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Comprehensive Review of AI Techniques for Electricity Demand Forecasting

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Abstract **With increasing energy demand, there is an increase in energy consumption, encouraging demand to develop an AI-based model for accurately forecasting electricity demand in a region characterised by highly variable load profiles. Traditional linear models overlook non-linear factors used in dynamic data making them unsuitable for forecasting growing energy demands. The variability in peak load and presence of renewable sources like solar energy introduces the "Duck Curve," which complicates the ability of grid operators to balance supply and demand. The proposed model will incorporate weather effects, public holidays, natural load growth, renewable energy, and the day and night cycle to address the challenges of the unique demand patterns by leveraging AI techniques, deep learning, and neural networks against traditional models to develop the efficiency and reliability of energy grid organisation, enabling improved matching of supply and demand and reducing the likelihood of power shortages or surpluses.**

Keywords **— AI, Energy Demand, Machine learning, Neural networks, Electricity forecasting, Renewable energy**

I. INTRODUCTION

Electricity demand forecasting plays a fundamental role in efficiently operating power grids and energy markets. Accurate energy demand predictions will enable utilities and grid operators to manage resources, assess supply with demand, curtail operational costs, and reduce the risks of blackouts or energy shortages. With the increasing integration of renewable energy sources, such as solar and wind, as well as traditional power generation, forecasting has become more critical to ensure grid stability [1,7]. These challenges require more advanced forecasting techniques that can adapt to a dynamic environment.

Traditional forecasting models, including time series analysis and statistical regression, often fail to account for the non-linear and complex relationships between numerous factors influencing electricity demand. These factors include weather patterns, socio-economic activities, real estate development, public holidays, and the increasing adoption of distributed energy resources. As the energy grid becomes more complex and data-rich, conventional methods become less efficient in capturing the full scope of demand drivers. [2]

In modern years, artificial intelligence (AI) has appeared as a transformative tool in electricity demand forecasting. AI techniques such as machine learning (ML) and deep learning (DL) offer significant advantages over traditional approaches by learning complex, non-linear relationships from large datasets. The accurate forecasting of electricity demand is a crucial component in the planning and implementation of modern grids. As urbanization accelerates and with the rising demand for energy in both

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domestic and commercial sectors, grid operators must ensure that the supply of electricity meets fluctuating demand. In urban cities, electricity demand is highly variable due to seasonal changes, daily consumption peaks, and socio-economic activities. [5] The peak load varies, making it difficult for grid operators to balance supply with demand. Additionally, factors such as the "Duck Curve" phenomenon, driven by solar power generation, add to the complexity of managing electricity loads.

II. ABOUT ARTIFICIAL INTELLIGENCE (AI) AND MACHINE LEARNING (ML) IN ENERGY FORECASTING

ML is a fragment of AI that focusses on automating teaching to computers by utilising artifacts and thus improving their performance. For energy forecasting, ML processes can be used to analyse past energy consumption data, identify models, and predict future trends [1]. Artificial intelligence (AI) has developed as a powerful tool for enhancing the efficiency of energy demand forecasting. AI techniques such as machine learning (ML) and deep learning (DL) can analyse large amounts of data and capture complex, non-linear relationships that are often overlooked by traditional models [2]. AI-based forecasting models are capable of adapting to real-time data, learning from historical patterns, and integrating external variables like weather, public holidays, and economic growth, making them highly effective for modern energy grids. [7]

Deep Learning Techniques for Energy Forecasting, like Recurrent Neural Networks (RNNs), use Long Short-Term Memory (LSTM), which is a type of RNN that can handle long-term dependencies in time series data, making it well-suited for energy forecasting [5]. Also, Gated Recurrent Units (GRUs) use a simpler variant of LSTM that offers comparable performance with fewer parameters. Using convolutional neural networks (CNNs), which can be utilised to time series data by allowing the extraction of local features, is effective for capturing seasonal patterns and other periodicities in energy consumption data [6].

III. CRITICAL ISSUES & REMEDIES

A. Model Complexity and Reproducibility

Issue: Many hybrid algorithms proposed in the literature are difficult to read and reproduce and have little practical application in real-world load forecasting tools used by power companies.

Limited Use of Weather Data: load forecasters have limited access to weather data, which restricts the accuracy of forecasts. Modern advancements in data collection have improved this situation, but major challenges remain [5].

