- Regulatory and policy changes: Policies promoting energy efficiency or carbon reduction impact energy demand and model designs.

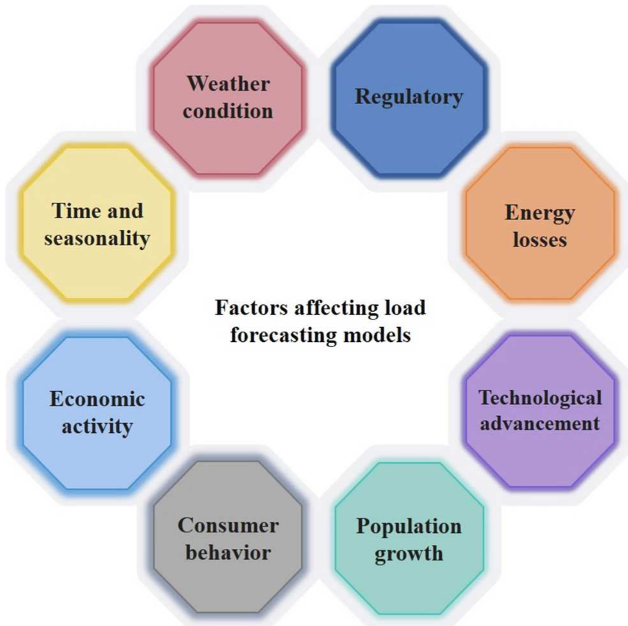

Figure 2. Key factors affecting load forecasting models in smart grids

One major challenge is dealing with unpredictable factors. Many review papers discuss load forecasting methods but often ignore important external factors like weather, consumer behavior, and economic trends. These factors can significantly impact prediction accuracy. Ignoring them can make even advanced models less effective. Future research should focus more on these external factors and develop strategies to address their effects. The next section reviews recent studies from the past five years. The main goal is to emphasize how AI has improved load forecasting accuracy across short-term, mid-term, and long-term horizons, with a particular focus on addressing the factors listed above.

A. Short-Term Load Forecasting (STLF)

The majority of studies have focused on STLF. STLF is critical in day-to-day grid operations and immediate decision-making. Several studies have analyzed the forecasting models accuracy during the COVID-19 pandemic. Ref. [53] proposed a short-term Markov corrector to improve the accuracy of a Prophet-based building load forecasting system. The corrector uses hourly power demand data collected in winter, considering how human activities and pandemic waves affect energy use. It should be noted that the effectiveness of the Markov corrector depends on data quality and variability. In [54], traffic data was combined with historical load, weather conditions, and time-related variables, to forecast short-term residential electricity consumption. Using random forest models and data from two distribution grid areas, the study explored how traffic patterns influenced forecasting accuracy before and during the pandemic. It aimed to understand whether traffic data, could enhance forecasting accuracy during the pandemic, considering that travel restrictions and reduced public transport affected electricity consumption.

Various learning techniques have been used to improve STLF accuracy. High-frequency data is often available for short-term periods, making it suitable for ML and AI models. Support Vector Regression (SVR), for example, is a supervised learning algorithm for regression analysis that uses kernel functions to map data and solve optimization problems. The authors in [55], tested SVR for demand forecasting using hourly data from the Greater Tehran Electricity Distribution Company. The results showed that SVR outperformed some ANNs in accuracy. Random Forest (RF) is another method that combines multiple decision trees to enhance predictions and minimize overfitting. In [56], an optimized RF model achieved higher accuracy than other statistical and machine learning methods by incorporating daily and weekly seasonality and calendar data. Gradient boosting which builds models sequentially to correct errors, was proposed in [56] for an energy management system using smart meters. The Proposed model incorporated various factors such as time, and energy consumption data. Results indicated that this method achieved better results than traditional approaches and other machine learning models like neural networks and decision trees.

Deep learning networks have become widely established in the STLF field because of their ability to model complex non-linear relationships and handle large datasets. The work in [6] explored load forecasting using four publicly available datasets. An attention-based 1D-CNN-GRU model was developed which enhanced data quality and generalization with preprocessing and data augmentation techniques. Additionally, the model parameters were optimized using a PSO technique.

