A Bibliometric Review and Taxonomy of Artificial Intelligence Applications in Electricity Load Forecasting

Nguyen Hoang LAN[1], Ha Thu HANG[2], Duong Thu THAO[3], Le Hoang VINH[4], Tran Dac BANG[5], Nguyen Dang TRUNG[6], Ha Xuan NAM[7], TOAN-Le Vu[8]

[1,2,3,4,5,6,8] School of Economics and Management, Hanoi University of Science and Technology, Hanoi, Vietnam

[7] School of Engineering, The Royal Melbourne Institute of Technology, Melbourne, Australia

[*]Corresponding author: thuhang215.fw@gmail.com

Abstract

This study presents a comprehensive bibliometric review and taxonomy of 469 peer-reviewed publications on AI-based electricity load forecasting from 1997 to 2024. Through performance analysis and science mapping, the paper identifies influential authors, emerging countries, research clusters, and collaboration patterns. A three-layer taxonomy is developed to categorize the literature based on forecasting horizon (ultra-short, short, mid, long term), forecasting scale (micro, meso, macro), and model type (basic machine learning, basic and advanced deep learning, hybrid, soft computing). Results reveal that short-term forecasting at micro and meso levels dominates the field, with deep learning models - especially Convolutional Neural Network and Long Short-Term Memory - playing a central role. Hybrid models integrating optimization and decomposition techniques are gaining popularity, while ultra-short, mid-, and long-term forecasting remain underexplored. Collaboration is still regionally fragmented, but there is a noticeable shift of research influence toward South Asia. The study provides a structured overview of the intellectual landscape and highlights key gaps, including the lack of long-horizon forecasts and the need for more generalized and collaborative AI solutions across spatial levels.

Research purpose:
This study provides a bibliometric review and taxonomy of AI applications in electricity load forecasting. It aims to systematically classify 469 publications (1997-2024) by forecasting horizon, application scale, and model category, while identifying influential authors, countries, and emerging trends.

Research motivation:
Electricity load forecasting is essential for reliable system operation, market efficiency, and energy transition planning. The increasing complexity of power systems with renewables and electric vehicles requires more advanced models. Despite rapid progress, there is still a lack of structured overviews to clarify research gaps, motivating this study.

Research design, approach, and method:
Data was retrieved from the Scopus database using a targeted search string combining electricity load forecasting with AI-related terms. Bibliometric analysis was applied through performance indicators and science mapping (co-authorship, co-keyword networks). A three-layer taxonomy was developed covering forecasting horizon, scale, and model type.

Main findings:
Short-term forecasting dominates the field, especially at micro and meso levels, using deep learning models such as Convolutional Neural Network and Long Short-Term Memory. Hybrid models integrating decomposition and optimization methods are increasingly popular, while ultra-, short-, mid-, and long-term horizons remain underexplored. China leads research output, followed by India and Pakistan, signalling a regional shift toward South Asia.

Practical/managerial implications:
The taxonomy and mapping provide a structured reference for scholars and practitioners. Identifying gaps-such as the lack of long-term and multi-level forecasting-can guide future research. For utilities and policymakers, the findings highlight the practical relevance of deep learning and hybrid AI models in improving system reliability and energy management.

N. D. Nguyen and P. T. K. Ngoc (eds.), *Proceedings of the International Conference on Emerging Challenges: Business Dynamics in Disruptive Economy (ICECH 2025)*, Advances in Economics, Business and Management Research 377,
https://doi.org/10.2991/978-94-6239-622-7_9

Keywords: *electricity load forecasting, artificial intelligence, deep learning, machine learning, bibliometric analysis*

1. INTRODUCTION

In the context of the vigorous energy transition, modern power systems are undergoing profound and unprecedented transformations. The rapidly increasing integration and development of renewable energy sources and distributed energy resources (DERs) (Gao et al., 2022), coupled with the growing prevalence of electric vehicles (EVs), has significantly amplified the complexity and uncertainty of power system operations (Kong et al., 2019). Additionally, factors such as temperature, wind speed, precipitation, and socio-economic activity patterns (e.g., peak versus off-peak hours, weekdays versus weekends, holidays, and pre-/post-holiday periods) (Weron, 2014) further contribute to a more complex operating environment characterized with random fluctuations in power, substantially impacting system reliability.

Within this context, electricity load forecasting has become a critically important technical element, serving as the foundation for power system planning, operation, and electricity market trading. The accuracy of load forecasting directly and profoundly impacts all aspects of power system operation, management, operational planning, market transactions, grid maintenance, and security. It also influences broader economic management. A forecast with excessive errors can lead to severe economic and technical consequences, including the unnecessary activation of expensive peaking power generation units, resulting in significant wasted resources. Conversely, it can lead to capacity shortfalls threatening system stability and frequency regulation, potentially even triggering large-scale blackouts with serious repercussions (Hahn et al., 2009). Accurate electricity demand forecasting ensures safe and economical energy supply, facilitates smooth socio-economic development, effectively reduces operational costs for power utilities, and satisfies the needs for development and economic operation of the power enterprises. Therefore, continuously improving forecasting accuracy is no longer merely an academic exercise but an operational necessity for the power industry.