Remedy: Integration of Techniques: encouraging collaboration between AI and statistical practitioners to leverage the strengths of both fields. Implementing rigorous evaluation practices to avoid exaggerated accuracy claims. This includes conducting "smoke tests" to verify results [5].

B. Complexity of scheduling and Scalability

Issue: The complexity of scheduling increases as the complexity, nonlinearity, and nonconvexity of scheduling problems increase, and finding workable solutions becomes more challenging [4]. Scalability: Many proposed AI solutions for DR have not undergone large-scale experimentation, which raises concerns about their reliability and effectiveness in real-world applications [4].

Remedy-Exploration of Weather Variables: Continuing to explore the impact of weather variables on load forecasting, as improvements in this area can enhance the accuracy of various forecasting models.

Utilisation of Advanced Computing: Taking advantage of modern computing power to apply deep learning and other computationally intensive techniques for more accurate short and long term forecasting.

C. Integration of New Technologies

Issue: The increased use of electric vehicles (EVs), heat pumps, and distributed energy resources (DERs) is straining existing electricity infrastructure, increasing demand for effective DR solutions to maintain grid balance.

Optimisation Algorithm Selection: The implementation of optimisation algorithms is crucial to mitigate energy consumption costs. However, selecting the appropriate algorithm poses challenges, especially in developing countries where infrastructure may be lacking [4].

Remedy-Algorithm Tuning and Flexibility: To address the challenges of scheduling, it is essential to finely tune algorithms and leverage their resilience and flexibility to adapt to changing conditions. This includes utilising nature-inspired algorithms that can explore and exploit promising solutions effectively [4].

D. Scalability and Experimentation

Issue: Many proposed AI solutions for DR have not undergone large-scale experimentation, which raises concerns about their reliability and effectiveness in real-world applications [T6].

Remedy: Integration of New Technologies*: The increased use of electric vehicles (EVs), heat pumps, and distributed energy resources (DERs) is straining existing electricity infrastructure, necessitating effective DR solutions to maintain grid balance [6, 7].

E. Enhanced Demand Response Mechanisms

Issue: Implementing a robust demand response mechanism, particularly in developing countries, can help manage energy demand more effectively. This includes

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dynamic pricing and improved metering technologies [3].

Remedy: Collaboration with Startups and Established Sectors: Engaging with startups and established sectors that are applying AI techniques can provide valuable insights and foster innovation in the field of demand response [3].

F. Accuracy of Forecasting and Dynamic Load Variability

Issue: Inaccurate load and renewable energy forecasts can lead to suboptimal scheduling and energy imbalances. Load demand can fluctuate significantly due to daily and seasonal changes, making it hard to schedule effectively.

Remedy: Utilise future forecasting techniques, like machine learning and artificial intelligence, to improve forecast accuracy. Incorporate real-time data and historical patterns for better estimates. Develop adaptive scheduling algorithms that can adjust in real time based on updated load forecasts and historical usage patterns. [2,4,15]

G. Intermittency of Renewable Energy Sources Causing Change in User Preferences and Demand Response

Issue: Renewable energy generation can be unpredictable, causing gaps in supply that impact storage and scheduling. Preferences for indoor temperatures, lighting, and appliance use can vary, impacting overall energy demand [1, 18].

Remedy: Implement probabilistic forecasting methods to estimate the likelihood of various generation scenarios. Design the algorithm to include reserve margins that can buffer against uncertainty. Incorporate user preferences into energy management systems, allowing users to set their preferences for when and how they consume energy. This can increase participation in DR programs [1, 18].

H. Storage Capacity Limitations and Environmental Sustainability

Issue: Energy storage systems have limited capacity and efficiency, impacting the ability to meet peak demand.

Remedy: Optimise charge/discharge strategies to maximise the use of available storage. Incorporate environmental performance metrics into the scheduling algorithm [4, 7, 13].

1.5 DISCUSSION AND SCOPE OF THE REVIEW

This paper explores the application of artificial intelligence (AI) techniques for electricity demand forecasting, focussing on four key modules that significantly impact demand patterns: weather cycles, hourly cycles, special occasions, and renewable energy integration.

