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Review article

Review on smart grid load forecasting for smart energy management using machine learning and deep learning techniques

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ABSTRACT

This review offers an in-depth examination of Deep Learning (DL) and Machine Learning (ML) techniques for smart grid load forecasting, emphasizing language precision, methodological rigor, and the exploration of novel contributions. The language used in this review is both technical and accessible, balancing complex concepts with clear explanations to cater to both specialists and general readers. It meticulously dissects contemporary DL models, including neural networks and ensemble methods, and evaluates their effectiveness through a detailed review of algorithms and frameworks. The methodology section systematically compares these techniques against traditional forecasting methods using performance metrics such as MAPE, RMSE, and MSE, ensuring a comprehensive assessment of their accuracy and scalability. A significant contribution of this review is its examination of real-world applications and case studies, which demonstrate how ML and DL techniques address practical challenges in energy management, such as grid stability and demand forecasting. Furthermore, the review introduces novel perspectives on the integration of probabilistic forecasting and ensemble methods, which offer innovative approaches for managing energy demand uncertainties. By identifying current limitations and proposing future research directions, this review not only advances the understanding of DL and ML applications in smart grids but also provides a foundation for future developments in this evolving field.

1. Introduction

Instances of highly variable distributed generation sources (Hussain et al., 2020a), such as electric vehicles (Ustun et al., 2012; Distributed Energy Resources DER, 2011), photovoltaic systems (Distributed Energy Resources DER, 2011; Hussain et al., 2020a), wind turbines (Dey et al., 2020; Patil et al., 2022), and energy storage devices (Das et al., 2022a; Haq et al., 2023), present challenges to the stability of power and distribution networks (Nadeem et al., 2019). These sources contribute to distributed generation, and their integration may potentially jeopardize system stability (Latif et al., 2020; Hussain et al., 2020b; Barik et al., 2021). The primary concern in many cases is the imbalance that can arise between power supply and demand (Farooq and Rahman, 2022; Safiullah et al., 2022). Such imbalances, observed in numerous case studies, can lead to disruptions in the network (Aftab et al., 2021), manifesting as voltage fluctuations and, in severe cases, blackouts (Ranjan et al., 2021a; Latif et al., 2021; Anonymous, 2021a). Furthermore, disturbances in the network are conceivable (Kamrul et al., 2024).

Potential network disruptions are a concern, which could lead to significant complications (Ustun et al., 2021a). The implementation of energy management systems allows achieving dual objectives: reducing peak loads during unforeseen periods and improving the equilibrium between supply and demand effectively (Hussain et al., 2022; Srivastava et al., 2022; Das et al., 2022b; Ustun and Hussain, 2020). This goal is accomplished through the establishment of energy management systems. Two fundamental categories can be applied to energy management classification (Fekri et al., 2023). The first category pertains to the supplier side, such as electric utilities, which involves the activation or deactivation of certain generators in response to variations in load demand (Ustun et al., 2022).

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The second category, termed demand-side management, focuses on consumer-side management of the market (Chauhan et al., 2021; Ranjan et al., 2021b). This entails consumers regulating their energy usage to meet the electricity demand created by generation-side implementation of demand-side management. This is done to meet the power demand. The primary objective of implementing energy management is to reduce operating and consumption costs (Singh et al., 2021), minimize energy losses (Sahoo et al., 2023). Another objective is to improve network reliability (Al-Shetwi et al., 2022; Dawn et al., 2021).

Load forecasting, illustrated in Figure 4, is resilient due to its capability to adjust to dynamic changes in energy demand and generation patterns, thereby enhancing grid stability and reliability. By integrating machine learning and deep learning techniques, forecast models can accurately capture intricate trends and fluctuations. The resilience is further bolstered by ensemble methods, which mitigate uncertainties and enhance forecast performance. Additionally, probabilistic forecasting provides a proactive approach to managing unpredictability, empowering decision-makers to make informed risk management decisions. Overall, the resilience of load forecasting ensures efficient resource allocation, grid optimization, and sustainable energy management, thereby contributing to a more robust and adaptable energy infrastructure.

The power utilities with different generation modalities (DGM) experience complexities & minimal error in predicting future load forecasting. It features diverse components including residential homes, commercial offices, and industrial facilities, all connected to a central power distribution tower. This highlights the process of collecting data through smart meters installed at each component location. This data is then transmitted to a central system for aggregation and analysis. The core of the process involves using advanced algorithms to forecast energy demand and supply needs based on historical and real-time data. By optimizing electricity distribution, smart grids enhance energy management, improve efficiency, and balance supply and demand through data-driven insights.

On the other hand, it has a significant future in which the majority of the research that is being done right now is concentrated on the development of complex algorithms and models in order to improve the management of the energy that is on the grid. This is being done in order to make the grid run more efficiently. The reason for this is that it has a good future ahead of it. For the purpose of satisfying the requirements of the customers and making their lives easier, it is essential that there be an increase in the quantity of power that is generated. The reason for this is that the need for energy is only going to continue to increase all across the world. On the other hand, the demand for electricity may result in difficulties for the operators of the electric utilities and the system as a whole. This predicament is the result of a variety of variables, the most important of which are the unpredictability of the electric load and the fact that there are more customers overall. In addition, there is a considerable possibility that high peak demands may occur at a variety of different times, which may pose a risk to the system's capacity to carry out its functions (Al-Quraan et al., 2023; Alsirhani et al., 2023).

For effective energy planning and management in power systems, load forecasting is crucial. It is divided into a number of groups according to the time prediction horizon.

Very Short-Term Load Forecasting (VSTLF): This category typically involves predicting load demand over minutes to a few hours ahead. VSTLF is crucial for real-time operations, such as unit commitment, dispatch scheduling, and grid stability. Techniques like autoregressive integrated moving average (ARIMA), artificial neural networks (ANN), and support vector machines (SVM) are commonly employed for VSTLF due to their ability to capture short-term dependencies and rapid load fluctuations.

Short-Term Load Forecasting (STLF): STLF extends the prediction horizon to a day, a week, or up to a month ahead. It aids in optimizing resource allocation, energy trading, and economic dispatch. STLF models often integrate weather forecasts, historical load data, and calendar effects. Methods such as ARIMA, exponential smoothing, and STLF applications frequently use machine learning techniques like gradient boosting and random forests.

Medium-Term Load Forecasting (MTLF): MTLF typically spans from several months to a year ahead. It facilitates capacity planning, infrastructure investment decisions, and policy formulation. MTLF models incorporate factors such as economic indicators, population growth, and industrial activities. Time series analysis, econometric models, and regression techniques are commonly used in MTLF.

Long-Term Load Forecasting (LTLF): LTLF involves predicting load demand several years or decades into the future. It informs long-term investment strategies, grid expansion plans, and renewable energy integration. LTLF models consider factors like demographic trends, technological advancements, and regulatory changes. Econometric models, scenario-based analysis, and system dynamics approaches are employed in LTLF due to the complexity and uncertainty of long-term forecasts.

In conclusion, each type of load forecasting has a specific function and makes use of specialized techniques to deal with the particular difficulties posed by various time horizons for prediction in power system planning and operation. On the other hand, the taxonomy for load forecasting approaches can be organized into three primary categories: statistical methods, machine learning methods, and deep learning methods. Here is a concise summary:

Statistical methods play a crucial role in load forecasting and analysis. Time Series Analysis is employed for load forecasting, utilizing strategies such as Exponential Smoothing and ARIMA (Auto Regressive Integrated Moving Average) (Dey et al., 2023). These techniques are effective in capturing temporal patterns and trends in historical load data. Regression Analysis is utilized to establish relationships between historical load data and other significant variables (Hamoudi et al., 2023). This method helps quantify the impact of various factors on electricity consumption patterns. Seasonal decomposition methods, such as the seasonal decomposition of time series, are employed to decompose load data into trend, seasonal, and residual components (Yadav and Malik, 2021). This approach aids in understanding seasonal variations and their influence on overall load patterns.

Machine Learning methods offer advanced techniques for load forecasting. Support Vector Machines (SVM) are utilized to predict future load by analyzing historical data and relevant characteristics (Chatterjee et al., 2024). SVMs excel in capturing complex relationships and patterns in data. Techniques such as Random Forest, an ensemble method, is effective in handling non-linear relationships and interactions between variables in load forecasting (Ustun et al., 2021a, 2021b; Yarar et al., 2023). By aggregating predictions from multiple decision trees, Random Forest enhances predictive accuracy. Similar approaches iteratively build a series of weak learners to create a robust learner for load forecasting tasks (Pattanaik et al., 2024). This iterative approach sequentially improves prediction accuracy by focusing on previously mis predicted data points.

Deep Learning methods, particularly Recurrent Neural Networks (RNNs) such as Long Short-Term Memory (LSTM) networks, are increasingly employed for sophisticated load forecasting. RNN architectures, notably LSTM networks, are adept at analyzing sequential data like time series, which is crucial for accurate load forecasting (Abdolrasol et al., 2023; Anonymous, 2021b; Ulutas et al., 2020). These networks excel in capturing long-term dependencies and temporal dynamics in data, making them well-suited for modeling electricity consumption patterns over time.

Each of these methods possesses distinct advantages and disadvantages, and Depending on the specific characteristics of the load data and forecasting requirements, their effectiveness may vary. Finding the best strategy for a given forecasting task requires conducting tests and validating findings. Based on the above discussions, this review provides a comprehensive overview of recent advancements in smart grid load forecasting methods. It underscores the critical importance of load forecasting within the realm of smart energy management, emphasizing its pivotal role in optimizing energy distribution and consumption strategies. The review explores the integration of advanced techniques from deep learning and machine learning, demonstrating their efficacy in enhancing the accuracy and reliability of load forecasting models. Furthermore, it identifies and discusses significant challenges encountered in smart grid load forecasting, including issues related to data quality, scalability, and model interpretability. These insights lay the foundation for future research directions aimed at addressing these challenges and advancing the field. Additionally, the review evaluates the potential of ensemble methods in bolstering load forecasting performance, highlighting their capability to mitigate uncertainties and elevate forecast accuracy in dynamic energy environments.

2. Review of load forecasting in power systems

The load forecasting problem in conventional and smart grids varies substantially due to the distinct characteristics and capacities of each grid system. Traditional systems commonly employ rudimentary statistical models and historical data to forecast future power demand in load forecasting. These models frequently fail to consider the ever-changing nature of energy consumption patterns and have limited capacity to adjust to changing circumstances.

