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A systematic review of machine learning and deep learning approaches for load and energy consumption prediction in contemporary power systems

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ABSTRACT

Background: Machine learning (ML) methods are prevalent forecasting model construction tools that outperform conventional methods. This study is a systematic review of machine learning method utilization for load and energy consumption forecasting between 2020-2025. In all ,157 studies were explored for the purpose of this review. The study covered a variety of methods, ranging from simple algorithms such as linear regression and support vector machines to complex deep learning models such as LSTM, Convolutional Neural Networks CNNs, Transformer models, Graph Neural Networks GNNs, and particular ensemble and hybrid methods. **Methods**: The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guideline was used to evaluate methodological quality in the review. Primary academic databases such as IEEE Xplore, ScienceDirect, SpringerLink, Scopus, and preprint servers arXiv were extensively searched. English-language peer-reviewed journal articles and high-quality preprints focused on Machine Learning ML-based electric load or energy demand forecasting were considered. Hardware or other domains' optimization was excluded. Data extraction targeted model types, application contexts, dataset characteristics, and evaluation metrics. **Findings:** Findings of this study revealed that CNN-LSTM models achieved top accuracy (MAPE: 3.1%–6.2%), followed by LSTM (4.2%–7.8%) and Transformers (3.8%–5.9%) with high resource demands. Traditional ML had higher errors (5.1%–9.3%) but remained useful for small data and interpretability. Above all, quality data and proper pre-processing always prevail over the effect of selected machine learning techniques. **Conclusion**: Machine learning has assisted energy forecasting a lot but falls short on usability and reliability. More technology and collaboration are required to succeed with renewable energy systems. **Novelty/Originality of this article:** This study describes new developments in Machine learning for energy forecasting and mentions trends and issues to be expected. It recommends what is in the pipeline for future research and applications.

KEYWORDS: deep learning; machine learning; power system.

1. Introduction

The global energy sector is experiencing a deep revolution driven by the urgent need to mitigate climate change, achieve sustainability, and ensure energy security. At the heart of this shift is the rapid growth of renewable sources of energy, which are now becoming technologically viable and economical, where it is plausible that renewables are able to provide 100% of energy requirements and help alleviate global energy requirements by 2040 (Bogdanov et al., 2021; Makarov et al., 2020). This shift gets traction through

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innovation in digital technology, which maximizes energy distribution, enhances efficiency, and facilitates smart energy management but poses issues like cybersecurity and workforce adjustment (Liu & Lu, 2021; Nazari & Musílek, 2023). All this has created new challenges for running energy systems, so providing effective forecasting of load and energy consumption has never been more critical (Mystakidis et al., 2024). The practical and efficient operation of power systems in the modern era relies on the ability to predict patterns of electricity load and energy use over various time frames. In the aftermath of the reshaping of the world's energy landscape due to the pressures of climate change mitigation and adopting renewable forms of energy, the complexity and challenge of energy forecasting have amplified considerably (Matijašević et al., 2022). The growing penetration of intermittent RES, such as solar and wind power, the spread of DERs, such as EVs and battery storage systems, and the move towards intelligent, interactive distribution networks bring unprecedented levels of uncertainty and variability into energy supply and demand (Chen et al., 2025; Matijašević et al., 2022). Therefore, traditional forecasting methods and linear statistical models are progressively unable to capture modern energy systems' complexity and non-linear dynamics. Accurate forecasting is critical to many operation and planning processes in the energy system. Short-term load forecasting (STLF), typically one week ahead, is crucial to real-time grid operation, economic dispatch, unit commitment, ancillary service procurement, and grid stability (Perçuku et al., 2025). STLF errors can result in sub-optimal utilisation of the resources, higher operating costs, and even violate system reliability. Medium-term forecasting (MTF), between a week and one year, guides fuel procurement, maintenance planning, and hydro-thermal coordination decisions. Long-term forecasting (LTF) has been critical for infrastructure planning, generation and transmission investment, and policymaking (Perçuku et al., 2025). Moreover, at the building level, accurate energy consumption prediction is essential in optimizing building energy management systems to engage in demand response and fully achieve zero-energy buildings (Chen et al., 2025).

In reaction to limitations with conventional approaches and motivated by the promise of enormous amounts of data from weather forecasts, sensors, and smart meters, machine learning (ML) techniques are becoming valuable tools for energy forecasting. ML methods, including traditional methods like linear regression, support vector machines (SVM) and tree models, and advanced DL architectures like Artificial Neural Networks (ANNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNNs), provide the ability to represent complex, non-linear relationships and learn from experience without explicit physical modelling (Matijašević et al., 2022; Perçuku et al., 2025). Other recent research has targeted numerous application ML models, from overall system load and building-level consumption prediction to RES production and efficiency management in intelligent distribution systems (Chen et al., 2025; Matijašević et al., 2022). The rapid development of ML methods and their far-reaching applications in the energy forecasting arena necessitate regular and periodic state-of-the-art updates.

The shift in the energy system fueled by the necessity to reduce climate change, achieve sustainability, and achieve energy security has not only fetched its dividends but also complex dynamics, which traditional forecasting abilities cannot handle (Bogdanov et al., 2021; Makarov et al., 2020). The coming of renewable sources, distributed energy resources (DERs), and smart grids brought an era of record uncertainty and volatility in the utilization of power generation (Chen et al., 2025; Matijašević et al., 2022). It has made the utilizability of exact and genuine forecasting tools more than ever necessary (Mystakidis et al., 2024). Machine and deep learning techniques have proved incredible capability in overcoming this challenge. They utilize complex, nonlinear patterns in modelling and handling massive, multi-source datasets such as weather patterns and economic and historical load readings (Matijašević et al., 2022; Perçuku et al., 2025).

Notwithstanding, the increase in research volume, earlier reviews tend to refer to past methods or one sub-domain. This leaves room for an encompassing, systematic review of progress at the methodological and application level between 2020 and 2025, a time of fast-paced innovation and the growing deployment of ML models into actual energy systems. The current study fills the gap by providing a well-structured synthesis of the novel models, tools, and validation methods used across forecasting applications.