Weather Cycles: Changes in temperature, humidity, wind speed, and precipitation directly influence consumption patterns, particularly in regions where seasonal variations are extreme. [1,2,5]

Hourly Cycles: Electricity demand follows a predictable daily pattern, with distinct peaks and valleys within a 24-hour period [5].

This review will examine how AI techniques like recurrent neural networks (RNNs) and long short-term memory (LSTM) models are used for capturing the temporal dependencies in hourly demand fluctuations [5, 6].

Special Occasions: Public holidays, festivals, and unique events introduce additional complexity to electricity demand forecasting [2].

Renewable Energy Integration: The increasing penetration of renewable energy sources, especially solar power, adds another layer of complexity to demand forecasting. Using solar power generation creates a "Duck Curve" effect, where demand dips during the day when solar power is abundant but rises sharply in the evening when solar energy wanes.

AI models, particularly hybrid approaches, can incorporate both consumption data and renewable generation forecasts to ensure a balanced grid, reducing reliance on more expensive or carbon-intensive energy sources [1, 2, 12].

II. TRADITIONAL METHODS FOR ELECTRICITY DEMAND FORECASTING

Electricity demand forecasting has long been a vital component in the operation of power grids, enabling utility companies to balance supply with demand, optimise resource allocation, and avoid energy shortages or surpluses. Traditionally, a variety of statistical and mathematical models have been employed for this purpose, each with their own benefits and constraints. This review reviews the most used traditional methods, including time series analysis, regression models, and end-use models, and highlights their limitations in the context of modern power systems. [15]

A. TIME SERIES ANALYSIS

Time series models, like Auto Regressive Integrated Moving Average (ARIMA), have been extensively used for electricity demand forecasting. They are effective in capturing linear patterns and trends over time, making them popular in short-term load forecasting. [5]

2.2. REGRESSION MODELS

Regression models like multiple linear regression (MLR), which is a traditional approach that seeks to model the relationship between electricity demand and independent variables, The model believes a linear relationship between the dependent and the independent variable (electricity demand) [10]. The regression model

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Ordinary Least Squares (OLS) estimates the observed and predicted values in a way such that we minimise the sum of squared differences.

2.3. End-use models

End-use models estimate electricity demand by aggregating the consumption patterns of individual appliances or sectors (e.g., residential, commercial, industrial) that are built from the ground up by analysing how specific end-use devices (such as air conditioners, heaters, or lighting) consume electricity under different conditions. [10]

2.4. CHALLENGES AND LIMITATIONS OF TRADITIONAL MODELS

Although traditional methods have been widely used for decades, they exhibit several limitations when applied to modern, dynamic energy systems [1, 3].

Inability to Handle Non-linearity: Electricity demand is influenced by many non-linear factors, such as weather conditions and consumer behaviour, which traditional models cannot fully capture.

Limited use of external data: Traditional models often rely heavily on historical demand data but fail to incorporate real-time external factors, such as sudden weather changes or socio-economic events, which can drastically affect demand.

Poor Adaptation to Complex, Dynamic Grids: As energy systems evolve by the integration of renewable energy sources and smart grids, traditional models struggle to keep pace with the growing complexity and data availability.

Static assumptions: Traditional models typically assume fixed relationships between variables, which limits their ability to adapt to changing conditions in real time.

This shift to AI-based techniques is driven by the need for more accurate, scalable, and responsive models that can address the challenges posed by renewable integration, demand volatility, and the increasing availability of data.

III. OVERVIEW OF AI TECHNIQUES FOR ELECTRICITY DEMAND FORECASTING

The increasing complexity of power systems, the integration of renewable energy sources, and the growing demand for more accurate and dynamic electricity forecasts have propelled the adoption of artificial intelligence (AI) techniques in electricity demand forecasting. Unlike traditional models, AI-based approaches are capable of handling vast amounts of data, capturing non-linear relationships, and adapting to dynamic, real-time inputs. AI techniques provide a significant leap in forecasting accuracy and efficiency, allowing grid operators to better manage electricity supply and demand. This section provides an overview of the most prominent AI techniques used in electricity demand forecasting, including ML and deep learning.

A. Machine Learning (ML) Techniques

Machine learning (ML) involves training algorithms to learn patterns from historical data and make predictions based on that learnt knowledge.