In addition, traditional grids do not possess the capacity to see and act in real-time, which creates difficulties in administering demand-response programmes and incorporating renewable energy sources. Load forecasting in smart grids use sophisticated technologies like sensors, smart metres, and communication networks to collect up-to-date information on electricity consumption, generation, and system conditions. Smart grid load forecasting utilises advanced machine learning and deep learning algorithms to analyse extensive data and detect intricate trends in energy consumption. This allows for more precise and detailed forecasts of electricity consumption, which helps improve the administration and optimisation of the power grid.

Furthermore, smart grids facilitate the implementation of dynamic pricing mechanisms and demand-response programmes, which enable utilities to motivate users to modify their electricity consumption in accordance with real-time system circumstances. In smart grids, load forecasting is characterised by its dynamic, adaptive, and data-driven nature, which sets it apart from conventional grids. This allows for enhanced efficiency, dependability, and sustainability in energy management.

When it comes to load forecasting, the classification into distribution of load forecasting, hierarchical load forecasting, and probabilistic load forecasting provides a systematic framework to tackle various parts of the forecasting process. Below is a detailed analysis of each category:

Forecasting the Distribution of Power Demand is the process of estimating the amount of power is known as spatial load forecasting. It is needed at different points within a specific region or network. This technique recognizes the regional variability in load patterns caused by factors such as population density, industrial activities, and climate fluctuations. Methods such as spatial interpolation, geographic information systems (GIS), and clustering techniques can be used to capture spatial relationships and forecast the load at specific areas. Efficiently managing generation, transmission, and distribution resources across multiple regions is of utmost importance for utilities, making spatial load forecasting a critical task.

Hierarchical Load Forecasting refers to the process of predicting the electricity demand at different levels of a hierarchical structure, such as at the national, regional, or local level. Hierarchical load forecasting acknowledges the hierarchical arrangement of the electricity grid, encompassing distinct tiers such as national, regional, and local grids. This methodology entails predicting the demand at every level of the hierarchy, considering the combination and separation of load data. Forecasts can be created for many levels of electricity demand, including national, regional, and specific load zones within regions. Hierarchical load forecasting enables efficient decision-making at different administrative levels and aids in coordinating load balancing tactics throughout the grid.

Probabilistic Load Forecasting: Probabilistic load forecasting extends beyond making single predictions by offering probabilistic forecasts that encompass the inherent uncertainty in load forecasting. Probabilistic forecasting involves generating a probability distribution of future load scenarios, allowing decision-makers to evaluate the probability of various events and make well-informed risk management choices, rather than anticipating a single value. Probabilistic load forecasting often employs techniques such as ensemble methods, Bayesian methodologies, and Monte Carlo simulations. This method is especially beneficial for utility companies and grid operators to accurately measure and control the unpredictability linked to fluctuations in power demand, market conditions, and the integration of renewable sources.

By integrating these classifications into the load forecasting paper, a thorough examination of the many aspects of forecasting methods and their practical ramifications in the energy industry may be achieved.

2.1. Background

Improving the transmission and consumption of electrical power in a smart grid for smart energy administration requires the use of load forecasting. Given the increasing demand for energy, In order to forecast load accurately and efficiently, Deep learning and machine learning must be applied. ML and DL algorithms utilize historical consumption patterns, weather conditions, and other pertinent data to forecast future electricity demand with greater accuracy compared to conventional approaches.

The Smart Grid increases the efficiency and dependability of electricity distribution by utilizing modern technologies, with load forecasting playing a crucial role in this system. Complex correlations within the data are captured by deep learning, or DL, models like neural networks and machine learning (ML) models like regression and decision trees. enabling more detailed predictions. This proactive strategy helps utility companies optimize resource allocation, minimize grid congestion, and avert future failures. Additionally, it gives customers the knowledge they need to make educated decisions about how much energy they use, which promotes a more economical and sustainable energy environment. When load forecasting is combined In the framework of a smart grid, machine learning (ML) and deep learning (DL) operational efficiency is increased and a more intelligent, resilient energy infrastructure that can meet the ever-changing needs of modern society is developed (Zafar et al., 2023; Onteru and Vuddanti, 2023).

2.2. Motivation

The motivation behind this review is to address the pressing need for effective load forecasting in Smart Grids for Smart Energy Management. With the increasing complexity of energy systems and the rapid integration of renewable energy sources, there is a critical demand for accurate prediction models. By focusing on the integration of Machine Learning techniques, particularly Deep Learning, this review aims to explore recent advancements and identify challenges in order to guide future research efforts. Ultimately, the goal is to contribute to the development of transparent, resilient, and human-centric smart energy management systems to meet the evolving needs of the energy industry.

2.3. Objectives of review

The review has multifaceted objectives designed to advance understanding and application in the field. Primarily, its goal is to assess the state of Deep Learning approaches today as they relate to load forecasting in smart grids. This entails a thorough examination of current models. This involves a comprehensive analysis of existing models, algorithms, and frameworks to assess their effectiveness, accuracy, and scalability.

Secondly, the review seeks to identify the practical implications of implementing ML and DL for load forecasting in Smart Energy Management. This includes evaluating their impact on grid reliability, energy efficiency, and overall system performance. By delivering into real-world applications and case studies, the objective is to distill valuable insights that can inform future deployments and improvements.

Lastly, the review aims to pinpoint challenges and limitations associated with ML and DL approaches, providing a critical examination of potential hurdles in deployment and suggesting avenues for further research. Through these objectives, the review strives to contribute to the ongoing evolution of Smart Grids for smarter and more sustainable energy management.

2.4. Scope and limitations

This review comprehensively examines the latest research trends and achievements in enhancing smart grid load prediction accuracy using deep learning and machine learning techniques. It covers diverse methodologies such as ensemble methods, time series analysis, and optimization techniques, highlighting the dynamic and evolving nature of this field. Emphasis is placed on key performance metrics like MAPE, RMSE, RRSE, and MSE. The focus is on demonstrating the effectiveness of complex algorithms, particularly neural networks, in addressing energy system challenges, supported by empirical case studies that connect theoretical advancements with practical applications.

Despite promising advancements, the review identifies several limitations, including the opacity of complex models and persistent cybersecurity concerns. These challenges highlight the need for ongoing research to develop transparent, resilient, and human-centric smart energy management systems. The review also underscores the importance of interdisciplinary cooperation to address emerging issues and advance towards a more intelligent and sustainable energy future. Continuous exploration is essential to fully harness the potential of advanced techniques in smart grids, ensuring their real-world applicability and long-term efficacy.

3. Literature review

A revolutionary trend marked by advancements in technology and a growing emphasis on sustainability can be seen in the historical development of load forecasting utilizing machine learning and Deep learning methods for intelligent energy management in the framework of smart grids.

Initially, load forecasting heavily depended on conventional statistical techniques, time-series analysis, and basic forecasting models. These methods have constraints in their capacity to comprehend the intricate and ever-changing characteristics of energy usage patterns, particularly in light of the growing urbanization and industrialization. With the increase in energy needs, it became clear that more advanced technologies were needed to tackle the changing issues of the power grid (Das et al., 2023; Kermani et al., 2023; Xin et al., 2022).

The advent of machine learning signified a significant shift in the existing methods. Machine learning algorithms, such decision trees and regression analysis, started to become more and more common in load forecasting in the late 20th century. These methods provided enhanced precision by taking into account past consumption data, weather trends, and other external variables. Machine learning introduced a methodology that relies on data analysis to predict future outcomes, allowing utilities to make better-informed choices regarding the allocation of resources & the grid's management.

The application of deep learning (DL) in the twenty-first century significantly changed how load forecasting works inside smart grids. Deep learning, especially neural networks, demonstrated an impressive ability to discover complex patterns and relationships inside large datasets. DL's capacity to autonomously extract characteristics and adjust to fluctuating circumstances renders it very suitable for the dynamic aspects of energy usage. The development of sophisticated models like This era saw major advancements in the estimation and prediction of energy usage over time produced by long short-term memory networks (LSTMs) and recurrent neural networks (RNNs) (Yao et al., 2022; Islam et al., 2022; Khan et al., 2022; You, 2022).

There was also a shift in the historical path toward real-time prediction. Modern sensor technology and the widespread use of smart meters have made it possible for utilities to collect data more often, which allows them to produce projections that are more accurate and timely. Since renewable energy sources and electric vehicles have become more prevalent, the real-time functionality has become crucial for controlling the increasing volatility & unpredictability of energy consumption patterns (Complementary and Medicine, 2023; Torres et al., 2023; Wang et al., 2023a; Yang et al., 2023).

As they evolved, smart grids were employed for purposes other than load forecasting. In order to maximize demand responsiveness, identify issues, and forecast maintenance needs, deep learning (DL) and machine learning (ML) techniques were applied. The goal of these all-inclusive approaches is to create energy ecosystems that are more robust and adaptive. Notwithstanding these developments, problems remained. The effectiveness of machine learning (ML) and deep learning (DL) models is significantly impacted by the quality and accessibility of data, according to historical trends. Biases or inaccuracies in prior data may affect the prediction's accuracy. Furthermore, the understandability of complex deep learning models has become a source for concern because awareness of the decision-making process is essential to promoting acceptance and confidence in real applications.

In the future, load forecasting will continue to grow as learning with deep neural networks (DL) and ML technologies grow (Nagarajan et al., 2022; Refaai et al., 2022). The historical review provides the foundation for this progression. The incorporation of explainable AI, reinforcement learning, and hybrid models that leverage the advantages of different techniques can enhance the precision and practicality of load forecasting in Smart Grids, ultimately leading to a more intelligent, efficient, and sustainable energy management approach.

3.1. Comparative evaluation of author contributions in comparison to other review papers

When assessing the authors' addition to the current collection of review articles on smart grid load forecasting, it is crucial to examine the thoroughness of their study, the originality of their findings, and their incorporation of recent breakthroughs in machine learning (ML) and deep learning (DL) techniques. The authors' contribution is notable in multiple ways when compared to prior review publications in the field.

Firstly, their historical overview offers a thorough analysis of the development of load forecasting techniques, documenting the shift from conventional statistical methods to the incorporation of machine learning (ML) and deep learning (DL) approaches. The thorough historical backdrop allows readers to understand the importance of recent achievements in the wider context of smart grid management.