Despite numerous studies applying artificial intelligence (AI) and machine learning (ML) to electrical load forecasting, existing reviews remain fragmented, primarily focusing on a limited set of model families or specific forecasting horizons, or emphasizing technical aspects without providing a comprehensive and systematic framework. Previous works on traditional models (Hahn et al., 2009), as well as recent surveys on smart grids (Habbak et al., 2023), are generally descriptive in nature and have yet to clarify the development structure and research trends of the field. Therefore, a study which conducts a bibliometric analysis combined with the construction of a three-dimensional classification system based on forecasting horizon, application scale and model type is essential. This approach not only helps delineate the overall research structure and its evolution but also identifies influential countries, authors, and collaborative networks, while highlighting existing research gaps such as the scarcity of medium- and long-term studies, limitations in multi-level integration, and the insufficient incorporation of socio-economic factors. Thereby, the study contributes both theoretically and practically to the advancement of AI-based electrical load forecasting.

Specifically, this study aims to address the following research questions (RQ):

RQ1: How has the number of publications on electric load forecasting using machine learning (ML) based methods evolved over time?

RQ2: What are the important countries and people in electric load forecasting using ML based methods?

RQ3: What are main ML based methods employed, and how can they be classified?

RQ4: What are the trends in research on electric load forecasting using ML based methods?

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Existing forecasting models for electricity load can be broadly categorized into two main types: statistical analysis methods (traditional models) and ML methods (Gao et al., 2022).

Traditional forecasting models, such as Linear Regression, Moving Average, and Auto Regressive Integrated Moving Average (ARIMA), primarily rely on classical mathematical, statistical, and operational research techniques. These methods often operate under assumptions of data stationarity, linearity, and periodicity, which simplifies the modelling and computational processes. Their advantages include low model complexity, fast prediction speed, no requirement for vast amounts of data, relative implementation simplicity, and ease of interpretation (Wang et al., 2022). However, the limitations of traditional models are clear as these models lack the accuracy of more advanced methods and struggle to handle non-linear relationships, complex seasonality, and particularly interactions with exogenous variables like temperature and humidity. They are also typically inadequate for dealing with missing data or extreme events. Furthermore, with the increasing complexity of modern power systems due to the rising share of renewable energy and distributed energy resources, the limitations of traditional models become increasingly evident (Habbak et al., 2023)

(Wang et al., 2024).

Compared to classical methods, AI models on average are able to have more flexibility and accuracy for datasets involving non-linear relationships. With the increasing abundance of computing power on a single device or those rented out by cloud computing network infrastructure, the ML techniques developed from a theoretical perspective have been brought to practical application, available to small groups of researchers or even individual researchers (Misiurek et al., 2025). With the environment conducive to research the number of newer techniques applied to electricity load forecasting increase with more prominent examples such as Artificial Neural Network (ANN), Long Short-Term Memory (LSTM) derived from Recurrent Neural Networks (RNN), Convolutional Neural Network (CNN), hybrid and ensembles of multiple techniques.

The development of novel ensembles and hybrids for the purpose of electricity load forecasting has been growing rapidly, which necessitates a comprehensive overview of the current body of literature for applying ML-based techniques on electricity load modelling and electricity load forecasting.

3. METHODOLOGY

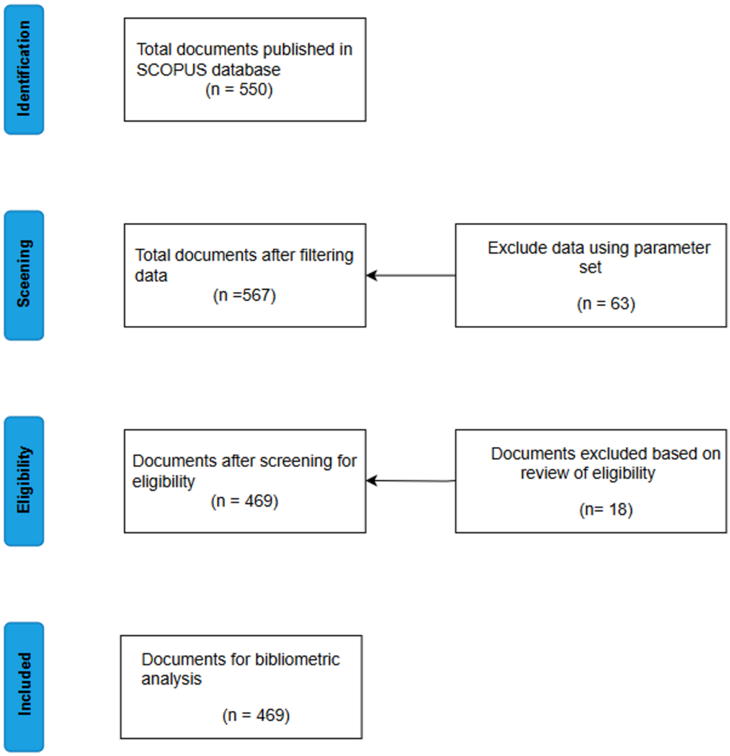

Figure 1. Data collected based on the PRISMA Process

This study employs a bibliometric analysis approach to comprehensively assess the body of research on the application of artificial intelligence (AI) in electricity load forecasting. Data were retrieved from the Scopus database, one of the largest and most reputable academic sources, using a search string specifically designed to capture publications whose titles, abstracts, or keywords refer to "electricity load forecasting" in combination with commonly used AI methods. The search was restricted to the subject areas of engineering, energy, computer science, and decision sciences; limited to journal articles and conference papers published in English up to the end of 2024; and excluded studies not directly related to electricity load forecasting, such as price forecasting, traffic load, wind load, and structural load.