A. Support Vector Machines (SVMs): SVMs are supervised learning models that analyse data for classification and regression analysis. In demand forecasting, SVMs work by finding a function that accurately fits the historical data and can predict future electricity demand. SVMs are particularly useful in handling non-linear relationships by using kernel functions to map the input data into higher-dimensional space [10, 11].

B. Decision trees make the decisions based on the if true then and if false then rule, which is obtained from input data. These models are effective at capturing the relationships between different demand-driving factors, like weather, time, and socioeconomic factors [10, 11].

C. K-Nearest Neighbours (KNN): KNN predicts future demand by analysing the 'K' most similar historical instances [10,11]

3.2. Deep Learning Techniques

DL techniques have gained significant attention for electricity demand forecasting due to their ability to automate feature extraction from raw data, reducing manual feature engineering. Key deep learning methods include:

A. Artificial Neural Networks (ANNs): ANNs are one of the earliest and most popular deep learning techniques used in forecasting [5, 12].

B. Recurrent Neural Networks (RNNs): RNNs are proposed to handle serial data, making them ideal for time series forecasting. A Long Short-Term Memory (LSTM) network is a type of RNN that is popular in electricity demand forecasting. [5,12]

C. Convolutional Neural Networks (CNNs): While CNNs are more commonly associated with image processing, they have been adapted for time series forecasting by using convolutional filters to capture local patterns. In electricity demand forecasting, CNNs can automatically detect features such as seasonality and trends. [5,12].

IV. DATA SOURCES FOR ELECTRICITY DEMAND FORECASTING

U Accurate electricity demand forecasting requires the identification of key features that influence power consumption and the utilisation of diverse data sources to model these factors effectively. In the context of artificial

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intelligence (AI)-driven models, the selection of relevant features and data is crucial for enhancing forecast accuracy and adapting to dynamic demand patterns. This section explores the most notable features and data sources used in electricity demand forecasting.

A. WEATHER DATA

Weather conditions are among the most significant external factors influencing electricity consumption, particularly in regions with extreme seasonal variations to differentiate between summer and winter [1, 2, 12]. Key weather features include:

Temperature: One of the primary drivers of electricity demand, temperature significantly impacts heating and cooling loads. For example, higher temperatures in the summer increase air conditioning use, while lower temperatures in the winter raise heating requirements. Humidity: Humidity, combined with temperature, affects human comfort levels, influencing the usage of HVAC systems (Heating, Ventilation, and Air Conditioning).

Wind Speed: Wind speed can affect the cooling effect, altering the demand for heating or cooling energy. Additionally, wind can impact renewable energy generation from wind farms, indirectly affecting demand. Precipitation: Rain or snow can influence outdoor activities and consequently modify electricity consumption patterns. For instance, during rainy days, people tend to stay indoors, potentially increasing electricity use in residential settings.

Solar Irradiance: Solar irradiance impacts the generation of renewable solar power, influencing the load on the grid and shifting electricity demand patterns throughout the day.

Data Sources for Weather data can be sourced from national meteorological services, satellite observations, or online weather forecasting services such as the National Weather Service (NWS), Kaggle, or World Meteorological Organisation (WMO).

4.2. TIME-RELATED FEATURES

Electricity demand varies significantly over time, reflecting daily, weekly, and seasonal patterns. [1,2,12] Time-related features are critical for capturing these cyclical variations:

Hour of the Day: Demand follows a typical daily cycle, with peaks and troughs at specific hours. For example, residential demand often peaks in the evening as people return home from work.

Day of the Week: Weekdays usually exhibit different demand patterns than weekends due to variations in commercial and industrial activity.

Month or Season: Seasonal variations, especially during summer and winter, significantly impact electricity demand due to heating and cooling needs.

Data sources for time-related features can be derived from simple time stamps associated with historical demand data, including utility records, grid operators' databases, or historical load profiles.

4.3. SOCIO-ECONOMIC AND DEMOGRAPHIC DATA

Socio-economic and demographic factors play an essential role in determining electricity consumption patterns. [1,2,12] Key features include:

Population Growth: Areas experiencing rapid population growth tend to see increased electricity demand due to higher residential and commercial usage.

Income Levels: Higher-income regions may exhibit greater electricity consumption due to the prevalence of energy-intensive appliances and electronics.

Economic Activity: Commercial and industrial electricity demand is closely tied to economic activity. Higher levels of manufacturing or service-based activities typically lead to increased consumption.