Though many reviews have been presented to the public domain, the subject continues to be active with new algorithm design, the fusion of complementary approaches, and areas of application. A comprehensive and recent review must summarize outcomes, indicate directions for new trends, analyze strengths and weaknesses of different methodologies in certain circumstances, lead towards chronic issues, and give the reader the direction for future research. More so, previous reviews have emphasized specific sub-domains or methodologies, but a general systematic summary for 2020 and beyond is helpful to gain insights into the contemporary scenario. Importantly, this paper is a systematic review of the applications of machine learning methods in load and energy consumption prediction with emphasis on literature from 2020 till the first quarter of 2025. The overarching aim of this study is to present an extensive overview of ongoing developments, applications, and challenges in the field. In particular, the review seeks to list and classify the most widely used Machine Language (ML) methods applied to load and energy forecasting over the past few years, describe the particular areas of application in which these ML methods are applied (e.g., STLF, building energy prediction, smart grid regulation), discuss the techniques employed, from the data to pre-processing, feature construction, and performance indicators, summarise the significant findings on the performance, strengths, and weaknesses of various ML methods from the literature, identify current research trends, current challenges (e.g., addressing uncertainty in the data, scalability, interpretability), and future research directions.

The structure of this research has been designed carefully to provide methodological solidity and academic uniformity. Section 1 provides a comprehensive introduction, setting the background, context, and purpose of the study. Section 2 provides a comprehensive literature survey wherein the scope and structure of related scholarly work are clearly described to provide scholars, practitioners, and policymakers with an apt and integrated conceptual framework. Particular emphasis is placed on the innovative applications of machine learning (ML) to address the challenges of load prediction and energy consumption forecasting in modern power grids. Section 3 outlines the methodological framework, which includes the research methodology, data sources, selection criteria, and analytical methods employed to ensure replicability and scholarly rigour. Section 4 presents a critical synthesis and systematic critique of the studies under investigation. This section compares the different methodological techniques, model settings, and evaluation measures employed within the chosen literature. It presents an in-depth comparative analysis of various ML techniques, highlighting their respective strengths, weaknesses, and areas for improvement.

In addition, this section presents the latest trends and technologies in the field, recognising their profound theoretical and practical importance, along with contemporary issues like data quality limits, generalizability, and the interpretability of high-dimensional models. Section 5 concludes with a concise yet critical overview, synthesising the key findings from the review and outlining an ambitious research agenda. The suggestions focus on methodological improvements, interdisciplinary, and policy relevance. The research, analysis, and methodological norms throughout are accurately weighed to enable a reasonable synthesis of recent developments in machine learning applications to energy systems. Moreover, the review not only sheds light on the state of affairs but also inquiries into the broader implications, possible avenues, and inherent limitations of ML applications in this case.

Although several studies on both Machine Learning (ML) and Deep Learning (DL) techniques have been published across various journals between 2020 and 2025, this present study systematically compiles evidence from a carefully selected set of 157 peer-reviewed journal articles. These papers were rigorously selected and appraised against pre-specified inclusion and exclusion criteria for relevance, methodological quality, and representativeness across a range of use areas. The complete list of studies analysed is presented in Table 2 of the Appendix and constitutes a strong basis for the comparative and thematic analyses conducted in this research. The rapid progress in machine learning (ML) and deep learning (DL) methods has revolutionised the field of energy load forecasting in recent years, with newer models consistently outperforming conventional statistical approaches. Some such models are Long Short-Term Memory (LSTM) networks, which have emerged as a prominent technique due to their high ability to extract long-term temporal patterns. Studies by Awais et al. (2020) and Zeb et al. (2020) achieved predictive accuracies of 96.3% and 98.6%, respectively, in proving that DL cutting-edge technology is justified. The use of CNNs combined with LSTM architecture has also enhanced predictability, as demonstrated by Wan et al. (2023), who achieved 7.3% and 5.7% improvements in short-term load forecasting over standalone LSTM models. Similarly, ensemble and hybrid techniques have gained prominence for their ability to optimise model performance across diverse data scenarios. For instance, Koukaras et al. (2023) reported mean absolute percentage errors (MAPE) as low as 5.39%, reaffirming the superiority of multi-model configurations.

There is a shift in paradigm towards ensemble and hybrid-based paradigms, advancing away from isolated algorithm forms, which directs current research directions. Initial attempts, like Bouktif et al. (2020), were the metaheuristic optimisation-based extension of an individual model. Current research increasingly depicts a trend towards selecting multiple paradigms of modelling for better generalisation and convergence. Hafeez et al., (2020) further presented the FS-FCRBM-GWDO hybrid model, which is more accurate and efficient than baseline models. Adnan et al. (2022) confirmed the efficacy of hybrid models about other different criteria. The same applies to 2025 research; for example, Liu et al. (2025) detailed how multi-task architecture and transfer learning are the underlying working principles for low-data hybrid energy systems.

Conversely, Heng (2025) introduced the MTL-GAN model and demonstrated how representation learning, in a joint manner, evolved from straightforward LSTM models to advanced multi-task networks that leverage multimodal energy data. Recent advancements also indicate an increased emphasis on the complexity of multi-energy load forecasting and the demands of integrated energy infrastructure. Yao et al. (2022) demonstrated the effectiveness of attention-based CNN-DBILSTM models in extracting correlations between electricity, heat, and gas loads, achieving a prediction accuracy rate of 97.99%. Geng et al. (2024) further linked load optimization with sustainability, showing that multi-scale CNNs could reduce carbon emissions by over 238,000 kg weekly. Building on decentralization and privacy, Wang et al. (2023) successfully deployed federated learning for community energy forecasting, achieving 97% accuracy and a 92% F1 score. Follow-ups on these developments will be focused on further development in 2025. For instance, Liu et al. (2025) demonstrated how transfer and federated learning approaches achieve the best performance while preserving data privacy in real-world field applications. Huang and Huang (2024) brought the field to a whole new height by creating energy-sustainable DL models with no computation burden at all but without sacrificing predictive accuracy. Altogether, these achievements bring ML forecasting to the height of new, green, smart, and privacy-conscious power grids.