The final query string applied in Scopus was structured as follows, with each part explained:

Component	Description
TITLE-ABS-KEY("electricity load forecast")*	Search for documents where the title, abstract, or keywords contain "electricity load forecast" or its variations.
AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR "ANN" OR "CNN" OR "RNN" OR "LSTM" OR "GRU" OR "transformer" OR "temporal fusion transformer" OR "TFT" OR "graph neural network" OR "GNN" OR "support vector machine*" OR "SVM" OR "support vector regression" OR "SVR" OR "random forest" OR "gradient boosting" OR "XGBoost" OR "LightGBM" OR "CatBoost" OR "extreme learning machine" OR "ELM" OR "k nearest neighbor*" OR "kNN" OR "decision tree*")**	Ensure that the papers specifically apply Artificial Intelligence techniques, including both traditional ML algorithms (SVM, kNN, decision tree, etc.) and advanced deep learning architectures (LSTM, Transformer, GNN, etc.).
AND (LIMIT-TO (SUBJAREA, "ENGI") OR LIMIT-TO (SUBJAREA, "ENER") OR LIMIT-TO (SUBJAREA, "COMP") OR LIMIT-TO (SUBJAREA, "DECI"))	Restrict the subject areas to Engineering, Energy, Computer Science, and Decision Sciences to maintain relevance.
AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "cp"))	Select only two document types: journal articles (ar) and conference proceedings (cp).
AND (LIMIT-TO (LANGUAGE, "English"))	Include only documents published in English.
AND (EXCLUDE (PUBYEAR, 2025))	Exclude papers published in 2025 to ensure the dataset is complete and stable at the time of retrieval.
AND NOT TITLE-ABS-KEY("price" OR "traffic" OR "wind load" OR "structural load")	Exclude irrelevant contexts such as price forecasting, traffic load, wind load, or structural load in civil engineering.

Table 1. Scopus query structure and explanation

Building upon the processed dataset, this study develops a three-layer taxonomy to systematically classify research on AI-based electricity load forecasting. Layer 1 (Forecasting Horizon) consists of four categories: ultra-short-term, short-term, mid-term, and long-term forecasting. Layer 2 (Application Scale) distinguishes three levels: micro (household/building/industrial park), meso (city or regional), and macro (national or international systems). Layer 3 (Model Category) groups forecasting approaches into five families: (i) Basic Machine Learning, including tree-based ensembles, support vector methods, and linear models; (ii) Basic Deep Learning, such as ANN, RNN, LSTM, GRU, CNN, and TCN; (iii) Advanced Deep Learning, encompassing transformer-based models and selected hybrid Deep Learning (DL) architectures such as CNN-LSTM; (iv) Hybrid Approaches, which integrate decomposition techniques or optimization-based tuning with AI models; and (v) Soft Computing, including fuzzy logic and related approaches. This taxonomy provides a structured framework for mapping the literature, enabling the construction of knowledge trees and mapping tables that reveal research distributions across horizons, scales, and model families, and subsequently identify emerging trends and research gaps.

4. RESULTS AND DISCUSSION

4.1 Results

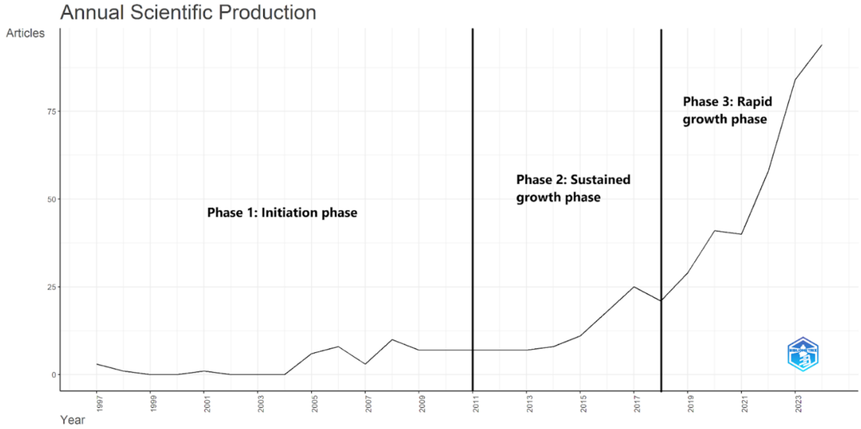

Figure 2. Number of publications 1997-2024.

Figure 2 presents the annual number of publications on AI-based electric load forecasting between 1997 and 2024. The line plot illustrates the trajectory of research output over time, which can be broadly divided into three distinct developmental phases, delineated by the vertical lines. Each node on the line represents the precise number of articles published in a given year.

Phase 1 (1997–2010): Initiation phase. The concept of AI-based load forecasting was first introduced in 1997. However, no further publications appeared until 2004. Research activity re-emerged in 2005 but remained scarce, with fewer than five publications per year. At this stage, studies were still exploratory and had not yet attracted significant attention.

Phase 2 (2011–2017): Sustained growth phase. During this period, the number of publications gradually increased and stabilized at around 10–20 per year. The topic gained more visibility as advances in AI demonstrated superior computational and data processing capabilities compared to traditional methods, which likely motivated further research in this field.

Phase 3 (2018–2024): Rapid growth phase. This period witnessed a sharp rise in research output, particularly after 2020 when annual publications surpassed 50 and peaked at over 80. The surge can be attributed to the widespread adoption of smart metering data, the rapid progress of ML/DL models, and the increasing demand for optimization in power systems operation. These developments underscore the growing importance of AI in modern load forecasting, extending beyond theoretical research toward practical applications.