Long Short-Term Memory (LSTM) networks are widely used in smart grid forecasting because they handle complex temporal relationships and patterns in time series data without the vanishing gradient problem common in traditional neural networks [57]. They can include factors like temperature, wind speed, and other environmental variables to improve prediction accuracy [58]. Many researchers have employed LSTM for load forecasting in the last 5 years. For example, authors in [59] studied STLF using deep learning techniques, specifically stacked unidirectional and bidirectional LSTM networks. Using a four-year dataset with hourly electricity consumption and temperature data, the study found that single-layer Bi-LSTM networks achieved the highest accuracy, outperforming other models like Uni-LSTM and SVR. Similarly, LSTM-based models in [60] accurately forecasted solar energy integration into power grids by considering variables like irradiance and seasonal components. The researchers in [61] compared the performance of the proposed LSTM model with a traditional ensemble model composed of Multilayer Perceptron (MLP), Radial Basis Function (RBF), and SVM cooperating with the autoencoder. Results showed that LSTM had superior performance in predicting 24-h load pattern and 1-h ahead load. The authors noted that individual consumer behavior has a higher impact on the total load in smaller regions. The authors in [62] used a recurrent LSTM neural network and two datasets from national and regional power system, examining hourly power demand over several years. The LSTM model achieved a high accuracy and was less sensitive to the type of database compared to traditional Feed-forward Neural Network (FNN). Ref. [63] introduces a novel hybrid CNN-LSTM using historical load data with a focus on non-linear patterns. Results showed that the proposed method achieves higher precision in various time horizons compared to traditional methods like LSTM, Radial Basis Function Neural Network (RBFNN) and eXtreme Gradient Boosting (XGBoost). In ref. [64], the researchers introduced an attention-based CNN-LSTM-BiLSTM model in integrated energy systems using historical load, temperature, cooling load, and gas consumption data from the past five days. The proposed model achieved better forecasting performance than CNN-BiLSTM, CNN-LSTM, BiLSTM, LSTM, BackPropagation Neural Network (BPNN), random forest regression, and SVR.

The researchers in [65] used a neuro-fuzzy system trained on data including temperature, humidity, solar irradiance, wind speed, and past load data. This hybrid approach enhanced prediction accuracy and grid stability. Ref. [66] proposes an optimum load forecasting strategy, using advanced techniques like the leopard seal optimization algorithm for feature selection, the interquartile range method for removing outliers, and the weighted k-nearest neighbor algorithm for accurate load forecasting. These methods reduced noise, improved feature relevance, and enhanced prediction precision.

B. Mid-Term Load Forecasting (MTLF)

Several researchers have worked on MTLF in smart grids focusing on seasonal patterns and economic trends mostly. For example, in [67] a multistep method using phase space reconstruction and SVM techniques improved accuracy and robustness over existing methods and showed that forecasting error does not diverge as the prediction step increases. The proposed method incorporated factors like seasonality, day type (working days, Saturdays, Sundays, and holidays), and historical load data. The study in [68] compared ARIMA, Wavelet-ARIMA, and ML models for MTLF, finding that ML models performed better with load data and climate factors like temperature and humidity.

To enhance the accuracy of mid-term power load forecasting, the study in [69] combined kernel principal component analysis with a BPNN optimized by particle swarm optimization. The model used data of load, temperature, and holiday events, to forecast daily peak loads. The paper also aims to address challenges such as random weight threshold selection and rolling prediction errors. This method achieved reliable forecasts for daily peak loads by simplifying input data and optimizing the neural network parameters.

Ref. [70] proposed a hybrid model for MTLF, combining exponential smoothing and a residual dilated LSTM network (RD-LSTM). This model used a pinball loss function with a penalty to reduce fluctuations, achieving better accuracy than classical statistical and machine-learning models. The model worked well even with limited data, forecasting monthly electricity demand across 35 European countries. Ref. [71] highlighted how factors like weather (temperature, humidity, wind speed, solar irradiance) and time (holidays, seasonal changes) influence electricity demand patterns. The authors utilized real-world hourly load data to test the efficacy of MLP, LSTM, and CNN in predicting load demands. It found that optimized deep learning models performed better for MTLF while MLP and LSTM performed better for STLF.