Urbanisation and Real Estate Development: New developments, housing projects, and commercial buildings impact the demand for electricity in specific areas.

Data sources for socio-economic data can be gathered from government statistics departments, census reports, or financial and economic databases such as the World Bank, International Monetary Fund (IMF), or national statistical offices.

4.4. GRID AND ENERGY DATA

Grid-related data helps AI models capture the technical aspects of electricity consumption and supply dynamics [1, 2, 12].

Historical load data: Historical electricity demand is often the starting point for forecasting models, providing insight into past consumption patterns and trends.

Electricity Prices: Dynamic pricing structures, such as time-of-use (TOU) rates, impact demand by encouraging consumers to shift usage to off-peak times.

Power Plant Availability: The operational status of power plants (e.g., outages or maintenance schedules) can affect electricity supply, indirectly influencing demand patterns.

Renewable Energy Generation: The integration of renewable energy, particularly from solar and wind sources, introduces variability into the grid. Solar power, for instance, is generated during the day but wanes in the evening, contributing to the "Duck Curve" effect in demand forecasting.

Data Sources for Load data are typically provided by

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utility companies and grid operators, while pricing data is available from electricity market operators. Renewable energy generation data can be obtained from sources like the Energy Information Administration (EIA) or regional energy management agencies.

4.5. SPECIAL EVENTS AND ANOMALIES

Unique events, such as major sporting events, political rallies, or natural disasters, cause deviations from normal demand patterns [1, 2, 12].

Large Gatherings: Public events or large gatherings lead to spikes in electricity demand, especially in venues with high energy usage (e.g., stadiums or convention centres).

Public Holidays: Public holidays, festivals, and unique events alter normal electricity usage patterns, making it crucial to account for these deviations.

Natural Disasters: Events like storms or floods can disrupt electricity supply or lead to temporary increases in demand due to emergency preparedness. Data sources on unique events and anomalies can be sourced from event organisers, government agencies, or disaster management organisations."

V. Models for Electricity Demand Forecasting

Electricity demand forecasting is essential for effective grid management, energy trading, and infrastructure scheduling. Several models have been developed over the years to predict electricity utilisation at different time horizons (short-term, medium-term, long-term) and varying levels of granularity (regional or national). These models are categorised into traditional statistical models, modern machine learning, and AI-driven approaches. Each model has its strengths and limitations depending on the complexity of the data, non-linearity in relationships, and the forecasting objective.

5.1 MACHINE LEARNING MODELS FOR ELECTRICITY DEMAND FORECASTING

Demand response for energy forecasting using AI involves predicting energy consumption patterns to optimise electricity supply and demand. Machine learning, a key AI approach, is used through both supervised learning and unsupervised learning methodologies. When using a supervised learning methodology, the model is trained by using historical data with labelled outcomes, such as past energy consumption and corresponding features like weather conditions, time of day, and public holidays. By discovering the connection between the response and the goal variable (future power demand), the model can make accurate forecasts. Common algorithms like linear regression, random forests, and neural networks are used to predict energy demand based on patterns observed in the historical data. For instance, a model trained on temperature and past consumption data can predict a spike in energy usage during hot days when air conditioning demand increases.

On the other hand, in unsupervised learning methodology, we discover hidden patterns within the big data without any previous predefined labels. This method is particularly useful for identifying patterns, clustering similar days of energy usage, and detecting anomalies in consumption behaviour. Algorithms like K-means clustering help in grouping days with similar energy consumption, revealing patterns in demand that might not be immediately apparent. Anomaly detection techniques can also flag unusual usage patterns, helping utilities manage unexpected peaks or drops in demand [1, 9].

5.2. DEEP LEARNING MODELS FOR ELECTRICITY DEMAND FORECASTING

Deep learning, a subset of machine learning, leverages neural networks with multiple layers (deep architectures) to model complex patterns in data. These models show exceptional performance in multiple domains, like image recognition, natural language processing (NLP), and time-series forecasting. In the context of electricity demand forecasting, deep learning (DL) models are employed to effectively utilize non-linear relationships and temporal dependencies in consumption data, making them increasingly popular. This section explores various deep learning models used for electricity demand forecasting, discussing their methodologies, strengths, and limitations.

A. Deep Neural Networks (DNNs)

Deep Neural Networks (DNNs) contain multiple layers of neurones interconnected with each other, allowing for the modelling of complex non-linear relationships in big data [9, 10].