Country	Frequency
CHINA	775
INDIA	127
PAKISTAN	83
AUSTRALIA	70
IRAN	51
USA	48
CANADA	45
UK	43
SAUDI ARABIA	38
INDONESIA	34
SPAIN	34

Table 2. Top 10 Countries in Load Forecasting Publications

Table 2 provides the number of publications from the top 10 countries that have made significant contributions to research on load forecasting using AI. The number of publications varies across countries, reflecting different levels of interest and investment in this field. Such differences can be explained by factors such as the scale of the power system, socio-economic context, and policy directions.

China dominates AI-based load forecasting research with 775 publications, underscoring its central role in Asia. The country's large-scale power system generates extensive datasets that provide a strong foundation for training, testing, and refining AI models. India and Pakistan follow in second and third positions, signalling the emergence of South Asia as an important research cluster—a notable outcome given the historical leadership of Europe and North America in this field. By contrast, the United States, Canada, and the United Kingdom have significantly fewer publications than their Asian counterparts. While this result is unexpected, their contributions remain influential, particularly through benchmark datasets (e.g., ISO/RTO) and methodological guidance. Overall, the distribution of research outputs indicates that AI-based load forecasting is no longer limited to major economies but is increasingly embraced by developing countries. This shift reflects their efforts to address rapid load growth and the demand for optimized power system operations, while also demonstrating the global relevance and widespread applicability of AI-driven forecasting approaches.

Author	h_index	Total Citation	Number of Publications	Year start
KOPRINSKA IRENA	8	608	12	2010
JAVAID NADEEM	7	293	10	2019
RANA MASHUD	6	387	8	2012
AGELIDIS VASSILIOS G.	5	269	7	2010
WANG JIANZHOU	5	102	8	2008
AYUB NASIR	4	233	4	2020
JEENANUNTA CHAWALIT	4	81	5	2017
SINGH PRIYANKA	4	114	5	2017
BENAOUDA DJAMEL	3	130	3	2006
DWIVEDI PRAGYA	3	92	4	2017

Table 3. Top 10 impact authors based on h_index

Table 3 presents the top ten most influential authors in AI-based load forecasting, ranked by h-index and total citations. Leading the list is Koprinska Irena (Australia), with an h-index of 8 and over 600 citations, underscoring her foundational contributions to the field. Other early contributors, such as Vassilios G. Agelidis and Jianzhou Wang, played a key role during the formative period (2008–2010), laying theoretical and methodological groundwork.

Meanwhile, a new generation of scholars - Nadeem Javaid, Mashud Rana, Ayub Nasir, Chawalit Jeenanunta, Priyanka Singh, and Pragya Dwivedi - has emerged with a strong and growing academic footprint. Despite their relatively recent entry, their high h-index and citation counts reflect both productivity and impact. Notably, five of the ten authors hail from South Asia, indicating the region's rising influence and growing international recognition in this domain.

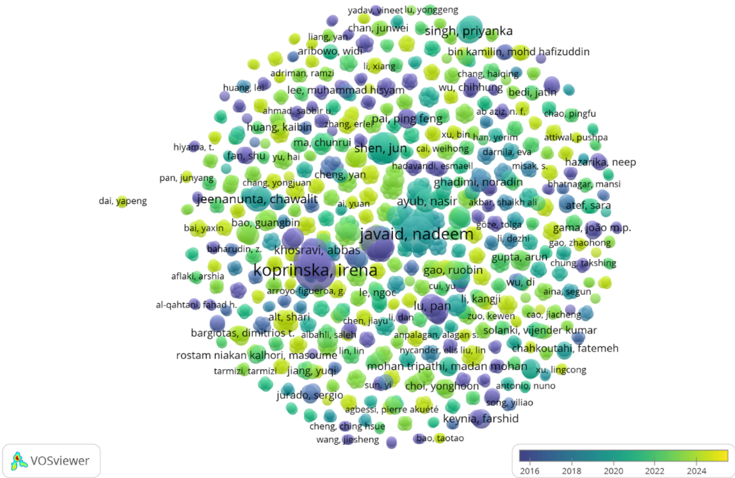

Figure 3. Science mapping: co-author

Figure 3 presents the co-authorship network in AI-based load forecasting. Larger nodes such as Koprinska Irena, Javaid Nadeem, Singh Priyanka, and Jeenanunta Chawalit represent key hubs with strong publication records. The color gradient shows the temporal evolution: dark clusters (2010-2015) highlight early contributors from Australia and China, while yellow clusters (2018-2024) reflect the rapid rise of South Asian authors, marking a regional shift in research activity. Contributions from Southeast Asia, for instance by Jeenanunta Chawalit, indicate the field's growing geographical diversity. Despite this expansion, the network remains fragmented, with weak links between senior and emerging scholars. Strengthening domestic and international collaboration is therefore essential to ensure continuity and improve research quality.