Particular uses of machine learning (ML) and deep learning (DL) in load forecasting, emphasising the efficacy of neural networks like long short-term memory (LSTM) and recurrent neural networks (RNNs) in collecting intricate patterns in energy consumption data is explored. The authors provide useful insights into the potential of deep learning approaches to tackle the issues posed by dynamic energy usage patterns in smart grids, by emphasising on this advanced methodology.

The authors highlight the significance of having the ability to predict in real-time, especially in the face of growing instability and unpredictability resulting from the incorporation of renewable energy sources and electric vehicles. This perspective that looks ahead emphasises the importance of their review in tackling the current and future issues that the energy business is facing. The authors of this review study also recognise the limitations and difficulties that come with ML and DL models, including problems with data quality and the absence of interpretability in intricate DL architectures.

Through a thorough evaluation of these obstacles, the authors present an impartial viewpoint on the tangible consequences of incorporating machine learning (ML) and deep learning (DL) methods in actual smart grid settings. Also suggest that future research should focus on integrating explainable AI and hybrid modelling techniques to improve the accuracy and applicability of load forecasting. The authors' commitment to moving the field beyond present restrictions is evident in their forward-thinking approach.

This approach highlights the potential significance of their work on defining future improvements in smart grid management. The authors' contribution to the current literature on smart grid load forecasting is notable for its thorough analysis, integration of recent breakthroughs, and forward-thinking approach to future research paths. The authors' comprehensive analysis of machine learning (ML) and deep learning (DL) approaches in the context of smart grids offers useful insights that contribute to the continuing discussion on sustainable energy management. Tables 1,2

3.2. Key concepts and definitions

The main ideas and terms surrounding load forecasting in relation to the supply of electricity. For the electricity system to remain reliable and to avoid possible disturbances like blackouts, load forecasting accuracy is essential. To gauge how accurate load forecasting methods are, a number of Key Performance Indicators (KPIs) have been identified. These are the definitions and main ideas that were discussed. Statistically speaking, the Mean Absolute Error (MAE) measures the average absolute deviations between the projected and actual values in a dataset. A straightforward method to assess prediction accuracy is to use the mean of absolute differences (MAE), which does not take error direction into account.

Table 2
Comparison of Machine Learning (ML) and Deep Learning (DL) Models Based on Validation Indices.

Author name/year	Methodology used	**Validation Indices**	**Ref.**
Guo/2021	Deep neural network (DNN)(Deep learning)	Simulation findings demonstrate that the prediction model's performance indices' mean absolute percentage error eMAPE and root-mean-square error eRMSE are 10.01 % and 2.156 MW. .	(Guo et al., 2021)
Asiri /2024	Deep learning, LSTM, CNN, optimization, performance.	LFS-HDLBWO outperforms other DL methods with error rates of 3.43 and 2.26.	(Asiri et al., 2024)
Alquthami/ 2022	Short-term load forecasting using machine learning methods and improved decision trees .	99.21 % accuracy in training, 100 % F1, 100 % precision, 99.9 % recall, and 99.70 % correctness in testing.	(Alquthami et al., 2022)
Muzumdar /2020	machine learning techniques include Random Forest and Support Vector Regressor (SVR) (RF).	MAPE=1.18	(Muzumdar et al., 2020)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - x| \tag{1}$$

The calculation of the Mean Absolute Percentage Error (MAPE) involves dividing the sum of all individual absolute mistakes by the total of all real values. This statistic normalizes the forecast accuracy in respect

Table 1
Literature summary.

Author name /Ref	Methodology used	Gap/ problem definition	Dataset used	Parameter measured
Jiang (Jiang et al., 2023)	Hybrid forecast-optimize tasks and efficient online data augmentation scheme.	Handling uncertainties in renewable energy integration and real-time energy dispatch.	CityLearn Challenge 2022 dataset for smart building energy management.	Energy dispatch accuracy, robustness, adaptation to real-time data distribution.
Chen (Chen et al., 2023)	ARIMA and Bi-LSTM models for solar power production prediction.	Accurate forecasting of solar power production for efficient grid management.	One year of real-time solar power production data for prediction.	Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).
Maghraoui (Maghraoui et al., 2022)	SVM, ANN, DT, and RF for hotel energy consumption prediction.	Optimizing energy efficiency in hotels to prevent grid overload.	Hotel building energy consumption data from a case study in Shanghai.	Accuracy of energy consumption predictions using MAE, RMSE, and efficiency.
Alsharekh (Alsharekh et al., 2022)	R-CNN and ML-LSTM for short-term electricity load forecasting framework.	Accurate multistep electricity load forecasting for smart grid management.	Residential IHEPC and commercial PJM datasets for electricity load forecasting.	Forecasting accuracy measured by error rates compared to baseline models.
Teekaraman Teekaraman et al., (2022a)	Optimizing smart grid video sensor networks for energy efficiency and performance	Optimizing energy consumption and quality of service in smart grid networks.	Wireless video sensor network dataset for optimizing energy and quality.	Power, energy consumption, delay, transmission rate, delivery rate, convergence rate, quality.
Ibrar Ibrar et al., (2022)	Predicting decentralized power grid stability using machine learning and resampling.	Addressing imbalances and enhancing prediction accuracy in decentralized power grid stability.	Data from an open machine learning library used to simulate a decentralized grid .	Grid stability parameters: electricity volume (p), cost-sensitivity (g), response times (tau).
Zhu Zhu et al., (2022)	DASG protocol using Chinese Remainder theorem for smart grid security.	resolving issues with data integrity in smart grid aggregation protocols.	Smart grid dataset, privacy-preserving, integrity, DASG protocol, homomorphic encryption, aggregation.	Smart grid parameters: status, privacy, integrity, DASG protocol, encryption, aggregation.
Sodagudi (Sodagudi et al., 2022)	Hybrid control system methodology for efficient power electronic interface in renewable energy	Voltage quality, harmonic distortion, and efficiency challenges in power electronics.	Dataset on power electronics, energy efficiency, and control systems evaluation	Battery SOC, charging voltage, battery current, ultracapacitor current, and DC load current.
Yu (Yu et al., 2022)	3-tier cloud-fog-consumer architecture; real-time VM migration for load balancing.	Network congestion and imbalance in cloud data centers for VMs.	Dataset on cloud data center size, VM growth, and load balancing.	Measured parameters: Cloud size, VM growth, network resources, load balancing, response time, cost optimization.

to the scale of the data and presents it as a percentage.

$$MAPE = \frac{1}{n}\sum\frac{|e_t|}{|a_t|} \tag{2}$$

There are two steps involved in calculating the Root Mean Square Error (RMSE). To obtain the Mean Squared Error (MSE), the squared errors are first averaged. After that, the square root of the MSE is used to calculate the RMSE, a gauge of forecast accuracy (Botchkarev, 2019).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \widehat{Y}_i)^2 \tag{3}$$

$$RSME = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \tag{4}$$

According to its definition, the Root Relative Squared Error The ratio of total squared mistakes between predicted and actual values to total squared errors between average value and actual values is known as the root mean square error (RRSE). It evaluates predicting effectiveness by comparing it to a reference value.

$$RRSE = \sqrt{\frac{\sum(f_t - a_t)^2}{\sum(a_t - \overline{a})^2}} \tag{5}$$

By comparing the standard deviation of anticipated mistakes to the mean of actual data, the Coefficient of Variation (CV) measures the accuracy of predicting. An alternative way to define it is as the RMSE, or Root Mean Square Error divided by the mean of real data, providing a normalized accuracy evaluation.

$$CV = \frac{RMSE}{\overline{a}} \tag{6}$$

These measurements are essential for evaluating the effectiveness of load forecasting techniques and guaranteeing the stability of power supply networks. By quantifying forecast accuracy, they enable effective monitoring and optimization of energy production, minimizing costs and system failures (Guo et al., 2021).

Based on their validation indices, the table offers a comparison of various machine learning (ML) and deep learning (DL) models. Several writers have commented on these indices across a range of years.

Guo (2021) utilised a deep neural network (DNN) in their prediction model. The simulation results revealed a mean absolute percentage error (eMAPE) of 10.01 % and a root-mean-square error (eRMSE) of 2.156 MW. Asiri (2024) investigated advanced deep learning methods such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM). They introduced a new model called LFS-HDLBWO, which outperformed previous deep learning techniques. The LFS-HDLBWO model achieved error rates of 3.43 and 2.26, demonstrating its superior performance.

Alquthami (2022) conducted a study that concentrated on machine learning algorithms used for predicting short-term electricity use, with a particular emphasis on improving decision trees. Their model demonstrated remarkable validation indices, including a recall of 99.9 %, an F1 score of 100 %, a precision of 100 %, a training accuracy of 99.21 %, and a testing accuracy of 99.70 %. Muzumdar (2020) utilised machine learning techniques, specifically Support Vector Regressor (SVR) and Random Forest (RF), and achieved a Mean Absolute Percentage Error (MAPE) of 1.18, demonstrating a high level of predicted precision.

Every study demonstrates the potential and efficacy of diverse approaches in the domains of deep learning and machine learning for distinct applications, such as load forecasting and prediction modelling. Although DL models such as DNN, LSTM, and CNN perform well in certain situations, traditional ML techniques like SVR and RF also show comparable performance. This highlights the significance of choosing the right methodology depending on the individual job and dataset. In the comparative analysis of load forecasting and prediction modelling, both machine learning (ML) and deep learning (DL) show promise. Both strategies use statistical methods and algorithms to examine data trends and generate precise forecasts.

Additionally, both ML and DL methodologies aim to optimize resource allocation and improve grid stability in energy management systems.The analysis of ML and DL lacks specificity regarding their contributions to energy management load forecasting research. Future directions for enhancing forecasting accuracy and addressing industry-specific challenges are needed to provide a more targeted and insightful perspective.

While literature acknowledges challenges in energy management forecasting such as data quality, model opacity, scalability, and dynamic energy systems, gaps persist in providing comprehensive solutions. While some research touches on these challenges, practical implementation and validation in real-world scenarios are lacking. Future efforts should focus on developing scalable, interpretable models that effectively address the complexities of dynamic energy systems, bridging the divide between theoretical advancements and practical applicability in energy management forecasting.

3.3. Main limitations and future research directions

Existing works on electricity load forecasting face several limitations, including issues with model accuracy, adaptability to dynamic environments, and scalability. Many traditional models struggle with high error rates in complex scenarios and lack the flexibility to accommodate real-time changes in energy consumption. Additionally, current approaches often fail to integrate diverse data sources effectively and may overlook the impact of emerging technologies and user behaviours. Future research should focus on developing more robust and adaptive models that leverage advanced machine learning techniques, such as hybrid models combining deep learning and traditional methods. Exploring real-time data integration, incorporating user behaviour analytics, and addressing the challenges of scalability and generalization will be crucial for advancing forecasting accuracy and improving smart grid management strategies.