The advancements in deep learning (DL) and machine learning (ML) over the years have dramatically increased the accuracy and credibility of load and energy consumption forecasting in contemporary power systems (Chandrasekaran & Paramasivan, 2024). Deep learning models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and their hybrids have a higher potential for learning complex spatial and temporal patterns in energy data. These models will likely surpass common statistical and conventional ML methods in short-term and medium-term forecasting scenarios (Zhang et al., 2023; Abujazar et al., 2023). These models specifically excel with the uncertainty from intermittent renewable power sources and volatile consumer demand, thus allowing for more powerful and responsive grid operations (Hussain et al., 2022; Ahmadi et al., 2022).

Other methodological improvements, such as dimensionality enhancement, spatiotemporal modelling, and hyperparameter optimization, have also been shown to improve model robustness and predictive ability (Jalalifar et al., 2023; Yahyaeian et al., 2023; Zhang et al., 2023). All such comparative analyses always shed light on the optimal performance of deep learning models, primarily Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), and Restricted Boltzmann Machines (RBMs), which have been found to achieve mean absolute percentage errors (MAPE) of less than 5% when integrated with multi-source data such as weather, economic, and historical load data (Jaber et al., 2023; Shirzadi et al., 2021; Tian et al., 2022).

While artificial neural networks (ANNs) and traditional ML techniques such as support vector machines (SVMs) and random forests remain applicable, recent literature increasingly favours DL approaches due to their ability to extract features and effectively manage high-dimensional, nonlinear relationships automatically (Abujazar et al., 2023; Ahmadi et al., 2022; Hussain et al., 2022). However, there are significant problems, i.e., in model explainability, data quality, and reliance on diverse and large datasets for the proper training of models. Therefore, current research efforts still seek to address the optimization of DL architectures, incorporation of domain knowledge, and design of hybrid modelling methods to enhance the prediction performance and facilitate the development of intelligent, adaptive, and green energy systems (Chandrasekaran & Paramasivan, 2024; Jalalifar et al., 2023; Yahyaeian et al., 2023).

The shift in the energy system fuelled by the necessity to reduce climate change, achieve sustainability, and achieve energy security has not only fetched its dividends but also complex dynamics, which traditional forecasting abilities cannot handle (Makarov et al., 2020; Bogdanov et al., 2021). The coming of renewable sources, distributed energy resources (DERs), and smart grids brought an era of record uncertainty and volatility in the utilization of power generation (Matijašević et al., 2022; Chen et al., 2025). It has made the utilizability of exact and genuine forecasting tools more than ever necessary (Mystakidis et al., 2024). Machine and deep learning techniques have proved incredible capability in overcoming this challenge. They utilize complex, nonlinear patterns in modelling and handling massive, multi-source datasets such as weather patterns and economic and historical load readings (Perçuku et al., 2025; Matijašević et al., 2022).

The above literature presents a definite trend towards the predominance of deep learning (DL) and hybrid models for energy load forecasting, where the use of LSTM, CNN-LSTM, and attention models consistently achieves better results compared to conventional statistical and traditional machine learning (ML) methods. Such a DL approach can provide increased complexity in energy data, including temporal and spatiotemporal correlations, with forecasting accuracy levels above 95%, as supported by the literature from Awais et al. (2020) and Chang et al. (2023). Ensemble and hybrid models, such as FS-FCRBM-GWDO (Khan et al., 2020) and MTL-GAN (Heng, 2025), exhibit greater convergence stability and generalization across datasets, with a trend in this direction. Development advances also lead to sustainable and integrated forecasting, whose application, for instance, attention-based CNN-DBILSTM, supports multi-energy load forecasting and environmental optimisation (Yao et al., 2022; Geng et al., 2024). Similarly, privacy-conscious approaches like federated learning (Wang et al., 2023) and computationally viable DL models (Huang & Huang, 2024) reflect the growth of the field in security, decentralisation, and computationally viable practice.

There is much yet to be explored in research. First, interpretability is one of the primary challenges of models, and the majority of deep learning models are "black boxes," posing a hindrance to trust, transparency, and regulatory compliance in the most critical energy applications. Secondly, the generalizability of the models across seasons, geography, and grid systems is limited, and hence, their level of applicability in real-world scenarios is modest. Domain adaptation and transfer learning techniques are becoming increasingly pertinent (Lie et al., 2025); however, a significant number of studies need to be done before dynamic flexibility can be attain. An enormous limitation is also data-centric: large, diverse, and high-quality data cannot be taken for granted everywhere upon which to train and run models at scale. In addition, while state-of-the-art models are highly accurate, their high computational requirements are a barrier to real-time or edge deployments. Future studies should thus prioritise models that are explainable, domain-generalizable, scalable and low-energy-intensive, as well as privacy-friendly data integration processes in order to harness the full potential of ML/DL in innovative and sustainable energy forecasting.

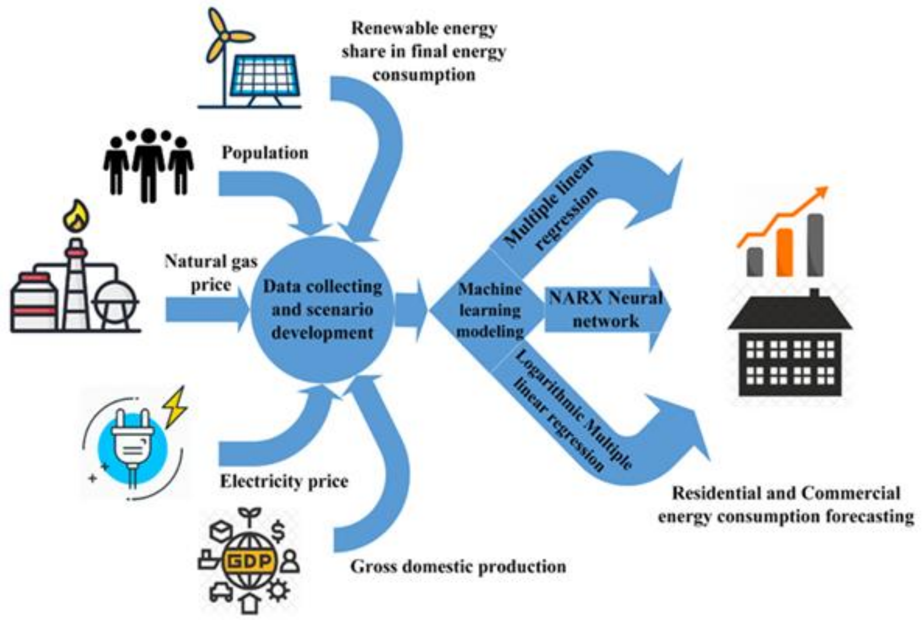

Fig. 1. Framework for forecasting residential and commercial energy consumption using machine learning models
(Nabavi et al., 2020)