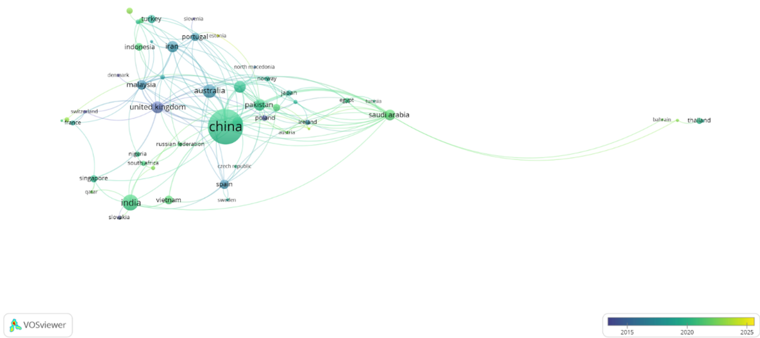

Figure 4. Science mapping: countries

Figure 4 illustrates international collaboration in AI-based load forecasting. China emerges as the largest and most central node, with strong ties to the UK, Australia, Pakistan, and India, indicating both regional and intercontinental partnerships. Saudi Arabia plays a bridging role for the Middle East, helping to integrate the region into the research map despite a modest publication volume. The US and Canada are present but surprisingly peripheral, reflecting weaker international linkages. Countries in Southeast Asia (e.g., Malaysia, Indonesia, Vietnam) also participate, though their connections remain limited.

Overall, collaboration is still mostly regional, with few cross-regional links. Yet, the growing involvement of South Asia, the Middle East, and Southeast Asia shows expanding efforts in energy innovation and signals future opportunities for more global cooperation.

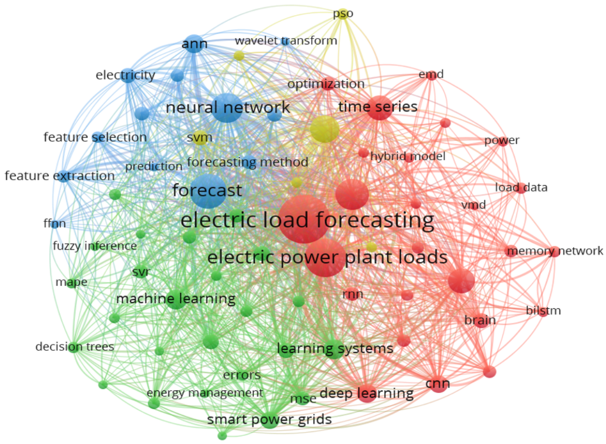

Figure 5. Science mapping: co-occurrence keywords

Figure 5 presents a network visualization of author keywords related to AI models in electric load forecasting, derived from an analysis of 2,123 keywords, of which 69 met the minimum occurrence threshold of 15. The node size corresponds to keyword frequency, node color indicates thematic clustering, and connecting lines represent co-occurrence strength. "Electric load forecasting" emerges as the most central and frequent keyword, strongly linked to core AI methodologies such as "LSTM," "neural network," "deep learning," and "machine learning," underscoring the field's shift toward AI-driven approaches.

The keywords are organized into four distinct clusters, each representing a major research direction:

The red cluster (Deep Learning for STLF) is the most prominent, highlighting the dominance of DL models in short-term load forecasting. "LSTM" and its variants (e.g., "Bidirectional LSTM") are widely adopted due to their ability to capture long-term temporal dependencies (Hochreiter, 1997). Recent advancements integrate "attention mechanisms" with LSTM, enhancing both forecasting accuracy and interpretability by emphasizing influential time steps. (Lin, Ma, Zhu, & Cui, 2022). Additionally, "CNN" (Convolutional Neural Networks) is frequently combined with LSTM in hybrid architectures to extract local patterns and reduce noise before temporal modelling. These combinations have demonstrated significant improvements in evaluation metrics such as MSE, RMSE, MAE, and R^2, establishing DL as the backbone of modern load forecasting research (Zhang, Chen, Cao, & Tan, 2023).

The green cluster (Traditional Machine Learning) includes foundational methods such as "Support Vector Regression (SVR)" and "Random Forest." While no longer at the forefront, these methods remain relevant for specific applications—such as small-scale tasks or high-dimensional noisy data—due to their computational efficiency, robustness, and minimal preprocessing requirements (Jia, Zhou, Wang, Lin, & Gao, 2025) (Lahouar & Ben Hadj Slama, 2015). Their associations with keywords like "smart power grids" and "energy management" reflect their ongoing utility in real-time energy control systems where interpretability and stability are critical (Biswal, Deb, Datta, Ustun, & Cali, 2024).

The blue cluster (Hybrid & Optimization) emphasizes integrated methodologies that combine preprocessing techniques with predictive modelling. Key terms like "wavelet transform" and "feature extraction" denote signal processing approaches used to decompose complex load data into simpler components (Amjady, 2006). These are often paired with artificial neural networks (e.g., "ANN" and "FFNN") to enhance model performance. Empirical studies confirm that hybrid models—such as wavelet-ANN combinations—outperform standalone models, particularly in handling non-stationary and noisy data distributions. (Wang, Guo, Ma, & Liu, 2022).

The yellow cluster (Soft Computing) represents niche yet valuable approaches tailored to scenarios involving high uncertainty and external variables like weather. Keywords such as "Particle Swarm Optimization (PSO)," "fuzzy logic," and "weather forecasting" indicate a focus on optimizing model parameters and integrating meteorological factors to improve accuracy. (Panda, 2025). PSO, for instance, is used to train neural networks and fuzzy systems, overcoming limitations of gradient-based methods and enhancing performance in renewable energy-influenced forecasting contexts. (Almaraashi, 2023)

Notably, the strong interconnections between clusters—especially between DL (red) and hybrid models (blue)—reflect a convergent trend toward hybrid and multi-method frameworks. This synergy highlights a broader shift in research philosophy: rather than relying on isolated models, researchers increasingly combine complementary techniques to address the complexity and variability of modern load forecasting challenges.