The method proposed in [72] used locally linear embedding to extract nonlinear features of load data affected by factors such as weather, economic trends, and distributed generation. This approach reduces data dimensions and uses a sequence-to-sequence LSTM network to predict the load in the low-dimensional space. Results indicate that the proposed approach achieves greater prediction accuracy compared to numerous existing methods in forecasting loads one week and one month in advance. The researchers in [73] considered factors like seasonality, trends, and the need for data preprocessing to compare performance of ARIMA model and a hybrid CNN-Bi-LSTM model. The study found that ARIMA model performed exceptionally well but required extensive data preprocessing while the neural network models were easier to implement but needed larger datasets for optimal performance.

The authors in [74] used ensemble learning models to forecast medium-term loads for isolated power systems. Factors like daily load values, calendar data, and previous load patterns were considered. The AdaBoost model, combining four linear regressions, achieved the highest accuracy. Finally, the work in [75] presented a two-stage forecasting framework for MTLF to improve accuracy over extended periods. This framework utilized BPNNs for initial short-term forecasts and RBFNN to forecast the remaining time steps and addresses data gaps and seasonal patterns.

C. Long-Term Load Forecasting (LTLF)

LTLF is distinct from STLF and MTLF primarily because of its focus on longer time horizons. This extended time horizon means that LTLF must consider trends like, population growth, GDP, and technology adoption. This makes ARIMA models and regression analysis suitable for LTLF because they are designed to handle time series data with trends and seasonality. These models are still widely used because they are simple and effective for large datasets.

Other AI techniques and methodologies have also been used to enhance forecasting accuracy over long time horizons. The study in [76] used fuzzy logic to forecast annual electricity demand. It considered the effects of population growth and GDP on electricity consumption across different sectors. This method worked better than the Holt Two-Parameter model, highlighting the importance of incorporating population growth and GDP. In [77], the researchers applied AI techniques like RNNs, FNNs and SVR for LTLF in a smart grid. FNNs achieved the most accurate results, with the lowest errors. Ref. [78] used an adaptive backpropagation algorithm with a MLP model. It considered energy consumption types and electricity outage periods. The proposed algorithm delivered the most accurate long-term forecasts compared to traditional methods like regression and even advanced AI models, such as RNNs.

The work in [79] proposed a hybrid modeling method using LSTM and Gated Recurrent Unit (GRU) networks to forecast the annual peak demand of distribution feeders. It included data like temperature, economic and demographic trends, and load composition to improve accuracy. The authors in [80] proposed a novel sequence to sequence LTLF framework based on a hybrid CNN-LSTM model, for forecasting monthly peak load three years ahead. This framework considered factors including average load, electricity price, population change, PV power generation pattern, and temperature. Ref. [81] introduced an LSTM-RNN model for five-year electricity demand forecasting using hourly load data. The model excludes weather data due to inaccuracies in weather predictions and focused on historical load patterns and time-based indicators instead.

It's worth noting that as it can be observed from the previous paragraphs that LSTM is less popular in MTLF and LTLF applications because of its high complexity and computation time [82].

D. Multi-Term Load Forecasting

Multi-Term Load Forecasting allows for a more dynamic energy system by addressing immediate fluctuations, medium-term trends, and long-term shifts in energy consumption patterns.

In ref. [83], a novel hybrid model named FARHAN is proposed for multi-term electrical load forecasting in smart grids, combining descending neuron attention, LSTM, and Markov-simulated neural networks. Using a dataset of 121,260 instances of electricity consumption data, it predicts monthly, yearly, and 14-year load trends. It also considers the impact of factors like historical consumption patterns, technological advancements, and the increasing demand from sectors such as electric transportation. The study in [84] suggested a hybrid CNN-LSTM model with seasonal adjustments for medium-term and long-term power load forecasting. The model used monthly power load data and seasonal turnover data and significantly improved the accuracy of monthly power load predictions.