As shown in Figure 1, the author predicts domestic and commercial energy consumption by applying these socio-economic variables and machine learning techniques. Moreover, we considered most of the conventional energy modelling approaches and chose the TD modelling according to the data availability (as defined in the preceding subsection). We examined the aforementioned factors (i.e., variables) and underlying trends. Furthermore, we forecasted future values of variables like POP, GDP, NGP, EP, and RESH using a feed-forward Artificial Neural Network (ANN). Subsequently, we simulated energy consumption by TD modelling tools, namely Multi-Linear Regression (MLR), Logarithmic Linear Regression (LMLR), and Nonlinear AutoregRessive with exogenous input (NARX). The models are tested and compared. Finally, the model proposed is utilized to predict energy consumption up to 2,040.

2. Methods

This systematic review followed a conventional methodological design to generate an open, rigorous, and replicable evidence synthesis on machine learning (ML) applications for predicting electricity load and energy consumption. A systematic search procedure was conducted across some scholarly databases (e.g., IEEE Xplore, Scopus, Web of Science) and preprint archives (e.g., arXiv) for English-language articles from January 2020 through May 2025 (see Table 1). The search utilized keywords associated with machine learning, prediction, and energy consumption using Boolean operators unique to each database. Inclusion comprised conference papers, peer-reviewed articles, systematic reviews of ML/DL methods applied in electricity forecasting, and exclusions on non-English language papers, non-ML research, and those not conveying empirical data and selecting articles involved abstract/title screening and full-text evaluation with data extraction prompted by a standardized template. The main information extracted was bibliographic information, ML method, datasets, performance measures, results, and directions for future studies. As shown in Figure 2, this procedure applied a systematic 12-step methodology for systematic reviews, maintaining methodological robustness and consistency in evidence integration.

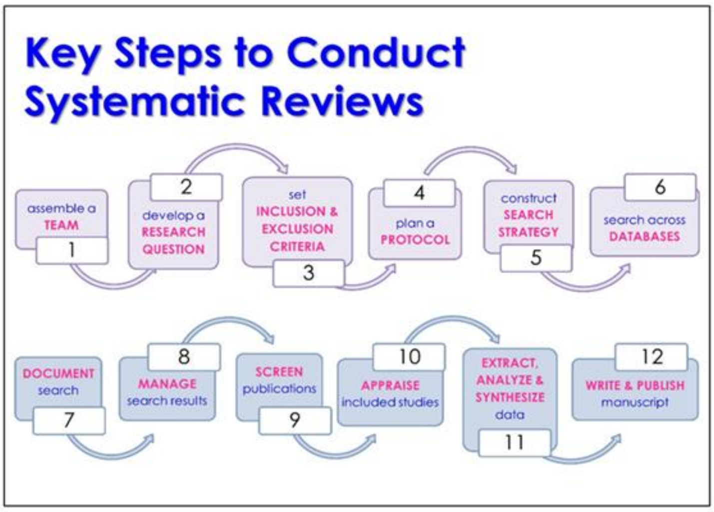

Fig. 2. Systematic review methodology
(The Chinese University of Hong Kong Library, 2024)

Figure 3 shows the six fundamental phases of a machine learning pipeline: data collection, data cleaning, feature engineering, model training and selection, model testing and deployment, and monitoring and maintenance. The phases form a loop to construct, deploy, and tune successful machine learning models.

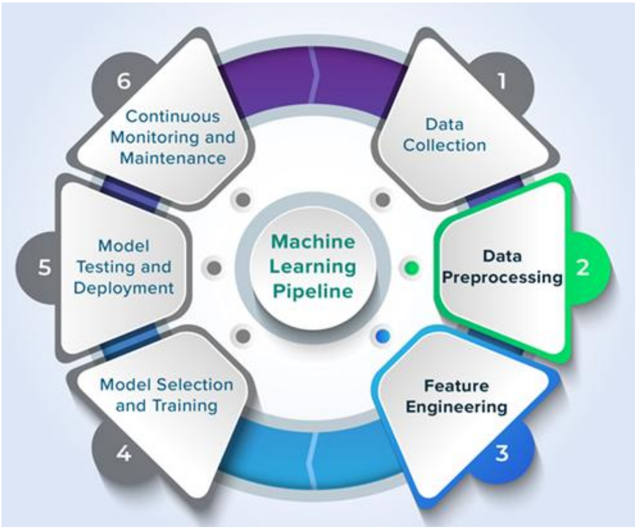

Fig. 3. Typical Data Pre-processing Pipeline for ML-based Energy Forecasting
(Parikh, 2024)

3. Results and Discussion

3.1 Study selection and characteristics

An exhaustive systematic literature searches across several scholarly databases produced 2,847 articles associated with applying machine learning methods for energy and load forecasting. An explicit screening approach was used against clearly specified inclusion and exclusion criteria to ensure methodological quality and review consistency. Duplicate entries were first identified and removed, after which each study was assessed for relevance based on title, abstract, and full-text evaluation. Only peer-reviewed English-language articles addressing machine learning or deep learning models for energy or load forecasting were retained. Studies on unrelated fields, untested empirically, or concentrating solely on hardware and sensor design without considering modelling were ruled out.

Following such rigorous screening, 157 papers were shortlisted for detailed analysis (see appendix, Table 2). The time trend of the shortlisted papers reflects a definite rising trend in scholarly attention during the review period 23 of these studies came out in 2020 and 28 in 2021. There were 35 in 2022, in line with the development of the application of advanced machine learning techniques to research energy systems. There were 42 total high research intensity studies in 2023. It fell to 24 studies in 2024 but was no less intense. At least five standalone papers were released in the first half of 2025, (see Figure 4) testifying to the continuation of this line of research and ongoing interest in the issue by the scientific and professional community interested in energy forecasting. This increase in publication activity is a consequence of the quickly growing interest and awareness about machine learning as a key tool to solve the complex issues about contemporary energy systems, especially regarding increased demand variability, renewable energy integration, and smart grid optimisation.