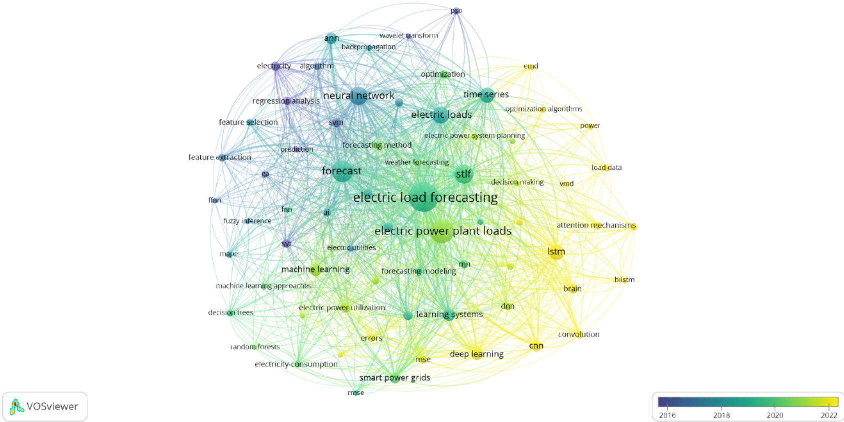

Figure 6. Science mapping: co-occurrence keywords (based on time)

Figure 6 illustrates the evolution of keyword trends in load forecasting, highlighting a clear shift from traditional methods to modern Machine Learning (ML) and Deep Learning (DL) techniques. Initially, models such as SVM and random forests dominated non-linear modelling. Recently, advanced DL approaches—such as LSTM, CNN, and attention mechanisms—have gained prominence due to their superior ability to handle long time series and complex feature extraction. Concurrently, hybrid models and optimization techniques (e.g., wavelet transform, VMD) have emerged to enhance accuracy and stability. The field has also expanded to include energy management and efficiency, reflecting a broader integration of AI and hybrid methods to address increasingly dynamic power system demands.

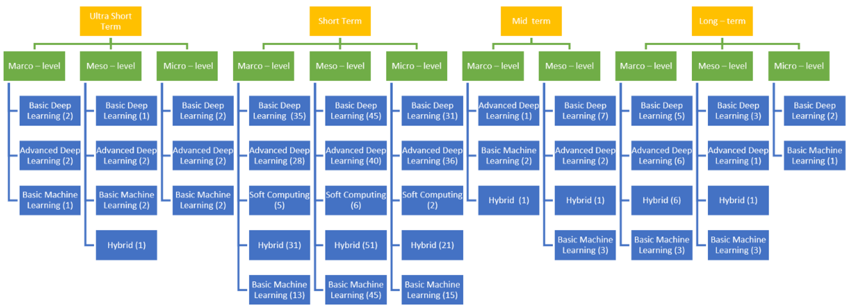

Figure 7. Three-layer taxonomy of AI-based load forecasting (horizon - scale - model)

Figure 7 illustrates a comprehensive three-layer taxonomy that classifies AI-based electricity load forecasting studies based on three key dimensions: forecasting horizon, forecasting scale, and model type. In terms of horizon, short-term forecasting overwhelmingly dominates in both volume and methodological diversity. These studies span all scales—micro, meso, and macro—and frequently employ basic and advanced DL models, with hybrid and soft computing methods also appearing. In contrast, research on ultra-short-term and long-term forecasting remains sparse, often limited to applications of DL at either the micro or macro scale. Mid-term forecasting receives moderate attention, primarily featuring advanced DL and hybrid models.

From the perspective of forecasting scale, short-term forecasting at the micro level (e.g., buildings or households) is the most common, often leveraging CNN and LSTM architectures. The meso level (city or region) also focuses on short-term tasks, with increasing adoption of attention-based and hybrid models. In contrast, the macro level (national or system-wide) encompasses a wider range of forecasting horizons and methodological diversity, reflecting its critical role in strategic power system planning.

In terms of model classification, basic ML methods are still present but increasingly marginalized, particularly in short-term forecasting. Basic DL models remain dominant, while advanced DL architectures—such as Transformer-based models or hybrid CNN-LSTM structures—are gaining ground in more complex forecasting settings. Hybrid models, which combine DL with optimization or decomposition techniques, are particularly common in mid-term forecasting. Meanwhile, soft computing approaches are less prevalent and typically function as auxiliary components.

Overall, the taxonomy highlights a strong research concentration on short-term, micro- to meso-scale forecasting using DL, whereas mid- and long-term horizons remain underexplored. This imbalance underscores key research gaps and promising directions for future investigation.

Forecasting Horizon	**Application Scale**	**Model Category**	**Paper**
Ultra Short Term	Macro-level	Basic Deep Learning	Wang et al., 2023
		Advanced Deep Learning	Bin Kamilin & Yamaguchi, 2024
		Basic Machine Learning	Koprinska et al., 2010
	Meso-level	Advanced Deep Learning	Luo et al., 2024
		Hybrid	Gama & Pereira Rodrigues, 2007
	Micro-level	Basic Deep Learning	Jumaa, 2023
		Basic Machine Machine	Majida et al., 2022
Short Term	Macro-level	Basic Deep Learning	Koprinska et al., 2015 Ghadimi et al., 2018
		Advanced Deep Learning	Xu et al., 2021 Zhou et al., 2020 Han & Zeng, 2024
		Soft Computing	Hasan et al., 2015
		Hybrid	Wang et al., 2022 Stratigakos et al., 2021
		Basic Machine Learning	Pallonetto et al., 2022 Pai & Hong, 2005
	Meso-level	Basic Deep Learning	Guo et al., 2018 Ömer, 2016 Lin, 2022
		Advanced Deep Learning	Moradzadeh et al., 2022
		Soft Computing	Chen et al., 2018 Zahid et al., 2019
		Hybrid	Wu et al., 2009
		Basic Machine Learning	Madrid & Antonio, 2021 Tong et al., 2018 Huang et al., 2016
	Micro-level	Basic Deep Learning	Navneet Kumar et al., 2012
			Li et al., 2021