The authors in [85] tested methods like ANN, Multiple Linear Regression (MLR), Adaptive Neuro-Fuzzy Inference System (ANFIS), and SVM for both short-term and long-term electricity load forecasting in Cyprus. Input parameters were time, temperature, humidity, solar irradiation, population, gross national income, and electricity price. SVM performed best for long-term predictions, while ANN was better for short-term analysis. The study in [86] introduces an improved sparrow search algorithm to optimize the hyperparameters of a SVM model for mid-long term load forecasting, using economic, social, and meteorological factors. The proposed model demonstrates great performance in forecasting accuracy and convergence speed compared to the original SVM, BPNN, MLR, and other models.

III. Hybrid models for Load Forecasting

Traditional load forecasting models often struggle with limitations that affect their accuracy, like failing to capture complex patterns and relationships in the data. On the other hand, AI-based methods are complex and need large datasets, leading to computational time increase. To address these issues, researchers have introduced hybrid models. These models aim to combine the strengths of different approaches and cover the limitations of single methods, such as statistical methods and machine learning.

In ref. [87] a STLF method is introduced using a hybrid seasonal autoregressive integrated moving average with exogenous regressors model and LSTM networks. The dataset includes information on energy consumption, day of the week, month, weather cluster, and holiday flag. This hybrid model performs better than using single models alone. Ref. [88] proposed an ARIMA-GM-LSTM model for medium-term and long-term electricity load forecasting. The researchers used monthly maximum load data for three Chinese provinces. This model improves compared to ARIMA, GM, and LSTM individually. It also generalizes well across datasets, showing consistent performance.

In [89], a novel combined probabilistic forecasting model has been developed for short-term electric load forecasting, by integrating Quantile Regression (QR) with a hybrid deep learning model. The researchers used load data, including total load and loads from two specific zones. The results demonstrated that the proposed model outperforms single models and traditional statistical models, in terms of reliability, resolution, and sharpness.

IV. Comparing Forecasting Methods and Addressing AI Challenges in Smart Grids

The aforementioned AI techniques, with their distinct advantages, play a crucial role in improving load forecasting. Table 1 provides a comprehensive comparison of both traditional statistical methods and AI-based techniques for different forecasting horizons. It highlights the most commonly applied methods for each forecasting horizon over the past five years and proposes solutions to address their limitations.

It is evident from Table 1 that ANNs are the most common AI-based techniques. Combining ANN with optimization techniques can reduce complexity and computational cost. This makes them effective and affordable for different forecasting needs.

It's worth mentioning that comparing the accuracy of all methods is difficult because there isn't a single, universal evaluation metric. Each metric focuses on different performance aspects, so it's important to use a specific set of metrics to make fair and meaningful comparisons. Many studies also don't include computational time. This makes it harder to judge how practical or efficient a method is, since different time horizons involve varying amounts of data.

Including computational time would help balance accuracy and efficiency for each method.

Table 1. An overview of most applied techniques in load forecasting across time horizons.

Forecast Horizon	Methods	Challenges	Solutions
STLF	ANNs SVR CNN-LSTM	Needs real-time, high-frequency data	Pre-process data in real-time using IoT
		Sensitive to noise and sudden events	Use noise reduction techniques (e.g., wavelet transforms), use hyperparameter optimization (e.g., PSO)
MTLF	RF GBM Hybrid AI-statistical models (e.g., NN-ARIMA, LSTM-ARIMA)	Low flexibility to sudden changes or anomalies	Combine AI and statistical models Use transfer learning for better adaptability
LTLF	Regression analysis Time series analysis ANNs	Traditional models may not capture non-linear relationships and sudden changes	Use advanced ML techniques to capture non-linear patterns
		Uncertainties in economic and policy changes	Update models regularly with new data, scenario analysis to address uncertainties

A. Future landscape of AI in smart grids

The future of load forecasting in smart grids will greatly improve with advanced AI techniques like deep learning, reinforcement learning, and hybrid models. These methods can handle the complexity of changing energy demand patterns. New techniques like transfer learning and federated learning will help AI models adapt to different grid scenarios. Better storage systems will allow AI to handle large amounts of data and make faster decisions.