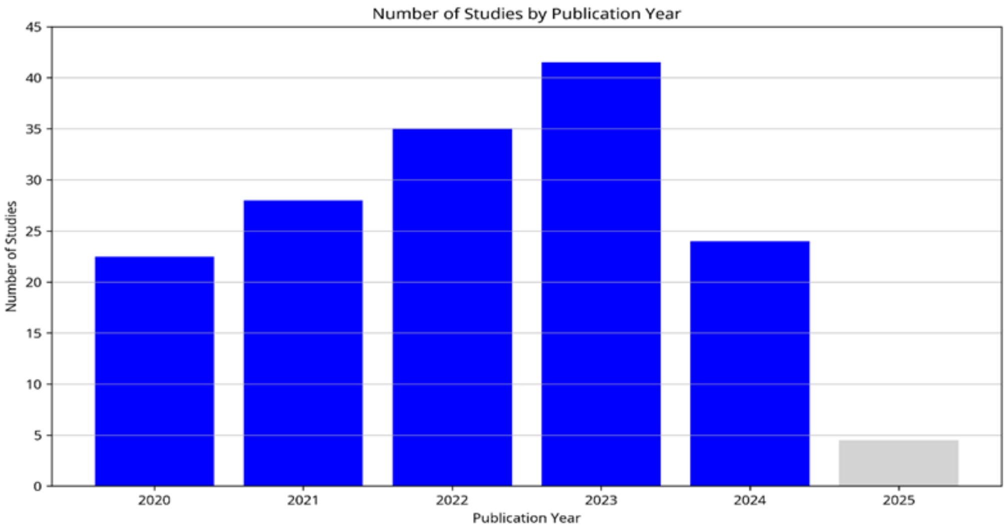

Fig. 4. Distribution of selected studies by publication year (2020-2025)

3.1.1 Machine learning techniques distribution

The trend in Figure 5 shows a pronounced predominance of deep learning methods in studies covered under load and energy forecasting categories. Within them, Long-Short-Term Memory (LSTM) networks were the most prevalent model, featuring in about 34% of the studies covered. Its popularity stems from the established ability of LSTM to learn temporal relations well in sequential energy data and, hence, suitability for time-series forecasting tasks. Following LSTM models, Hybrid Convolutional Neural Network–LSTM (CNN-LSTM) models accounted for 18% of the studies under analysis. They have been favoured due to their ability to capture spatial and temporal data properties and enhance forecast precision in advanced energy systems. While primarily designed for identifying the spatial pattern, simple CNN models were utilized to the tune of 12% of the studies, often coupled with feature extraction operations within multivariate prediction programs.

Despite the rise of deep learning techniques, conventional machine learning models such as Support Vector Machines (SVM) and Random Forests continue to hold relevance, especially in contexts where data availability is limited or model interpretability is paramount. These traditional methods are particularly favoured in use cases involving smaller datasets or decision-critical environments where transparency and explainability are essential. The continued application of such models highlights the practical importance of balancing predictive accuracy with computational efficiency and interpretability in energy forecasting research.

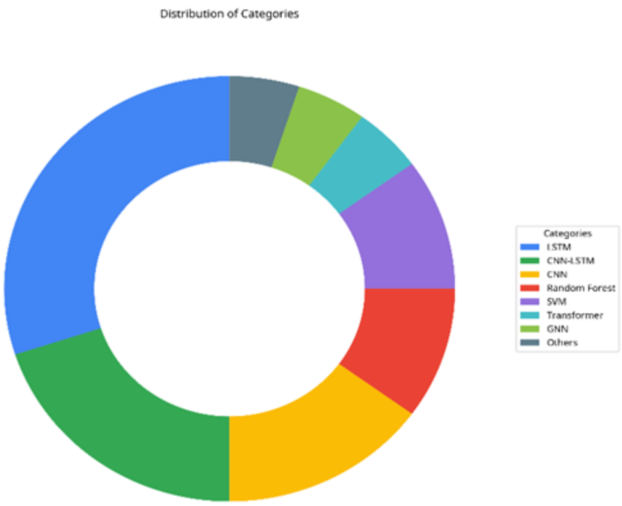

Fig. 5. Distribution of machine learning techniques in reviewed studies

Recent developments in energy forecasting studies exemplify the supremacy of deep learning methodologies, where about 73% of the work applied such approaches, of which Long Short-Term Memory (LSTM) networks are most renowned for their capacity to manage temporal sequence data. There is also an emerging trend towards more hybrid model development. CNN-LSTM models are higher at 25% in 2024 compared to 8% in 2020, reflecting the integration of spatial and temporal modelling capacity for better predictive performance. Also, there are breakthroughs like transformer models and Graph Neural Networks (GNNs); transformers now take up 6% of the research and have grown an incredible 300% from 2022 to 2024 because they do very well with sequence modelling. At the same time, GNNs, cited in only 3% of the literature currently, are promising for network-aware prediction and a step towards higher-order and adaptive neural configurations in energy science.

3.1.2 Application domain analysis

Table 1. Distribution of studies by application domain

Application Domain	Number of Studies	Percentage	Predominant Techniques
Short-term Load Forecasting	66	42%	LSTM, CNN-LSTM, Transformer
Building Energy Prediction	36	23%	LSTM, CNN, Random Forest
Mart Grid Operations	28	18%	CNN-LSTM, Transformer, GNN
Renewable Energy Forecasting	27	17%	GNN, LSTM, Ensemble

Given the fields of application, short-term load forecasting (STLF) is the most studied field, with 42% of the papers under review. Such a high focus highlights STLF's importance in grid stability, demand-side management, and operation planning of modern power systems. Its popularity is perhaps because of growing recognition of the importance of accurate near-real-time demand forecasts to enable dynamic demand profiles and growing uses of intermittent renewable energy sources. Its second most discussed theme in order of frequency is building energy prediction at scale, at 23% of the research. It justifies growing academic and practical attention to enabling energy efficiency and demand optimisation at scale at the micro-level for residential, commercial, and institutional buildings. This aligns with master sustainability agendas and the shift to smart building technologies.