		Advanced Deep Learning	Fekri et al., 2021 Gholizadeh & Musílek, 2022
		Soft Computing	Sergio et al., 2015
		Hybrid	Hamed et al., 2015 Yaslan & Bican, 2017 Yousaf et al., 2021
		Basic Machine Learning	Zhang et al., 2016 Wu et al., 2009
Mid term	Macro-level	Advanced Deep Learning	Oreshkin et al., 2021
	Meso-level	Basic Deep Learning	Shirzadi et al., 2021 Askari & Keynia, 2020
		Advanced Deep Leaning	Zhou et al., 2020
		Hybrid	Chahkoutahi & Khashei, 2017
Long Term	Macro-level	Basic Deep Learning Hybrid	Dursun et al., 2014 Aslam et al., 2021
		Basic Machine Learning	Solyali, 2020. Sharma et al., 2023
	Meso-level	Basic Deep Learning	Jha et al., 2021
		Advanced Deep Learning	Cui et al., 2024
	Micro-level	Basic Deep Learning	Navneet Kumar et al., 2012

Table 4. Representative Studies on Forecasting Models Categorized by Horizon, Scale, and Model Type

Table 4 provides a systematic classification of recent literature across different forecasting horizons, application scales, and model categories. The representative papers listed serve as the foundation for the subsequent discussion, where each forecasting horizon is analyzed in detail to highlight methodological trends, advantages, and limitations at different scales.

ULTRA SHORT TERM

Recent studies on Ultra Short-Term (UST) load forecasting reveal a diversity of modelling approaches spanning macro, meso, and micro levels. At the macro level, advanced DL architectures such as the TransformGraph, which integrates Transformer and Graph Convolutional Networks, demonstrate superior accuracy and stability in capturing complex spatial-temporal dependencies under high renewable penetration (Qingyong et al., 2023). Similarly, resilience-oriented methods like the Collective Intelligence Predictor (CIP) employ a three-level modular network to address missing values and enhance robustness against disruptions in smart cities (Bin Kamilin & Yamaguchi, 2024). Notably, there is also evidence that basic ML models combined with feature selection can remain competitive in UST horizons such as 5-minute-ahead forecasting, particularly when datasets are small and rapid inference is required (Xia et al., 2023). At the meso level, research focuses on hybrid and online approaches. For instance, a stacking integration framework based on CNN-BiLSTM-Attention combined with XGBoost has significantly reduced forecasting errors, highlighting the potential of hybrid ensembles to leverage both sequential and local features (Luo et al., 2024). In parallel, stream-based forecasting methods process continuous high-speed data flows using incremental clustering and adaptive neural networks, enabling real-time model updates in dynamic environments (Gama & Pereira Rodrigues, 2007). At the micro level, the growing availability of smart meter and AMI data enables the application of DL hybrids such as CNN-BiLSTM-Attention, CNN-LSTM, and GRU, which have been shown effective for ultra-short-term household and campus-level demand forecasting while supporting demand-side response integration (Jumaa, 2023). Meanwhile, for scenarios with limited data and strict computational constraints, lightweight three-step ML pipelines still provide cost-efficient and deployable solutions (Xia et al., 2023).

SHORT TERM

In the dataset, short-term forecasting (STLF) emerges as the most dominant horizon, with studies evenly distributed across micro-, meso-, and macro-levels.

At the micro level, the volatility of load profiles, characterized by noise and user behavior unpredictability, presents unique modelling challenges (Hamed et al., 2015). DL models such as ANN, RNN, LSTM, GRU, and CNN have been widely adopted due to their ability to capture temporal dependencies from high-resolution smart meter data (Jetcheva et al., 2014). For example, CNN achieved a Mean Absolute Percentage Error (MAPE) as low as 2.21% in 24-hour-ahead predictions (Lin, 2022). Hybrid models incorporating wavelet transforms and optimization techniques are also frequently applied to enhance prediction accuracy.

At the meso level, research emphasizes scalable and reliable models suited for city- or regional-level forecasting. DL shows clear advantages in handling multivariate, large-scale datasets thanks to its non-linear learning capacity and GPU/TPU acceleration (Huy et al., 2021). However, when deployed across heterogeneous regions, such models require extensive tuning. Traditional ML models like SVR struggle to scale effectively with large datasets (Wu et al., 2009). Hybrid models have gained popularity for their noise reduction and feature selection capabilities, particularly when supported by flexible preprocessing and metaheuristics, allowing transferability across systems.

At the macro level, models must accommodate complex seasonal trends and region-specific consumption patterns. Decomposition-based hybrid models like SSA-LSTM (Stratigakos et al., 2021) and VMD-CISSA-LSSVM (Wang et al., 2022) have demonstrated improved performance by isolating trend and noise components prior to prediction. Advanced architectures such as Transformers and Graph Convolutional Networks (GCNs) are increasingly employed to capture spatiotemporal dependencies. For instance, a curve-to-curve regression method achieved a MAPE of 1.10% on French half-hourly load data (Xu et al., 2021), while a VMD-TCN model reported MAPE values as low as 0.274% (6-step) and 0.405% (24-step), underscoring the superiority of such approaches (Zhou et al., 2022).