AI will also work with other technologies like blockchain, edge computing, and 5G to improve grid operations. Blockchain will secure data and support decentralized energy trading. Edge computing will process data faster by working closer to its source.

Additionally, AI models will improve predictions for renewable energy sources like solar and wind. This will help manage energy storage and demand-response strategies. By improving the grid's capacity to handle unpredictable energy sources, this capability will support the transition to a low-carbon future. Smarter grids will become more self-sufficient. They will predict outages, optimize operations, and adjust to changes in demand and the environment.

As AI models become easier to interpret, grid operators will trust them more. This will make it easier to use AI in regulated systems and support the transition to a low-carbon future.

B. Challenges in AI adoption for smart grids

While numerous data-driven methods have made progress in solving smart grid issues, AI adoption in smart grids still faces several challenges:

- Integration with current energy systems [39], [90]: Most power grids were originally designed for centralized energy production relying on fossil fuels. This makes it hard to add modern technologies like advanced batteries, hydrogen fuel cells, and carbon capture systems. Renewable energy sources like solar and wind add more complexity, because they depend on weather and can cause fluctuations. Another critical concern is cybersecurity. AI must not only protect smart grids from cyberattacks but also maintain consistent grid performance.
- Managing Big Data: One big challenge is improving how smart grids handle large amounts of data for AI applications, especially as data volume grows. Real-time data from smart meters could improve forecasting accuracy, but challenges like delays and format mismatches make this difficult [91].
- Data Quality and Availability: AI models need clean, labeled, and comprehensive data, which is hard to get. Important variables such as weather conditions and consumer behavior must be included in the data. Preprocessing methods, such as filling in missing data and standardizing information, are essential for accurate predictions.
- Feature Extraction for Complex Datasets: Many AI models struggle with complex datasets, especially when unpredictable factors like seasonal variations influence electricity use. Advanced techniques like deep learning or hybrid models can help solve this problem. These approaches are better at uncovering hidden patterns and adapting to unpredictable factors. Unsupervised learning and attention mechanisms can also improve accuracy by focusing on the most relevant data features.

Addressing these challenges will improve the reliability and trust in AI-powered smart grids.

V. CONCLUSIONS

This paper reviews recent advancements in AI-based load forecasting for smart grids. Unlike many reviews that focus only on short-term forecasting, this paper examines studies across all forecasting timeframes. It helps researchers compare methods and results, giving them a wider view for future work.

AI techniques are becoming a preferred choice over traditional statistical methods because they are more accurate and better at handling complex patterns. For short-term forecasts, ANNs with optimized settings work well. It is recommended to include uncontrollable factors like weather data to make the prediction more accurate and reliable. For medium-term forecasts, deep learning models combined with statistical methods like ARIMA work well because they can handle large datasets effectively. Including seasonal patterns and economic trends into input data could be significantly helpful. The simplicity and effectiveness of traditional models make them suitable for long-term forecasting, but they will face challenges with large, non-linear data. In these cases, utilizing hybrid ANN-based approaches would be helpful. Despite the advancements, the success of AI models depends on several factors, like the model architecture, hyperparameter selection, and the quality of the input data. Hybrid models that combine AI with statistical methods are promising for better results. Future studies should focus on improving data integration, simplifying models, and making them more efficient.

Researchers should also study the impact of variables such as weather, seasonal variations, time-of-day patterns, and consumer behavior on load forecasting. Additionally, Future studies should explore how factors like weather, seasonal changes, time-of-day, and consumer behavior affect load forecasting. Long-term trends like population growth and economic factors, such as GDP and income, should be included in yearly forecasts. This will make models more useful for energy planning and help create smarter, more sustainable grids.

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