At 18% of the studies, forecasts of renewable energy are intended to make more accurate predictions of solar and wind energy. Also, naturally fluctuating and non-repeating energy sources. Integrating renewables onto the grid and reducing reliance on fossil-fuel-generated electricity is more important. Finally, intelligent grid operation accounts for 17% of the literature. It is concerned with attempts to utilise advanced forecasting methods to maximise grid flexibility, decentralised control, and real-time energy supply. These statistics, presented in Table 1, not only describe the overall contribution of STLF in existing research but also the augmented focus towards decentralised and sustainability-based energy management techniques in various application domains.

3.1.3 Performance analysis and benchmarking

Variation in predictive precision between studies considered here mirrors considerable divergence, most of which can be attributed to the selection of approach to modelling and the particular application domain in which it is used. For short-term load forecasting (STLF), which still tops the list of most studied application fields, the best-performing models reproduce mean absolute percentage errors (MAPE) of less than 3% (see Figure 6). This precision is required to undertake grid reliability and optimal energy dispatch computations.

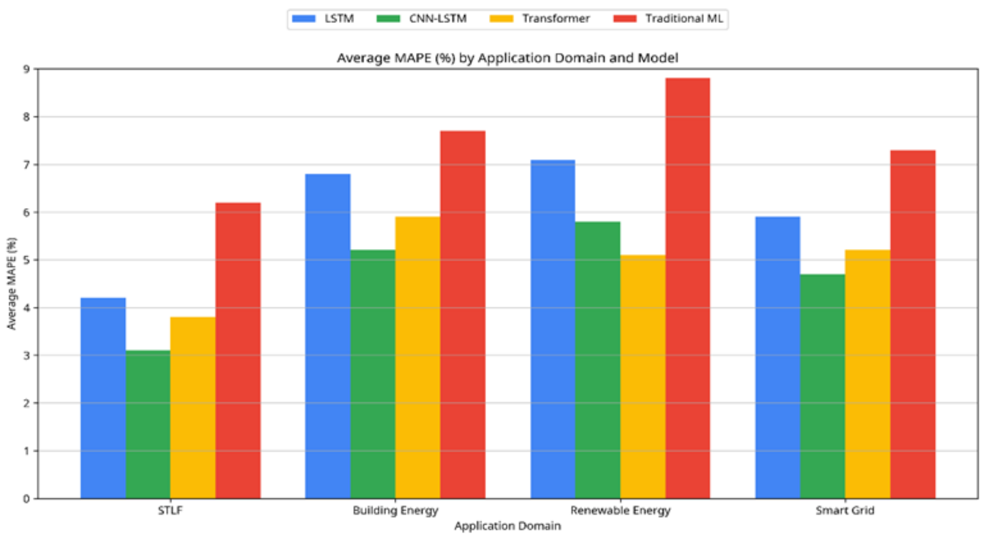

Fig. 6. Average MAPE performance by technique category across application domains

Among the methods studied, the hybrid deep learning models, i.e., Convolutional Neural Networks-Long Short-Term Memory Network (CNN-LSTM) hybrids, made more accurate predictions than standalone methods. The hybrid methods take advantage of both the spatial feature extraction capability of CNNs and the temporal sequence modelling capability of LSTMs to enable better control of the complex spatiotemporal dynamics in the energy demand data. The overall over-performance of CNN-LSTM hybrids underscores an increasing trend towards leveraging complementary deep learning methods to enhance prediction accuracy and robustness. Such a finding also underscores application-specific and data-specific model selection in realising the best performance results for various energy forecasting applications.

3.1.3.1 Key performance insights

Long Short-Term Memory (LSTM) networks perform exceptionally well across various forecasting classes, achieving mean absolute percentage errors (MAPE) ranging from 4.2% to 7.8%, particularly excelling in learning long-term temporal patterns. CNN-LSTM hybrid models also demonstrate outstanding performance, with MAPE between 3.1% and 6.2%, especially in handling complex spatial-temporal data patterns. Transformer models are highly effective in long-sequence prediction tasks, delivering MAPE values between 3.8% and 5.9%; however, they require significantly high computational resources, which can be a limiting factor. On the other hand, traditional machine learning methods, while delivering slightly less accurate forecasts (MAPE: 5.1%–9.3%), are advantageous for less

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computationally demanding tasks and offer greater model explainability, making them suitable for scenarios where interpretability and efficiency are prioritized.

3.1.3.2 Dataset size impact

Analysis shows the advantages of deep learning for data from more than 10,000 samples. With small data sets (<5,000 samples), standard ML methods will likely compare or surpass performance at a much lower computational cost.

3.1.4 Data pre-processing and feature engineering trends

Good data pre-processing is a key success factor for all the studies under review. The most frequently used pre-processing methods are normalization (94% of the studies), detection and deletion of outliers (78%), imputation of missing values (67%), and feature scaling (89%). The evolution of feature engineering has shown increased sophistication over time. Approximately 68% of the studies incorporated weather-related features, while 45% utilized calendar or temporal variables. Economic indicators were included in 32% of the studies, and 23% considered social or behavioral features. Moreover, advanced feature selection techniques, such as mutual information and correlation analysis, were applied in 56% of the reviewed literature to enhance model input relevance and improve forecasting performance. Automated feature engineering is also emerging as a notable trend, particularly in papers published between 2023 and 2024. Around 18% of these studies employed automation techniques such as genetic algorithms and neural architecture search, signaling a shift toward reducing manual effort and increasing efficiency in the model development process.

3.1.5 Evaluation metrics and validation approaches

The study mentions standardization across the evaluation measures, where MAPE (89% of articles), RMSE (78%), and MAE (72%) are most frequently reported. However, measures specific to the domain are used more often nowadays, such as ramp rate accuracy in renewable forecasting and peak demand accuracy for load forecasting. Regarding validation techniques, 67% of the studies utilize time series cross-validation, indicating a stronger emphasis on preserving temporal relationships during model evaluation. Nevertheless, 23% of the studies still apply random train-test splits, which may lead to overly optimistic and less reliable performance estimates due to their disregard for time dependencies inherent in energy data.