3.4. Key results and comparison of existing techniques

In recent literature, various techniques have been explored for electricity load forecasting. For instance, ARIMA models have been praised for their simplicity but are often criticized for inadequate handling of non-stationary data, resulting in higher forecast errors. On the other hand, Deep Learning models like Bi-LSTM have demonstrated superior accuracy, with lower MAE and RMSE compared to ARIMA, as seen in studies predicting solar power production. Additionally, R-CNN with ML-LSTM has shown significant improvements in multistep forecasting tasks, outperforming traditional models by reducing error rates in both residential and commercial datasets. While Support Vector Machines (SVM) and Random Forest (RF) are effective for various energy prediction tasks, advanced deep learning models consistently deliver better performance in complex scenarios. This comparison underscores the shift towards integrating sophisticated algorithms and real-time data for improved forecasting accuracy.

3.5. Challenges & gaps

The review identifies several challenges and gaps in the application of DL and ML techniques for smart grid load forecasting. Key challenges include the need for large and high-quality datasets, the complexity of model training, and the computational resources required. There are also gaps in integrating these advanced techniques with existing grid infrastructure, and in addressing issues related to data privacy and security. Furthermore, the review highlights a lack of standardized evaluation metrics and benchmarks, which complicates the comparison of different models. Addressing these challenges and gaps is crucial for the broader adoption and effectiveness of DL and ML in smart grid applications.

The review's methodology involved a systematic comparison of DL and ML techniques against traditional forecasting methods. Key performance metrics such as MAPE, RMSE, and MSE were used to evaluate accuracy and scalability. The analysis began with a comprehensive literature review to identify state-of-the-art models and algorithms. These models were then applied to real-world datasets to assess their effectiveness in practical scenarios. Additionally, the review included a meta-analysis of case studies and real-world applications to illustrate the practical challenges and successes of implementing DL and ML in smart grid load forecasting. This rigorous approach ensured a thorough and balanced evaluation of the techniques.

3.6. Evolution of research in the field

There have been several significant developments in the field of load forecasting research as it relates to smart grids and machine learning and deep learning for intelligent energy management. These advancements exemplify an ongoing pursuit for more precise, adaptable, and efficient techniques for forecasting. At first, research mostly concentrated on conventional statistical techniques for load forecasting. Nevertheless, with the emergence of machine intelligence, specifically in the context of regression models and time series analysis, researchers initiated investigations into more advanced methods for capturing intricate patterns and interconnections in energy consumption data. The introduction of neural networks—more especially, neural networks with recurrent architectures and long short-term memory (LSTMs and RNNs)—caused a significant change. These deep learning architectures have shown exceptional ability in managing temporal dependencies, allowing for more precise forecasts of load patterns, particularly in situations with dynamic and nonlinear connections (Ma et al., 2021; Zhang et al., 2020).

Ensemble learning approaches have evolved as a crucial field of study, utilizing the combined intelligence of numerous models to improve the accuracy and reliability of predictions. Bagging and boosting approaches gained popularity as they provided effective techniques to reduce uncertainty and enhance the overall dependability of load projections. The utilization of real-time data obtained from smart meters became a primary emphasis, allowing for ongoing monitoring and prompt adjustment to fluctuating load situations.

This advancement was a notable achievement in improving the speed and precision of load forecasting models, especially under constantly changing conditions. Explainable AI (XAI) strategies have become popular in order to tackle the issue of interpretability in complicated machine learning & deep learning models (Yang et al., 2020). As these models became more complex, comprehending the underlying reasoning behind forecasts became essential for establishing trust and acceptance. The incorporation of Explainable Artificial Intelligence (XAI) methodologies allowed researchers to provide significant insights into the model's decision-making processes, hence augmenting the lucidity and comprehensibility of load forecasting results.

Edge computing has lately emerged as a new and innovative area of study in load forecasting (Wang et al., 2023b). Integrating processing capabilities at the edge, in close proximity to the data source, reduces delay and improves the effectiveness of forecasting models, especially in real-time scenarios. To summarize, as load forecasting research in smart electricity systems using ML and DL has advanced, traditional statistical techniques have given way to more advanced, flexible, and transparent methodology. The sector is constantly evolving, with ongoing advancements that tackle obstacles and open up new opportunities for effective and dependable smart energy management.

3.7. Significant milestones

The use of ML and DL in Smart Grid demand forecasting for Smart Energy Management has experienced numerous noteworthy achievements, demonstrating the progress and transformational changes in energy forecasting methods and technologies. Integrating ML and DL algorithms into load forecasting models is a major achievement. This departure from typical statistical methods allows the models to adapt to complex energy usage data patterns and non-linear linkages. RNNs, or recurrent neural networks, and LSTMs have significantly better load estimates, notably for temporal linkages and complicated patterns. Intelligent meter live data streams are another major breakthrough. Smart meters gather data often and continuously, it makes machine learning (ML) and deep learning (DL) possible.

AI & ML models to adapt to shifting load patterns (Kumar et al., 2023; Healthcare Engineering, 2023). Real-time information availability improves forecast accuracy and makes it possible to put more flexible energy management techniques into practice.

Ensemble learning has greatly increased load forecasting model dependability. Ensemble techniques combine model forecasts for accuracy and reliability. Bagging and boosting reduce uncertainty and improve load forecasting systems. Applying Explainable AI (XAI) techniques in load forecasting is a recent achievement that focuses on making ML and DL models more interpretable. As these models increase in complexity, comprehending the reasoning behind their predictions becomes essential. Integrating explainable Artificial Intelligence (XAI) techniques facilitates the understanding of how models make decisions, promoting transparency and building confidence in the accuracy of the forecasted results.

The incorporation of edge computing in load forecasting is a developing achievement. Edge devices, such as sensors and smart meters, have the ability to do calculations locally because to their built-in processing capabilities. By minimizing latency, the efficiency of load forecasting models is enhanced, particularly in real-time applications (Zhou et al., 2020; Xu et al., 2020; Singh and Khan, 2017). Finally, The discipline has advanced toward more accurate, detailed forecasting of load in smart grids with the application of machine learning (ML) and deep learning (DL) techniques. Adaptable, and transparent energy forecasting systems. The continuous development of smart energy management is driven by computational breakthroughs, real-time data integration, and the emergence of new technologies.

4. Methodology

The study's selection criteria for Load forecasting in Smart Grid for Smart Energy Management using ML DL employ a targeted approach to ensure the incorporation of pertinent and high-caliber literature. Inclusive sources must explicitly center on load forecasting applications within the utilizing deep learning (DL) and machine learning (ML) methods in a smart grid setting to provide intelligent energy management. Academic papers, conference proceedings, and esteemed journals presenting empirical research, case studies, or inventive methodologies at this specific intersection are deemed suitable. Only peer-reviewed publications in English are considered to uphold scholarly rigor. Exclusions consist of non-peer-reviewed sources, promotional materials, and studies lacking direct relevance to load forecasting in smart grids with ML and DL applications. These refined selection criteria aim to assemble a focused and credible collection of sources conducive to an exhaustive exploration of the topic (Wawale et al., 2022; Bolla et al., 2022).

Improved prediction accuracy and more economical energy use can result from the application of machine learning (ML) and deep learning (DL) techniques to load forecast in smart grids for smart energy management.

Thus, it is possible to use multiple data sources. History of energy use data is a valuable source of knowledge since it sheds light on patterns and variances in use across time. Comprehending the historical context is essential for training machine learning (ML) and deep learning (DL) models to appropriately identify and react to seasonal fluctuations, dynamic shifts in energy consumption, and recurrent patterns. Smart meter real-time data is a vital and useful source of regular, in-depth updates on energy consumption. Since smart meters provide a steady stream of data, deep learning (DL) /machine learning (ML) algorithms can swiftly adapt to erratic fluctuations in demand.

By making them more responsive, this improves the efficacy of load forecasting algorithms (Almadhor et al., 2022). Meteorological data serves as an additional powerful source of information. The amount of energy used is directly influenced by the weather, and models that take weather-related variations in energy demand into consideration can be developed with the use of meteorological data. Weather factors like temperature, humidity, and energy consumption can be correlated with one other using ML/DL techniques.

This approach has the potential to greatly increase the accuracy of load forecasting in smart grids. Demographic and economic data provide significant contextual information. Comprehending the demographic makeup of a region and its economic operations helps in forecasting energy consumption patterns by considering elements such as population density, industrial activities, and economic trends. Moreover, comprehensive grid infrastructure data, encompassing details about the structure and capability of the electricity distribution network, is necessary.

By taking into account the grid's capabilities and limitations, this data enables deep learning (DL) and machine learning (ML) models to make sure that load estimates align with the network's operating parameters (Nayagam et al., 2022; Sujatha et al., 2022; Zhang et al., 2022). A complete data collection technique is employed in smart grid load forecasting, encompassing historical consumption data, real-time data from smart meters, meteorological conditions, demographic insights, and grid architecture characteristics. Through the integration of several data sources, machine learning (ML) and deep learning (DL) models may generate accurate and flexible load predictions, hence augmenting the efficacy of smart energy management. Figs. 1–3

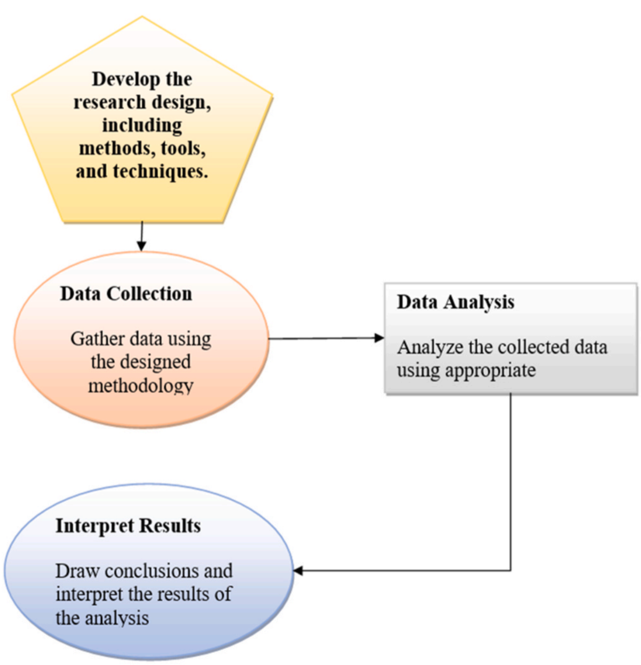

Fig. 1. Flowchart of the Methodology used in this research.