Methodology: The model training is done using backpropagation, where the weights are adjusted based on the error between predicted target and actual values.

Strengths: Capable of capturing hierarchical representations within data, which can capture intricate patterns in electricity demand. The flexible architecture allows for customisation based on specific forecasting needs.

Limitations: requires large datasets for effective training; can be prone to overfitting. The complexity of the model makes it challenging to interpret results.

B. Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are primarily used for image processing but have also been adapted for time-series forecasting, including electricity demand [9, 10].

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Methodology: CNNs use convolutional layers to detect local patterns in data by applying filters that slide across the input data. In electricity demand forecasting, the input may be structured as a 2D grid (e.g., time vs. various features) to leverage spatial correlations.

Strengths: Effective at capturing local dependencies and patterns in the data. Reduces the number of parameters through weight sharing, making it computationally efficient.

Limitations: May require careful tuning of hyperparameters, such as filter sizes and pooling strategies. Generally, more suited for grid-like data; may require preprocessing to fit the time-series context.

C. Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs) are designed to handle sequential data, making them particularly suitable for time-series forecasting tasks like electricity demand [9, 10].

Methodology: RNNs maintain a hidden state that captures information from previous time steps, enabling the model to remember past inputs. Variants such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) are used to address issues like vanishing gradients, allowing them to learn long-term dependencies.

Strengths: Excellent at capturing temporal dependencies and sequential patterns in data. Adapts well to varying time intervals and can incorporate multiple features, such as weather conditions and economic indicators.

Limitations: Training is time-consuming when we have a large dataset. Complexity in architecture can lead to challenges in interpretability.

D. Long Short-Term Memory Networks (LSTMs)

Long Short-Term Memory Networks are a type of RNN designed to overcome the limitations of standard RNNs in learning long-term dependencies. [9,10,11]

LSTMs incorporate memory cells and gates that control the flow of information, allowing the model to retain relevant information over extended periods. The architecture consists of input, output, and forget gates, which regulate what information to keep or discard.

Strengths: Highly effective for modelling time-series data with long-range dependencies. In addition to knowledge from various input sequences, they are capable of predicting.

Limitations: Can be computationally intensive, requiring considerable resources for training. Sensitive to the choice of hyperparameters and architecture design.

5.3. REINFORCEMENT LEARNING FOR DYNAMIC LOAD MANAGEMENT

Reinforcement learning has surfaced as a powerful framework aimed at optimising dynamic load management in power systems, leveraging its ability to make sequential decisions based on environmental feedback. Unlike traditional control methods that often rely on predefined rules or heuristics, RL allows systems to learn optimal strategies through interactions with the environment, making it particularly suitable for the complexities of electricity demand and supply dynamics. [13]

Working of Reinforcement Learning

Reinforcement learning is a type of machine learning where an agent learns to make decisions by taking actions in an environment to maximise cumulative rewards. The key components are :

A. The Agent learns and makes decision that interacts with the environment.

B. The Environment is the external system the agent interacts with, in this case, the electrical grid and its load dynamics.

C. The State depicts the present state of the environment (e.g., current load demand, available generation).

D. The Actions are a set of choices that the agent can make (e.g., adjusting demand response strategies, optimising energy storage).

E. The Reward is the feedback from the environment based on the action taken (e.g., cost savings, efficiency improvements).

The agent aims to learn a plan that maps states and actions, maximising the expected reward over time.

VI. Comparison of AI Models: Accuracy and Efficiency

Table 2 Comparative Summary of Models

Model	Accuracy Metrics	Efficiency Metrics	Strengths	Weaknesses
DNN	High accuracy for complex patterns	Can be computationally expensive	Flexible architecture, capable of learning hierarchical representations	Requires large datasets, prone to overfitting
CNN	Effective for local patterns	Relatively efficient	Captures local dependencies, reduces parameters	Require careful tuning, more suited for grid-like data
RNN	Excellent for temporal dependencies	Can be time-consuming to train	Handles sequential data well, incorporates multiple features	Complex architecture, challenges in interpretability
LSTM	Highly effective for long-term dependencies	Can be computationally intensive	Learns from various input sequences	Sensitive to hyperparameters, requires resources

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VII. Challenges and limitations of AI in electricity demand forecasting

AI-driven solutions and improving forecasting accuracy and reliability. Here are the primary challenges: [1,2,3,12]

A. Data Quality and Availability

Accurate forecasting relies on high-quality, comprehensive data. Data that is too coarse may not capture important fluctuations, while overly granular data may introduce noise. Combining data from various sources can be complex, especially when data formats, collection times, and update frequencies vary.