3.1.6 Emerging technologies and innovation trends

Explainable AI (XAI) techniques are increasingly integrated into energy forecasting models, with 31% of 2024 studies incorporating some form of interpretability analysis. SHAP values and attention visualization are the most commonly used approaches, addressing critical needs for model transparency in operational environments. While still emerging, federated learning has been applied in 7% of studies and shows significant promise for privacy-preserving energy forecasting across multiple stakeholders. Early results demonstrate comparable performance to centralized approaches while ensuring data privacy. The integration of physical constraints and domain knowledge—commonly referred to as physics-informed models—is observed in 12% of recent studies. These models exhibit improved robustness and generalization, particularly in applications related to building energy modelling. Meanwhile, quantum machine learning is at a nascent stage, with 3% of the studies exploring its use. These primarily focus on optimization problems and indicate strong potential for future computational advantages in energy forecasting.

3.2 Discussion

3.2.1 Key findings and implications

This study's findings produced several critical insights with meaningful research and practical implications for the application of machine learning in energy forecasting. First, deep learning maturity is evident in the large-scale adoption of LSTM and CNN-LSTM hybrid models, marking a transition from experimental deployment to mature, deployable technologies. Their increasing prevalence reflects not only their predictive power but also their flexibility in addressing complex forecasting tasks. However, this advancement comes with the trade-off of higher model complexity and computational costs, which may pose challenges in resource-constrained settings. These results align with the work of Aalami et al. (2020) and Ayesha et al. (2025), who demonstrated that CNN–LSTM hybrids consistently outperformed standalone models in predicting environmental indicators such as dissolved oxygen (DO) and *chlorophyll-a* (Chl-a), reaffirming the superior predictability of hybrid neural models.

Second, performance remains highly context-dependent. No single algorithm performs optimally across all datasets and forecasting scenarios. Factors such as dataset size, temporal granularity, forecasting horizon, and application domain significantly affect model performance. This reinforces the importance of selecting forecasting methods based on specific application needs rather than relying on general trends or algorithm popularity. Finally, the quality of data emerges as the most consistent determinant of success. Across all reviewed studies, high-quality data and sophisticated pre-processing techniques had a more significant impact on model accuracy than the specific ML algorithm employed. Properly designed data pipelines—including cleaning, normalization, and feature engineering—consistently led to better forecasting outcomes. This finding echoes the conclusions of Pandey and Kale (2024), who found that robust data preparation often had a greater influence on prediction quality than the choice of learning model itself.

3.2.2 Persistent challenges and limitations

The study identified several critical challenges that have important implications for both research and practical applications in energy forecasting: First, there exists a notable trade-off between performance and interpretability. While deep learning models generally yield higher prediction accuracy, their characterization as "black boxes" poses significant challenges for mission-critical applications where transparency, explainability, and regulatory compliance are essential. This trade-off is especially problematic in contexts where model reasoning must be clearly understood to ensure safety and accountability. The findings echo those of Zhang and Zhu (2018), Liu et al. (2021), and Yang and Xu (2024), underscoring the necessity for models that strike a balance between high performance and interpretability in sensitive forecasting scenarios.

Second, the issue of generalization remains a major concern. Although many experiments demonstrate excellent performance on the training datasets, their inability to generalize to different situations—such as varying times of the year, diverse geographies, or other external conditions—significantly reduces their practical applicability. Wickramarachchi et al. (2023) have highlighted this problem as a key barrier to the successful field deployment of these models, emphasizing the need for adaptable approaches in large-scale implementations. Third, despite advances in average forecasting accuracy, current methods are largely inadequate at predicting rare events, such as extreme weather conditions, sudden spikes in electricity load, or abrupt demand fluctuations. This limitation is especially critical for grid stability and emergency response applications, as demonstrated in the work of Lusa and Blagus (2017) and Wickramarachchi et al. (2023).

Fourth, both deep and shallow learning models, despite their robust predictive capabilities, often suffer from high computational costs. This limitation renders them less suitable for real-time applications, particularly in environments with limited computing resources. Lusa and Blagus (2017) and Zhao et al. (2025) have noted that this computational burden is a significant drawback for distributed or low-resource systems. Finally, data privacy and security remain underexplored yet crucial issues. The use of personal and otherwise sensitive consumption information in advanced forecasting models raises significant privacy concerns. In the current body of literature, less than 12% of the studies address privacy issues in any detail, indicating a substantial gap. Researchers such as Lusa and Blagus (2017), Juwara et al. (2023), and Zhao et al. (2025) have underscored the importance of incorporating robust data protection and ethical considerations in model development.

3.2.3 Methodological principles and best practices

The findings also highlight several key methodological insights that shape the direction of future research. First, the improved performance of hybrid models—particularly CNN-LSTM ensembles—demonstrates the strength of combining multiple complementary techniques. These ensembles consistently outperform single-model approaches, confirming the strategic value of ensemble and multi-model frameworks in energy forecasting applications. Second, the significance of feature engineering cannot be overstated. Studies that employ advanced feature engineering techniques consistently outperform those relying solely on raw temporal data. The integration of diverse features such as weather, calendar-based variables, economic indicators, and behavioral patterns significantly enhances model performance by providing richer contextual understanding for prediction tasks. Lastly, the review underscores notable inconsistencies in validation methodology across the literature. Many studies apply inappropriate cross-validation strategies for time series data, such as random splits, which risk inflating performance metrics. The adoption of proper temporal validation techniques is essential to ensure realistic and reliable evaluation of forecasting models.

3.2.4 Emerging opportunities anad future directions

The future trajectory of machine learning in energy forecasting involves several cutting-edge directions with high transformative potential. First, the integration of Explainable AI (XAI) techniques marks a critical advancement. The state-of-the-art application of XAI now offers models that achieve peer-level performance while meeting essential interpretability standards. However, there remains a pressing need to develop explainability frameworks specifically tailored to the operational and regulatory contexts of power systems. Secondly, multi-modal data fusion is poised to significantly enhance forecasting accuracy. The blending of diverse data sources—such as satellite imagery, economic indicators, IoT sensor data, and even social media sentiment—can offer richer insights and enable real-time, context-aware predictions.