4.1. Search strategy

The search technique entails a methodical and focused attempt to obtain pertinent literature and research works in the topic. Commencing the exploration on scholarly resources such as IEEE Xplore, Science Direct, and PubMed provides the opportunity to retrieve peer-reviewed publications, conference papers, and journals pertaining to smart grid technologies, load forecasting, and machine learning applications in energy management. To ensure precision in search queries, it is advisable to utilize terms such as "load forecasting," "smart grid," "smart energy management," and "machine learning."

Aside from academic databases, conducting searches on online repositories like as arXiv and Google Scholar expands the range of available resources to encompass preprints, technical reports, and publications that might not be found in conventional databases. Utilizing boolean operators, such as and or, in conjunction with phrase searching enhances the precision of the search outcomes.

Analyzing relevant workshop and conference data about machine learning and smart grid applications, such as those from the IEEE PES General Meeting or The International Conference on Clean Energy Technologies and Smart Grids (ICSGCE), offers valuable insights into the most recent advancements and research patterns in this domain. Browsing through the institutional repositories of universities and research organizations aids in locating theses, dissertations, and technical publications pertaining to load forecasting in smart grids (Teekaraman et al., 2022b; Li et al., 2022; Boum et al., 2022; Anantha Krishnan et al., 2022).

Government publications from energy agencies and organizations, such as the Department of Energy (DOE), can provide valuable information on policy aspects and practical applications. Moreover, the analysis of references in important papers and reviews aids in the identification of influential works and establishing connections with a wider range of pertinent literature. For the most updated information on the most recent advancements in the subject, you should subscribe to alerts for relevant keywords and monitor recently published articles. With regard to load forecasting in smart grids, this thorough search approach seeks to gather a broad range of sources, including theoretical frameworks, empirical research, and real-world applications. The emphasis is on applying deep learning and machine learning techniques to smart energy management.

4.2. Inclusion and exclusion criteria

To ensure the Caliber, applicability and focus of the data collected, inclusion and exclusion have been developed. The inclusion criteria are satisfied by academic magazines, conference procedures and publications that in particular deal with the load forecasts in the context of the intelligent grids. To create intelligent energy management techniques, deep learning (DL) and machine learning (ML) in these projects. Presentations should include examples of cases, new techniques or legitimate research on the relationships between different fields. The publications that do not discuss in particular the applications of machine learning (ML) and the deep learning (DL) are subject to the exclusion criteria. which are not directly related to load forecasting in smart grids. To maintain consistency and cognitive integrity, advertising messages (Ghislain et al., 2022) are used.

The analysis of database results includes several critical dimensions. It starts with assessing the number of articles retrieved and the specific search terms used and provides insight into the scope and relevance of the search query. In addition, reviewing the database sources consulted provides insight into the breadth and comprehensiveness of the literature reviewed. Analyzing the distribution of publications over time reveals trends in research activity and development in the field, shedding light on the evolution of researchers' interest. Metrics such as keyword frequency and citation counts are used to assess the depth and impact of the literature retrieved from databases, thereby assessing the

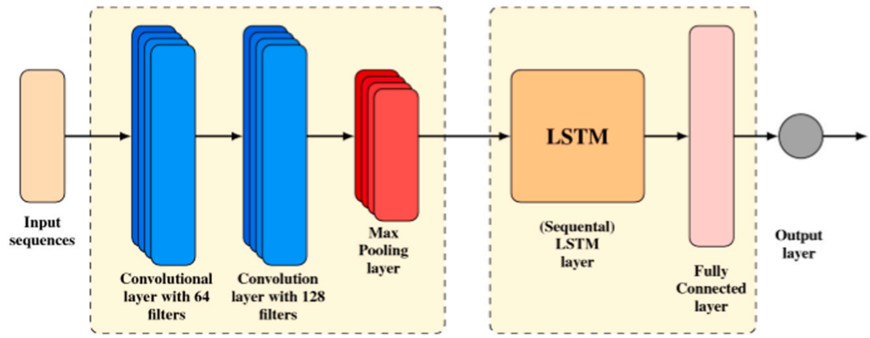

Fig. 2. CNN LSTM Model (Livieris et al., 2020).

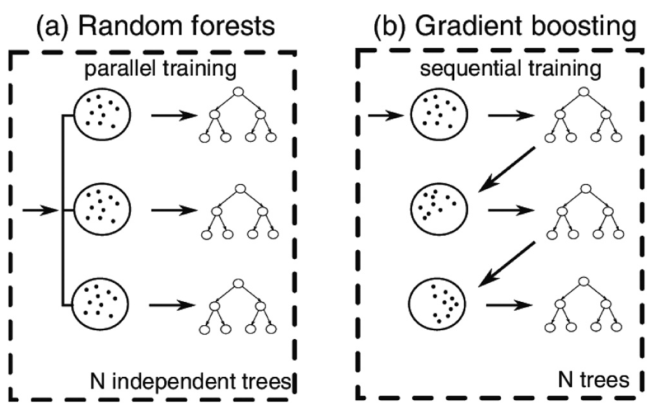

Fig. 3. Random Forest and Gradient Boosting (Kowalek, 2019).

importance and influence of the research findings. Together, these elements form a holistic approach to analyzing database results, providing valuable insights into the current state and dynamics of scientific research on the topic.

Search refinement involves several systematic steps to improve accuracy and comprehensiveness. Initially, the integration of synonyms and specific terms ensures that the search effectively captures the relevant literature. Studies are selected according to clear criteria based on relevance, methodology and publication date. In addition, screening of additional databases will help to fill possible gaps in the existing literature. Advanced filters are applied to refine the results with a focus on quality and relevance. Thorough selection processes ensure that relevant studies that meet the defined criteria are included.

Smart meters provide real-time data on electricity consumption and provide instantaneous information. Typically, data collection intervals vary based on deployment and utility needs, ranging from every 15 minutes to hourly intervals in practice.

5. Classification of studies

Research on load forecasting in smart grids for smart energy management can be divided into a number of significant areas that cover diverse aspects of this multidisciplinary topic and make use of deep learning and machine learning (ML and DL) (Hasan et al., 2022; Ganesan et al., 2022; Balasubramaniam et al., 2022).

The creation and optimization of machine learning (ML) and deep learning (DL) algorithms, with a focus on load forecasting, have been the subject of extensive research. In order to improve prediction accuracy, this entails making advancements in neural network topologies, optimization methods, and ensemble learning approaches.

The efficient management of temporal dependencies in load forecasting models is a task taken on by academics. In order to efficiently capture time series data's sequential patterns and dependencies, more research is required on advanced deep learning architectures like recurrent neural networks (RNNs) and (LSTMs) networks.

An essential aspect pertains to the incorporation of up-to-the-minute data derived from smart meters and other sensors. This section examines the optimal utilization of continuous, high-frequency input streams to enhance the load forecasting models' responsiveness and accuracy, especially in situations that are dynamic and changing quickly.

The primary objective of this branch of artificial intelligence is to create models and algorithms that are capable of giving comprehensible justifications for their choices and actions. The need of enhancing the interpretability of deep learning (DL)/machine learning (ML) models has increased due to their growing complexity. Gaining more insight into the decision-making processes used by models is the aim of Explainable Artificial Intelligence (XAI) research. This knowledge contributes to increased openness and confidence in the precision of forecasted results (Su, 2022; Xiong et al., 2022; Prasath et al., 2022; Khan et al., 2021a, 2021b).

Ensemble learning delves into the amalgamation of many forecasting models to generate ensemble approaches. The effectiveness of bagging and boosting strategies is examined in order to reduce uncertainties, enhance resilience, and ensure accurate load predictions.

A burgeoning field of study focuses on the incorporation of edge computing into load forecasting. Scientists are investigating the potential benefits of processing data at the edge, which is closer to where the data is generated. This approach aims to reduce delays, increase efficiency, and make real-time load forecasting applications more practical.

Certain studies explore the amalgamation of load forecasting with renewable energy sources. This means that demand forecasting models must be improved to account for the erratic nature of renewable energy sources and account for variations in energy production.

Research on load forecasting in Smart Grids is categorized along several dimensions: algorithmic development, temporal dependency management, real-time data integration, interpretability, ensemble learning, and the combination of edge computing and renewable energy sources. Each element has an impact on the overall development of intelligent energy management systems (Alazzam et al., 2021; Mehmood et al., 2021; Srisomboon et al., 2021).

5.1. Thematic grouping

The combination of machine learning (ML) and deep learning (DL) techniques in smart grids has substantially changed energy management, especially in load forecasting. This cutting-edge technology makes it easy to design incredibly complex and adaptable systems for optimizing energy use.

"Smart Energy Management" is a primary area of emphasis in thematic classification. Deep learning (DL) and machine learning (ML) models are crucial in forecasting energy usage patterns, enabling proactive decision-making to optimize resource allocation. By analyzing historical data and taking into account several important factors, these models are crucial in accomplishing accurate load forecasting. Taking this proactive stance increases grid reliability and makes it easier to successfully integrate renewable energy sources, which increases sustainability (Duangsuwan et al., 2021; Zhong et al., 2021; Tang et al., 2021; Xu et al., 2021).

The "Smart Grid" itself is a further focus. The smart grid infrastructure can adapt more flexibly to changing demand patterns thanks to machine learning/deep learning algorithms, which reduce energy loss and increase grid efficiency. The grid can now automatically adjust and react quickly to changes thanks to these technologies, making the energy distribution system more resilient and responsive.

Additionally, load forecasting is made more sophisticated and sophisticated by the incorporation of machine learning (ML) and deep learning (DL) techniques. This is known as "Intelligent Grid Operation." With the use of sophisticated analytics, these technologies help utilities more effectively distribute electricity, predict periods of peak demand, and manage the power system. This intelligence enhances energy conservation, reduces expenses, and ensures a more dependable power supply for end users.

Ultimately focused on the subjects of intelligent grid operation, smart energy management, and smart grid augmentation. These thematic areas work together to propel the energy sector toward a more intelligent, efficient, and sustainable future by fusing machine learning/deep learning techniques.