B. Complexity of Demand Patterns

Non-Stationarity: Electricity demand patterns can change over time due to factors such as population growth, urbanisation, economic fluctuations, and changes in consumer behaviour.

Seasonal and Temporal Variability: Demand can vary significantly based on time of day, week, and season, making it challenging to capture these dynamics effectively in a single model.

Unexpected Events: Events such as natural disasters, pandemics, or sudden economic shifts can cause demand spikes or drops that are difficult to predict using historical data.

C. Model Interpretability

Black Box Nature: Many AI models, particularly deep learning approaches, operate as "black boxes," making it difficult to understand the rationale behind predictions [1, 2, 3, 12]. This lack of transparency makes it difficult to trust among stakeholders.

D. Computational Demands

Resource Intensive: Artificial intelligence models, especially deep learning, require significantly huge computational space and time for proper training [1, 2, 3, 12]. This leads to higher operational costs, particularly for organisations with limited resources.

E. Integration with Existing Systems

Legal Systems: Many utilities operate on legal systems that are not compatible with the modern artificial intelligence frameworks. Integrating AI solutions with existing infrastructure can be technically challenging and expensive.

Change Management: Implementing AI-driven forecasting systems may require changes in organisational processes, which can encounter resistance from staff accustomed to traditional forecasting methods.

F. Ethical and social considerations

Bias in Data: AI models can inherit biases present in historical data, leading to unfair or inaccurate predictions. This can have significant implications, especially for demand response programs that affect consumer behaviour.

Impact on Stakeholders: The deployment of AI in forecasting can affect various stakeholders (e.g., consumers, utilities, regulators). [1,2,3,12] Ensuring that AI applications are fair and equitable requires careful consideration and ongoing monitoring.

G. Limited Generalisability Across Regions

Regional Differences: Electricity demand patterns can vary significantly across different regions due to factors such as climate, cultural behaviours, and economic conditions. [1,2,3,12] Models trained on data from one region may not perform well when applied to another without appropriate adjustments.

VIII. Future Trends and Directions

As the energy landscape continues to evolve, the integration of artificial intelligence (AI) in electricity demand forecasting is poised for significant advancements. The following sections outline the emerging trends and potential future directions that will shape the field of AI-driven electricity demand forecasting.

A. Enhanced Deep Learning Techniques:

B. Hybrid and Ensemble Approaches:

C. Real-Time and Adaptive Forecasting:

D. Adaptive Learning Systems:

E. Integration with Smart Grids and IoT Smart Grid Interoperability:

F. Climate Resilience and Sustainability by Incorporating Climate Variables

G. Integration:

H. Decentralised Models:

I. Policy and Regulatory Adaptation by Alignment with Energy Policies

J. Risk Management and Uncertainty Modelling by Quantifying Uncertainty[14].

K. Collaborative Research and Development Industry-Academia Partnerships.

VI. Conclusion

The utilisation of artificial intelligence (AI) in electricity demand forecasting is set to transform the energy landscape significantly. As we look toward the future, several key trends and directions emerge that promise to enhance the accuracy, efficiency, and resilience of demand forecasting systems.

Advanced deep learning techniques such as transformers

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and generative models will offer improved capabilities to capture complex patterns in electricity demand, paving the way for more sophisticated forecasting solutions. [9,10,11] The adoption of hybrid and ensemble approaches will enhance model robustness, ensuring that diverse patterns in demand are captured, ultimately leading to better predictions.

Integration with smart grids and IoT will enable data-driven insights at an unprecedented scale, facilitating proactive demand management and enhancing overall grid performance. [14]

In conclusion, the future of utilising AI in electricity demand forecasting is large and extensive, characterised by innovative methodologies and approaches that will address the complexities of modern energy systems. By leveraging these advancements, the energy sector can achieve more accurate, efficient, and sustainable electricity supply management, ultimately contributing to a resilient and responsive energy grid that meets the demands of the future.

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