Third, the integration of edge computing presents a promising solution for distributed energy systems. Deploying lightweight, efficient models at the network edge allows for real-time forecasting while addressing crucial issues of latency, data privacy, and bandwidth constraints. Lastly, quantum-enhanced algorithms are emerging as a potential breakthrough in solving complex energy forecasting challenges. Although still in early development, quantum machine learning shows promise in tackling large-scale, multi-objective, and constraint-heavy optimization problems that are otherwise computationally prohibitive using classical methods.

3.2.5 Key implications and limitations of the systematic review on machine learning applications in energy forecasting

Future practical implementation of machine learning in energy forecasting will require strategic operational planning and cross-sector collaboration. One key approach is the incremental deployment strategy, which involves the gradual integration of ML models into existing forecasting infrastructure. This method allows for real-world validation, model calibration, and risk minimization before full-scale adoption. Hybrid techniques that blend traditional statistical methods with ML during transitional phases have shown promise in easing this process.

Equally important is the development of continuous learning systems. Given the dynamic and evolving nature of energy systems, models must be capable of adapting to changing patterns in data. Techniques such as transfer learning and online learning offer pathways for such adaptability. However, these must be applied carefully to maintain model integrity and avoid degradation over time due to concept drift or poor retraining practices. Lastly, collaborative stakeholder engagement is essential for successful deployment. Seamless cooperation among ML researchers, domain experts, utility companies, and regulatory bodies ensures that developed models meet operational needs, adhere to compliance requirements, and are practically viable for real-world application. This integrated approach bridges technical innovation with policy and operational realities.

3.2.6 Limitations of this review

Although this review offers valuable insights into the application of machine learning methods for energy prediction, several limitations should be acknowledged when interpreting its findings. First, the restriction to English-language publications may have introduced language bias, potentially overlooking significant research published in other languages. Second, publication bias remains a concern, as studies reporting positive or significant results are more likely to be published, which could lead to an overestimation of model performance across the literature.

Additionally, given the rapid evolution of this field, even a review spanning from 2020 to mid-2025 may not fully capture the most recent innovations or emerging next-generation tools. The high methodological heterogeneity—including differences in datasets, application domains, and performance evaluation metrics—further complicates direct comparisons between studies and limits the ability to draw universal conclusions. Lastly, the review does not encompass proprietary or confidential industrial applications, which are often unpublished. These implementations could offer critical insights into real-world scalability, operationalization, and practical deployment challenges, but remain inaccessible for academic synthesis.

4. Conclusions

From the foregoing, this systematic review confirms that machine learning (ML) and deep learning (DL) methodologies have transformed energy forecasting on a broad scale from being largely experimental setups to operational deployment in mission-critical settings. Comparative performance metrics throughout the literature reviewed invariably show that DL models like LSTM, CNN-LSTM, and Transformer architectures surpass conventional forecasting accuracy, temporal resolution, and scalability measures. Nevertheless, collating the findings by theme reveals repeated concerns over the interpretability of the models, generalisability over wide geography and seasons, and computational tractability for low-resource or real-time deployment. Addressing these challenges is not only a matter of algorithmic innovation; it involves strong frameworks that gain trust, increase transparency, and are applicable in practice. A cross-disciplinary interdisciplinary effort among researchers, industry actors, policymakers, and end-users is needed to align technological possibilities with genuine needs. The growing need for trustful forecasting, especially with consideration of global electrification and renewable energy integration, makes such alignment more urgent. Future research should prioritise the development of sustainability-aware models, causal inference techniques, and adaptable forecasting frameworks that integrate cross-domain transfer learning. Moreover, the convergence of 5G/6G technologies, quantum computing, and edge AI holds promise for achieving real-time, scalable, and decentralised energy forecasting. Human-AI collaboration must also be central, promoting transparency and ethical decision-making in energy management. Collectively, these strategies form a forward-looking roadmap for enhancing forecasting systems that are intelligent and efficient but also resilient, equitable, and sustainable.

To researchers, some best practices in methodology can enhance follow-up energy forecasting research through improved robustness and effectiveness. One applies systematic validation techniques, especially cross-validation from time series, which is important in identifying temporal dependency in energy data. To enable generalizability, researchers must validate models using different datasets, time horizons, and geographic locations. Interpretability may be incorporated at the beginning of model building for model output transparency. Universal benchmarking datasets and evaluation metrics must also establish fair and informative performance comparisons across studies. Finally, researchers must actively incorporate data privacy and security-related concerns into research design about the ethical and legal considerations of utilizing data for energy. On the other hand, to the actual practitioners who are engaged in deploying machine learning models, model selection based on context is of top priority. Rather than working with cool models in bulk, practitioners must be prepared to accept model selection based on their environment's unique requirements and needs. Strong pre-processing pipelines and high-quality data should also be important since they are the primary drivers of model validity. Progressive deployment strategies whereby models are extensively tested before widespread deployment successfully nip the threat in the bud and allow level performance to become accessible. Frequent monitoring and occasional re-estimation of the models are necessary to support adapting conditions and forecasting validity. Close coordination among machine learning specialists and domain subject-matter experts will also fill knowledge gaps and provide stronger, more applied, interpretable prediction tools.

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All the authors made substantial contributions to this research study. Engr. Oluwadare Olatunde Akinrogunde contributed to the conceptualisation and design of the study, data analysis, and manuscript drafting. Engr. Adeola Amos Adelakun participated in data acquisition, literature review, and substantive revision of the manuscript. Mr. Edwin Ejike Theophilus contributed to developing software tools used in the research and interpretation of results. Mrs. Temitope Grace Thomas was involved in the critical review and editing of the manuscript and approved the final version for submission. All authors have read and agreed to the published version of the manuscript.

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Ethical Review Board Statement

This study did not require ethical approval as it did not involve human participants, animals, or sensitive personal data.

Informed Consent Statement

Informed consent was waived due to the study's nature, which involved analysing previously published literature and secondary data that are publicly accessible and do not involve interaction with human participants or the collection of personally identifiable information. As such, the research posed no foreseeable risk to individuals, and ethical approval deemed informed consent unnecessary for this type of data usage.

Data Availability Statement

The data supporting the findings of this study are derived from previously published articles and publicly accessible databases. All sources used in the review are cited appropriately within the manuscript. No new data were generated or collected for this study. Additional details extracted from the included studies are available upon reasonable request from the corresponding author.

Conflicts of Interest

The authors declare no conflict of interest.

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