5.2. Methodological approaches

Many methodological strategies are employed, including deep learning (DL) and machine learning techniques. in load forecasting for Smart Grids. The goals are precise forecasting and effective energy management. One important methodological approach involves analyzing historical data. ML and DL models utilize historical consumption patterns, weather conditions, and other pertinent information to detect trends and correlations. Through the analysis of these historical data sets, the models can acquire knowledge and adjust to the distinct attributes of energy consumption patterns, hence enhancing their ability to generate more accurate forecasts. Another method involves feature engineering, which involves incorporating domain-specific information to improve the model's comprehension of the data. Engineers and data scientists analyze crucial factors that influence energy usage, such as holidays, special events, and economic indicators. These features are added to the model, which improves prediction accuracy and increases system flexibility in response to varying energy demand.

Ensemble methods offer an alternative strategy by amalgamating predictions from numerous models to attain a more resilient and precise forecast. Ensemble approaches boost the overall reliability of load forecasting by combining results from various machine learning (ML) and deep learning (DL) models, thereby reducing the risk of individual model biases.

Furthermore, the ongoing process of updating and refining the model is an essential methodological approach. ML and DL models are dynamic and require frequent modifications to accommodate changing patterns and variables. Ongoing retraining guarantees that the models stay up-to-date and efficient in reflecting the complexities of evolving energy usage patterns over time. The methodological approaches in load forecasting for Smart Grids utilizing ML (Machine Learning) and DL (Deep Learning) involve analyzing historical data, creating relevant features, employing ensemble methods, and continuously retraining the models. These approaches jointly enhance the creation of precise, flexible, and robust energy management systems within the framework of Smart Grids.

6. Key findings

The combination of deep learning (DL) and machine learning (ML) technologies has made significant progress in energy management by incorporating several study areas of load forecasting in smart grids. These technologies have introduced a new period characterised by improved effectiveness, dependability, and environmental friendliness in smart grids. A notable accomplishment in this domain is the substantial enhancement in load forecasting precision facilitated by deep learning (DL) and machine learning (ML) models. These advanced algorithms use previous consumption data, weather trends, and other pertinent elements to generate more accurate energy demand estimates. The improved precision is essential for optimising grid operations, guaranteeing a steady power supply, and facilitating efficient resource allocation. The versatility of Smart Grids equipped with Machine Learning (ML) and Deep Learning (DL) models is emphasised by their capability to handle variations in energy consumption patterns. These systems have the ability to promptly react to fluctuations in demand by analysing and interpreting data in real-time, thus improving the durability and adaptability of the energy distribution grid. The ability to adapt is crucial when it comes to incorporating renewable energy sources, which by nature are subject to change, into the power grid.

The results further emphasise the significance of deep learning (DL) and machine learning (ML) in promoting proactive energy management measures. These technologies enable utilities to forecast periods of highest demand, optimise the distribution of energy, and execute efficient demand control approaches. This not only reduces energy wastage but also contributes to sustainability objectives by encouraging more effective utilisation of resources. The utilisation of ensemble techniques, which merge projections from numerous models, has greatly enhanced the dependability of predictions. Ensemble approaches enhance the accuracy and reliability of future energy needs by reducing the influence of individual model biases and uncertainties. This approach showcases the adaptability of deep learning (DL) and machine learning (ML) in tackling the difficulties of load forecasting in ever-changing Smart Grid situations.

Another crucial finding is the imperative need for ongoing model retraining. Ensuring that ML and DL models are regularly updated to reflect changing energy usage patterns guarantees that these models maintain constant accuracy as time progresses, these improvements underscore the significant influence of deep learning (DL) and machine learning (ML) technologies in determining the future of energy management. The enhanced accuracy in load prediction and the adaptability of Smart Grids lead to a more intelligent, efficient, and environmentally-friendly energy future. The ongoing integration of machine learning (ML) and deep learning (DL) into energy management systems is advancing. These findings provide vital insights into the crucial role these technologies will have in the development of the future Smart Grids and their contribution to a robust and sustainable energy landscape.

6.1. Trends & patterns

The energy systems sector is undergoing a significant transformation, driven by key trends and patterns in load forecasting for Smart Grids, particularly through the use of Machine Learning (ML) and Deep Learning (DL). A prominent trend is the growing reliance on advanced ML and DL methods for load forecasting. These technologies enable more accurate predictions by analyzing large datasets and accounting for various factors, allowing for better adaptation to dynamic shifts in energy usage patterns. This shift represents a move away from traditional forecasting techniques toward data-driven, intelligent approaches, resulting in unprecedented accuracy in predicting future energy needs. Another key trend is the increasing emphasis on real-time responsiveness within Smart Grids. ML and DL models empower Smart Grids to continuously analyze incoming data and generate insights, enabling swift reactions to changes in energy demand. Real-time responsiveness is crucial for optimizing grid operations, managing renewable energy integration, and ensuring a robust and adaptable energy distribution system that can meet the evolving demands of a dynamic society. The growing popularity of ensemble approaches in load forecasting is another significant trend. By combining predictions from multiple models, these methods harness the strengths of different algorithms, reducing individual model limitations and enhancing the overall reliability of predictions. Ensemble methods are particularly valuable in achieving more resilient and precise forecasts in the face of uncertainty. Additionally, there is a clear movement towards integrating Smart Energy Management principles into broader sustainability initiatives. ML and DL techniques in load forecasting enable utilities to take proactive steps in managing energy resources, improving grid efficiency, and promoting energy conservation. This aligns with global efforts to transition to cleaner and more sustainable energy systems, marking a significant shift toward intelligent and environmentally conscious energy management practices. These trends and patterns highlight a major transition towards intelligent, adaptive, and sustainable energy systems. The integration of advanced forecasting techniques, real-time adaptability, and ensemble methods points to a future where technology plays a critical role in optimizing energy use, enhancing grid reliability, and fostering a robust and sustainable energy ecosystem.

6.2. Emerging themes

One emerging theme is the pursuit of Explainable Artificial Intelligence (XAI) in energy forecasting models. As ML and DL techniques advance, there is an increasing recognition of the need for transparency and interpretability in these models' decision-making processes. The use of complex algorithms, particularly deep neural networks, often results in "black box" models, where the internal workings are difficult to understand. This lack of transparency poses challenges in critical applications like energy management, where stakeholders need a clear understanding of the reasoning behind specific forecasts or actions. XAI aims to address this issue by integrating transparency into ML algorithms. Practitioners are developing methods to interpret and understand the predictions made by these models. In load forecasting, XAI seeks to clarify how the model incorporates historical data, accounts for external variables, and assigns importance to different factors when making predictions. The growing importance of XAI is driven by its ability to build trust and encourage broader adoption of advanced predictive models in the energy industry. Stakeholders such as utility providers, regulatory bodies, and end-users often require a thorough understanding of the factors influencing energy forecasts to make informed decisions, allocate resources efficiently, and maintain grid stability, the incorporation of XAI aligns with regulatory requirements that demand transparency in decision-making processes, especially in critical infrastructure like Smart Grids. It also addresses ethical concerns by promoting transparency and reducing the risk of biases in decision-making, thus supporting the responsible and reliable integration of AI in energy management.

As the energy sector increasingly leverages ML and DL for load forecasting, XAI is becoming a crucial consideration. XAI enhances transparency and interpretability, ensuring the reliability and acceptance of advanced forecasting models. Additionally, it provides a foundation for the ethical and responsible application of AI in the Smart Grid domain.

7. Key challenges & knowledge gaps

Based on the observations of evolving trends and patterns, it is crucial to recognise that implementing load forecasting in Smart Grids utilising Machine Learning (ML) and Deep Learning (DL) techniques is not free from difficulties. The intricacy of the energy system poses a significant obstacle. Smart Grid ecosystems consist of various interconnected elements, such as different energy sources, varying consumption patterns, and changing external influences. To accurately anticipate loads, machine learning (ML) and deep learning (DL) systems must navigate intricate linkages and adapt to altering conditions, capturing the full spectrum of this complexity. The process is further complicated by the accuracy and availability of data. Machine learning (ML) and deep learning (DL) models heavily depend on extensive datasets for the purposes of training and validation. However, the presence of inconsistent, inadequate, or flawed data might hinder the accuracy of their predictions. Smart Grid technology continues to face the difficulty of consistently obtaining high-quality data from several sources, the opaque nature of numerous deep learning (DL) and machine learning (ML) models poses challenges in comprehending their decision-making mechanisms. Transparency and interpretability are essential, particularly when stakeholders require comprehension of the variables impacting energy estimates. Cybersecurity is a major issue of concern. Cyberattacks can exploit weaknesses that arise from the integration of Machine Learning (ML) and Deep Learning (DL) technologies in Smart Grids. To guarantee the dependability and safety of Smart Grids, it is imperative to implement strong cybersecurity protocols in conjunction with the creation and upkeep of Machine Learning (ML) and Deep Learning (DL) models. To tackle these difficulties, it is necessary to foster collaboration among specialists in energy systems, data science, cybersecurity, and regulatory frameworks. In order to fully harness the capabilities of load forecasting in Smart Grids and guarantee the secure and efficient deployment of intelligent energy management systems, it is imperative to address these challenges as the industry progresses.

7.1. Deficiencies in current literature

The literature evaluation emphasises various significant research gaps that have been highlighted in recent publications. The gaps encompass uncertainties in managing energy in smart grids, the structural aspects of constructing large-section shield tunnels, the utilisation of machine learning in urban energy systems, the integration of renewable energy, and the recognition of cities using machine vision.

(Khan et al., 2022) explicitly identifies deficiencies in the management of energy in smart grids, highlighting the necessity for a more thorough examination. These gaps include areas of uncertainty, strategies for optimisation, and the integration of stakeholders, all of which are essential for guaranteeing stability and efficiency in smart grid operations. This highlights the need for more extensive study to tackle these intricacies and improve the overall efficiency of smart grid energy management systems.

(You et al., 2022) identified a research gap related to the load-bearing capacity and large-section shield tunnel failure characteristics at high water pressure.

The call for comprehensive evaluation and control procedures highlights the need for a deeper understanding of the structural aspects of such tunnels, pointing towards a gap in the existing literature on tunnel engineering and safety under challenging conditions.

(Almadhor et al., 2022) emphasized a dearth of research on machine learning methods for calculating electrical power requirements in urban settings and encouraging the production of renewable energy. This underscores a gap in literature regarding the application of machine learning techniques to address energy challenges in urban environments, where sustainability is a growing concern.

(Nayagam et al., 2022) drew attention to the lack of grid integration of hybrid renewable energy sources' energy management systems. The disparity necessitates more investigation into accurate and effective strategies and technology for incorporating renewable energy sources into the systems that exist today.

(Liu and Liu, 2022) highlighted a research gap in machine vision-based intelligent city recognition, particularly in maximizing the effectiveness and precision of threshold segmentation algorithms. This indicates a need for more detailed investigations into the challenges and advancements in machine vision applications for intelligent city recognition, focusing on improving segmentation algorithms for enhanced accuracy.

To summarize, the gaps identified in the literature emphasize the necessity for further research in several areas, including smart grid energy management, tunnel engineering, machine learning applications in urban energy systems, integrating renewable energy sources, as well as machine vision-based intelligent city recognition. Rectifying these deficiencies would enhance the advancement of more resilient and effective systems within the realm of intelligent power grids and urban sustainability.

8. Methodological critique

The evaluation of research techniques highlights the dynamic and diverse nature of load forecasting for Smart Grids, based on the previous discussion of trends and issues in this sector. Researchers utilise a range of methods to tackle the intricacies of load forecasting and intelligent energy management, with Machine Learning (ML) and Deep Learning (DL) playing crucial roles. These methods entail the creation and refinement of algorithms that utilise past consumption data, weather patterns, and other pertinent aspects to produce accurate predictions. Typical methods involve using supervised learning algorithms like regression and neural networks, which can analyse intricate patterns in data to generate precise predictions. Time series analysis is a widely used approach in load forecasting. This methodology carefully analyses past data to detect repetitive patterns and trends within certain time periods. ARIMA and its variations are frequently employed to address temporal dependencies in energy consumption patterns.

Ensemble approaches, which combine predictions from numerous models, have become well-known for their efficacy. Methods such as bagging and boosting leverage the advantages of different algorithms, leading to load estimates that are more resilient and precise. These strategies aid in reducing the constraints of individual models, hence improving the overall reliability of predictions. Optimisation strategies improve the efficiency of energy management systems. Metaheuristic techniques, such as genetic algorithms and particle swarm optimisation, are used to optimise model parameters, enhancing their performance in load forecasting.

the assessment of these approaches strongly depends on case studies and practical implementations. Researchers verify the accuracy and usefulness of their models by using real Smart Grid data. The integration of computer science, electrical engineering, and data analytics in this interdisciplinary approach enables a thorough comprehension of the complexity of Smart Grid and aids in the creation of strong forecasting models.

8.1. Advantages and limitations

The analysis uncovers both advantages and disadvantages in the methodologies employed for energy management and forecasting. An important advantage is the utilisation of machine learning (ML) and deep learning (DL) techniques, which employ advanced algorithms and past data to detect patterns and generate precise load forecasts. These methods are highly proficient in managing extensive datasets and adjusting to dynamic fluctuations in energy usage, leading to more accurate predictions. Ensemble methods improve the accuracy of predictions by minimising uncertainty and aggregating the results of several models. Optimisation approaches enhance the overall efficiency of a system by modifying the parameters of a model, hence improving accuracy and adaptability.

Nevertheless, these sophisticated methods are accompanied by inherent difficulties. The opaque nature of many ML and DL models might obfuscate their decision-making processes, rendering the interpretation and reliance on forecasts challenging. Data-related challenges can provide substantial obstacles; datasets that are biassed, inconsistent, or insufficient can compromise the accuracy of load estimates and impact the dependability of energy management systems. Moreover, machine learning (ML) and deep learning (DL) models might require significant computational resources, which can pose challenges in terms of scalability and efficiency, especially in real-time applications.

8.2. Areas for enhancement

These problems present numerous opportunities for improving research and practical applications. Enhancing the interpretability of models presents a valuable chance to establish confidence and comprehension among stakeholders by tackling the problem of opacity. Furthermore, there is a possibility for advancement in data quality and pre-processing techniques to tackle inconsistencies and biases. Investigating innovative ensemble methods and optimisation strategies could significantly improve the resilience and effectiveness of load forecasting models. The collaboration between academia and industry can enhance the widespread implementation of research findings and the incorporation of practical knowledge. Examining energy storage alternatives and incorporating them into forecasting models offers a chance to enhance the resilience and dependability of the power grid in the face of changing supply and demand trends.

9. Integration and synthesis

Comparative analysis reveals that various studies employ distinct methodologies and provide diverse contributions. The repeated motif revolves around the utilization of deep learning (DL) and machine learning methodologies, underscoring their importance in raising the accuracy of load forecasting. Certain studies highlight the use of ensemble techniques, including merging forecasts from several models, to improve load forecasting's resilience. By using this method, the shortcomings of individual models are lessened and the accuracy of energy demand predictions is increased.

By contrast, other studies highlight the variety of approaches in the field by concentrating on model parameter optimization through the use of metaheuristic algorithms. In addition, a noteworthy trend is the inclusion of real-world case studies. Research that employ real Smart Grid data to validate their models offer useful information about the suitability and efficiency of various forecasting techniques (Zhou et al., 2022; Aguilar et al., 2021) However, studies on stakeholder integration, optimization strategies, and uncertainty for grid stability and efficiency highlight the significance of a comprehensive approach to energy management. Even though using ML and DL is similar, there are differences in the techniques used and the level of analysis.

While some studies take a more comprehensive approach and examine the entire system dynamics and integration issues, others focus on the finer points of certain algorithms. The multifaceted nature of load forecasting in smart grids is reflected in this diversity. the comparative analysis emphasizes how diverse load forecasting research in smart grids for ML DL smart energy management is. Although there are certain similarities, including the use of sophisticated algorithms, the area is dynamic and ever-evolving as evidenced by the variations in approaches and focal points. This variety opens the door for future solutions that will be more flexible and successful by fostering a thorough awareness of the opportunities and problems in smart energy management.

9.1. Synthesizing key concepts

Performance measures are essential for assessing the precision and efficacy of machine learning (ML) and deep learning (DL) models since they encapsulate important concepts. Quantitative measurements are used to evaluate forecasting models' accuracy in predicting future events. The MAPE, or refers to absolute percentage error, Root Mean Squared Error (RMSE) or RRSE & Mean Squared Error are some examples of these measures. The mean squared error (MSE) is the primary metric used to calculate the average squared disparity between the actual and anticipated data. RMSE, which is derived from MSE, provides a more understandable statistic by computing the square root and reporting the average magnitude of errors in the projected values.

A relative version of RMSE that scales the error in accordance with the range of actual values is RRSE, a standardized metric of prediction accuracy. The average deviation between the observed and expected values is displayed using a percentage-based metric called the Mean Absolute Percentage Error, or MAPE. Because it expresses forecast accuracy plainly, this statistic is particularly useful when working with diverse energy consumption scales. Performance metrics, which summarize key ideas, are crucial for evaluating the accuracy and effectiveness of deep learning (DL) and machine learning (ML) models.

The accuracy with which forecasting models can predict future events is assessed using a variety of quantitative metrics, such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Relative Root Mean Squared Error (RRSE), and Mean Absolute Percentage Error (MAPE). The mean squared error (MSE) is the primary metric used to calculate the average squared disparity between the actual and anticipated data. RMSE, which is derived from MSE, provides a more understandable statistic by computing the square root and reporting the average magnitude of errors in the projected values. A standardized indicator of prediction accuracy, RRSE, is a relative form of RMSE that scales the error according to the actual values' range.

A percentage-based metric known as the Mean Absolute Percentage Error, or MAPE, shows the average variation between the observed and expected values. In particular, this statistic is especially helpful when dealing with different energy consumption scales because it clearly communicates forecast accuracy. A thorough understanding of model performance that strikes a balance between precision and interpretability is produced by combining these crucial variables. Researchers often combine these measures to perform a detailed analysis of their forecasting models and provide a more comprehensive picture of prediction accuracy.

This enables them to consider metrics that are relative as well as absolute. These metrics serve as both benchmarks for researchers and assistance to practitioners in selecting models that satisfy specific forecasting objectives. Combining the findings of the MSE, RMSE, RRSE, and MAPE facilitates a thorough evaluation. This demonstrates the necessity of developing models that not only minimize errors but also account for the size and context of the energy forecasting issue. All of these core concepts, which are firmly grounded in performance metrics, highlight the importance of careful quantitative evaluation in advancing the field of load forecasting. The emphasis on accuracy metrics draws attention to the continuous work being done to enhance and optimize ML and DL models for more trustworthy and effective smart energy management in the rapidly evolving field of smart grids.

9.2. Frameworks and models

The methodological groundwork for creating and putting into practice intelligent energy management systems is provided by frameworks and models in load forecasting for smart grid for smart energy management. These models rely heavily on machine learning (ML) as well as deep learning (DL) frameworks, which provide a variety of methods for handling the intricacies of load forecasting. TensorFlow, PyTorch, and scikit-learn are popular machine learning frameworks that offer a powerful toolkit for performing ensemble techniques, time series analysis, and regression. These frameworks make it easier to create models that can adjust dynamically to shifts in the patterns of energy consumption, maximizing the efficiency and dependability of grid operations.

DL models are essential parts of load forecasting frameworks, and they are frequently implemented using neural network architectures. LSTM networks and CNNs are attractive candidates due to their capability to extract spatial patterns and temporal dependencies from energy data. These deep learning techniques enhance the accuracy of load predictions by discovering intricate connections within the data. The essence of CNNs lies in the convolutional operation, where filters are applied to input data, generating feature maps.

$$Z_{i,j}^{(l)} = \sum_{k=0}^{F-1}\sum_{l'=0}^{F-1} X_{i+k,j+l'}^{(l-1)} \cdot W_{k,l'}^{(l)} + b^{(l)} \tag{7}$$

Where:

Z (i,j)(l) represents the value at location (i,j) of the feature map in layer l. It is calculated by summing the values of the previous layer's feature map, denoted as Z (i+k, j+l)(l-1), within a specific range.

The value at location (i+k, j+l′) in layer l-1 is denoted as (l-1) and is obtained by multiplying the input at position (i, j′) in layer l-1 with the weight Wk,l′.

(l) Represents the weight at the point (k, l′) of the filter in layer l. b (l) represents the bias term in layer l.

The size of the filter is denoted by F.

LSTM equation

$$o_t = \sigma(W_{io} \quad \bullet x_t + b_{io} + W_{ho} \bullet h_{t-1} + b_{ho}) \tag{8}$$

(xt) represents the input at time (t), (h_{t-1}) represents the prior hidden state. (W) and (b) are the weights and biases respectively. (sigma) refers to the sigmoid function.

Ensemble techniques, which integrate predictions from various algorithms to resolve uncertainties and improve forecasting reliability, are essential models. Examples of these techniques are Random Forests and Gradient Boosting. Due to their ability to mitigate the constraints of individual models, these models enhance the robustness of energy management systems (Xiong et al., 2022).

Given an input sample X, the projected output Y is obtained by combining the predictions Yi from each individual decision tree i in the forest. In regression tasks, the average prediction might serve as the benchmark.

$$\widehat{Y} = \frac{1}{n}\sum_{i=1}^{n} Y_i \tag{9}$$

The symbol "^" represents the predicted value.

The variable n represents the quantity of trees present in the Random Forest.

Yi represents the forecasted value made by the i-th decision tree.

Gradient Boosting Equation:

$$\widehat{\mathscr{Y}} = F_M(x) \tag{10}$$

The symbol (F_M(x)) denotes the model obtained at iteration (M) in the process of Gradient Boosting. An ensemble of weak learners is successively updated to minimize the loss function (L), which quantifies the discrepancy between predicted and true values. During each iteration (m), a weak learner (h_m(x)) is trained using the negative gradient of the loss function. The step size (gamma_m) defines how much (h_m(x)) contributes to the overall model (F_m(x)). The ultimate forecast (hat{y}) is the result of the boosted model following (M) iterations.

The use of optimization frameworks, which make use of metaheuristic algorithms such as particle swarm optimization or genetic algorithms, is essential for optimizing model parameters and achieving higher efficiency. These frameworks match the unique needs of Smart Grids with the ML and DL models, optimizing their performance. The models and frameworks used in load forecasting for smart grids are a complex toolbox that includes optimization approaches, ensemble methods, machine learning, and deep learning. By combining these methodological techniques, we can create intelligent and flexible energy management systems that will lead to more sustainable, dependable,

Table 3
Comparison table of existing work.

Model	Performance	References
Long Short-Term Memory (LSTM)	Accuracy 0 f 84 %	(Rabie et al., 2024)
CNN model	Accuracy of 94.5 %	(Zhang et al., 2023)
CNN model	Accuracy of 98.83 %	(Mohsin et al., 2023)
LSTM model	Accuracy of 77.86 %	(Yanmei et al., 2024)

and effective energy sources in the future.

Table 3 titled "Comparison Table of Existing Work" presents a summary of the performance of different models used in a specific research context, showcasing their accuracy. The first entry is the Long Short-Term Memory (LSTM) model, which achieved an accuracy of 84 %. LSTM models are known for their ability to handle sequential data and long-term dependencies, making them suitable for tasks such as time series prediction and natural language processing.

Next, the table lists two entries for Convolutional Neural Network (CNN) models. The first CNN model achieved an accuracy of 94.5 %. CNNs are typically used in image and video recognition due to their proficiency in capturing spatial hierarchies in data. The second CNN model significantly outperformed the first, with an accuracy of 98.83 %. This high accuracy indicates the model's superior performance in the given task, potentially due to more advanced architecture or better training data. The final entry is another LSTM model, which had a lower accuracy of 77.86 %. This variation in performance between LSTM models may be due to differences in dataset characteristics, model tuning, or implementation details. The table effectively highlights the comparative performance of LSTM and CNN models, with CNN models generally showing higher accuracy in this context.

10. Future directions

Future research can be classified under six distinct categories which are explained below.

1) Intelligible AI for Forecasting Loads

   One major obstacle that still needs to be overcome is making machine learning and deep learning models interpretable. Subsequent investigations may concentrate on creating and refining explainable AI methods in order to offer perceptions into the reasoning processes of intricate models. This would boost confidence and make it easier for these models to be used in more practical contexts.
2) Renewable Energy Source Integration

   Studying how to successfully include renewable energy sources into load forecasting models is important as the world progresses toward a more sustainable energy future. For grid stability and efficiency, it is essential to address the intermittent character of renewable energy and optimize its integration with traditional sources.
3) Smart Grid Cybersecurity

   As Smart Grids depend more and more on digital technology, cybersecurity becomes critical. Subsequent investigations must to focus on creating strong cybersecurity defenses against possible cyberattacks on Smart Grids, guaranteeing the confidentiality and integrity of data and energy infrastructure.
4) Advanced Computing for Instantaneous Prediction

   One interesting area of investigation might be the use of edge computing in load forecasting. By processing data closer to the source, edge computing lowers latency and facilitates real-time decision-making. This can be especially helpful when it comes to patterns of energy consumption that are dynamic and changing quickly.
5) Energy Management Systems Focused on Humans

   Incorporating user preferences and behavior into energy management systems may result in more individualized and human-centered strategies. Subsequent investigations could examine the integration of social sciences and behavioral economics to enhance comprehension and modeling of the human elements impacting energy usage.
6) Interaction across Domains

Research collaborations between data scientists, energy specialists, and policymakers may help close the gap between policy implementation and technology improvements. The development of Smart Grids will be aided by interdisciplinary research that takes into account both technical and socioeconomic factors.

Future studies can advance load forecasting in smart grids and make energy systems more resilient, sustainable, and able to adapt to the changing demands of society by tackling these topics. These areas of research could influence smart energy management in the future and help the world's energy systems become cleaner and more efficient.

10.1. Technology and methodology advancements

The field of energy forecasting is changing due to significant technological and methodological breakthroughs in load forecasting in Smart Grid for Smart Energy Management. Advances in machine learning (ML) and deep learning (DL) technologies are improving the accuracy and flexibility of load forecasting models. Neural networks and ensemble techniques are examples of advanced machine learning algorithms that are constantly developing to handle complex interactions seen in energy consumption data.

Predictions become more accurate when deep learning architectures, such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN), are integrated. This allows for the modeling of intricate temporal and spatial patterns. Beyond algorithmic complexity, methodological advances include areas such as explainable AI. There is a current endeavor to improve the interpretability of models by increasing the transparency of their decision-making procedures.

Gaining acceptability and trust is contingent upon this, especially in situations where stakeholders must comprehend the reasoning behind energy estimates. Likewise, real-time load forecasting capabilities have been added with the rise of edge computing. Faster decision-making is made possible by processing data closer to the source, which is crucial for controlling the dynamic and quickly shifting nature of energy consumption. Forecasting models are further refined through the inclusion of optimization techniques through the use of metaheuristic algorithms.

By bringing energy management systems into compliance with the unique needs and limitations of smart grids, this optimization increases the effectiveness of those systems. It represents a paradigm-shifting period in energy forecasting due to the convergence of technology and methodological advances. These developments contribute to the development of intelligent and sustainable energy infrastructures by increasing prediction accuracy and efficiency and opening the door for more transparent, flexible, and real-time energy management systems.

10.2. Predictions for the futurework

In the realm of energy management, a multitude of projections shape a future rich with intriguing possibilities. The evolution of machine learning algorithms holds the promise of yielding forecasting models that are progressively more precise and adaptable, capable of navigating a spectrum of dynamic energy use patterns. Addressing the interpretability challenge, Explainable AI is poised to gain popularity, fostering wider acceptance of intricate models and resolving the intricacies associated with their outputs.

Real-time decision-making, a pivotal aspect in steering the fluctuating demands of energy systems, is on the horizon with the integration of edge computing. This integration will empower swift responses to changing energy needs, ensuring efficiency and resilience in energy management. Emphasizing a comprehensive approach to smart energy management, interdisciplinary collaboration among data scientists, energy experts, and policymakers is slated to become more prevalent.

This collaborative effort will be instrumental in navigating the complexities of the evolving energy landscape. Anticipated innovations in forecasting models are set to revolutionize the field by incorporating user preferences and behaviors. This shift towards individualized and human-centered energy solutions aligns with a vision of a more personalized and responsive energy management system. Collectively, these forecasts paint a compelling vision of the future – one where technology-driven, transparent, and responsive energy management systems play a pivotal role in establishing resilient and sustainable smart grids. The integration of cutting-edge technologies and collaborative approaches is poised to transform the energy sector into a dynamic and adaptive ecosystem, capable of meeting the challenges of tomorrow.

11. Conclusions

This work provides a distinctive exploration of Deep Learning (DL) and Machine Learning (ML) techniques applied to smart grid load forecasting within energy management systems. Unlike traditional literature reviews, which primarily classify and analyze individual studies, this paper adopts a forward-looking approach by not only assessing current methodologies but also proposing novel research directions. The review underscores the critical role of AI and ML in advancing load forecasting accuracy and scalability, highlighting their integration into real-world applications through comprehensive evaluations of neural networks, ensemble methods, and probabilistic forecasting techniques.

The study reveals a dynamic landscape characterized by technical innovation and interdisciplinary collaboration, emphasizing precision, transparency, and sustainability in smart energy management. By systematically comparing DL and ML techniques against traditional methods using performance metrics such as MAPE, RMSE, and MSE, the review provides a robust assessment of their efficacy in addressing challenges like grid stability and demand forecasting. Real-world case studies demonstrate how these advanced techniques contribute to practical solutions, enhancing the reliability and efficiency of energy systems.

A distinguishing feature of this review is its forward-looking perspective, which not only examines current methodologies but also proposes future research directions. By identifying key challenges such as data quality issues, scalability concerns, and the need for interpretability, this review sets the stage for addressing these issues in future studies. Moreover, it emphasizes the integration of AI and ML into practical applications within energy management, showcasing their potential to optimize grid stability, enhance demand prediction, and manage uncertainties effectively.

Moving forward, the review suggests exploring hybrid models, refining prediction frameworks, and developing standardized evaluation metrics to further advance the field of load forecasting in smart grids. These insights not only contribute to academic understanding but also provide a roadmap for implementing robust and efficient energy management strategies in real-world scenarios

CRediT authorship contribution statement

Subhasish Deb: Writing – review & editing, Writing – original draft, Conceptualization. **Biswajit Biswal:** Writing – review & editing, Writing – original draft, Conceptualization. **Taha Selim Ustun:** Writing – review & editing, Writing – original draft, Conceptualization. **Subir Datta:** Writing – review & editing, Writing – original draft, Conceptualization. **Umit Cali:** Writing – review & editing, Writing – original draft, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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