Overall, the field of STLF is experiencing a transition from conventional models toward advanced DL and hybrid architectures, which offer superior accuracy, robustness, and adaptability in complex forecasting scenarios.

MID TERM

Recent studies highlight that hybrid and DL approaches have achieved remarkable success in mid-term electricity load forecasting (MTLF). Combining multilayer perceptrons (MLPs) with metaheuristic optimizers such as Particle Swarm Optimization (PSO) and the Ant Lion Optimizer (ALO) enhances forecast accuracy while reducing training time, thanks to their ability to perform global search and avoid local optima (Askari & Keynia, 2020) (Chahkoutahi & Khashei, 2017). At the same time, modern deep architectures like N-BEATS—a deep stack of fully connected layers with forward and backward residual links—have reported MAPE values below 4% across 35 European countries, requiring no signal preprocessing and controlling bias via the pinball-MAPE loss (Oreshkin et al., 2021). These findings confirm that DL can remain effective even in small-data regimes through ensemble and residual connections. Moreover, domain-specific models are emerging to integrate load forecasting into Integrated Energy Systems (IES), allowing the inclusion of multi-energy interactions and macro-economic factors such as GDP, energy policy, and climate in mid-term forecasts (Zhou et al., 2020) (Shirzadi et al., 2021). This evolution—from traditional ANNs, through metaheuristic-hybrid models, to modern DL (e.g., N-BEATS and Transformer-based architectures)—reflects a clear trend toward reducing bias, improving generalization on small datasets, and coupling load forecasts with market and policy contexts.

LONG TERM

In the context of long-term load forecasting (LTLF), recent studies have increasingly explored ML and DL techniques to cope with the high uncertainty arising from climatic, socio-economic, and policy-related factors. Traditional neural network models such as FFNN and MLP, when optimized for hidden neuron selection and training methods, have shown improved accuracy compared to classical statistical approaches, as demonstrated in a case study on electricity consumption in Thailand (Navneet Kumar et al., 2012). More advanced approaches leveraging deep neural architectures have reported superior performance; for example, Jha et al. (2021) employed LSTM and Random Forest models for smart grid load forecasting, achieving an average accuracy above 96% and confirming the feasibility of AI-driven LTLF. Parallel research has pioneered multi-task forecasting by jointly predicting load and price through a CNN-based ensemble tested on ISO-NE data in the U.S., thereby opening new directions for market-oriented forecasting (Aslam et al., 2021). Transformer-based methods such as the Informer, enhanced with a season-aware block, have further demonstrated strong capability in capturing long-range periodic patterns, with up to 19% improvement in MSE on provincial data from Zhejiang, China (Cui et al., 2024). Beyond model architecture, several works have emphasized the importance of incorporating socio-economic and climatic factors, as in long-term forecasting for Cyprus (Solyali, 2020) or multi-year hydropower generation forecasting in Turkey (Dursun et al., 2014). Overall, these findings highlight the great potential of AI for LTLF but reveal persistent gaps such as the lack of probabilistic forecasting frameworks, limited integration of cross-domain drivers (economic-social-climatic), and the absence of studies addressing cross-country or system interoperability.

4.2 Discussion

Electric load forecasting using machine learning (ML) and deep learning (DL) is a rapidly evolving research field, significantly influenced by the distinct application requirements of different forecasting time horizons.

Firstly, Short-Term Load Forecasting (STLF) remains the primary focus of most research, dominating both in terms of publication volume and the diversity of applied models. The predominance of STLF is an inevitable consequence of its critical role in real-time grid operation and power market bidding (Hong & Fan, 2016). While traditional models such as ARIMA, non-linear regression, and ANN continue to be used, the principal trend is a distinct shift towards DL models like LSTM, CNN-LSTM, and Seq2Seq (Smyl, 2020). This is particularly evident in the robust development of Hybrid Models that integrate Attention Mechanisms, Temporal Convolutional Networks (TCN), and Optimization-based Preprocessing techniques such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO). Next, Ultra-Short-Term Load Forecasting (USTLF), though currently represented by a more limited number of studies, is demonstrating significant emerging potential through the integration of DL with data streaming. For instance, a hybrid model based on CNN and BiLSTM proposed in 2025, enables visual interpretability in USTLF at the minute or hour level (Yang et al., 2025). This indicates that USTLF is becoming a promising research direction, particularly for supporting grid digitalization and automation, which require ultra-low latency for applications such as frequency regulation, power system dispatch, and other real-time grid management tasks.

Meanwhile, Mid-Term Load Forecasting (MTLF) is undergoing a pronounced transition from traditional ANNs to modern hybrid and DL models. This marks an evolution of the problem from pure regression to complex multivariate time series modelling. The extended time frame of MTLF necessitates that models capture not only historical load data but also seasonal patterns, weekly and holiday variations, and long-term trends. Contemporary trends are increasingly focusing on integrating signal decomposition techniques—such as Wavelet Transform and Variational Mode Decomposition (VMD)—to disassemble the load series into more predictable sub-components. These components serve as optimized inputs for DL architectures, which are further enhanced with Attention mechanisms and Transformer-based models to improve modelling capabilities. For example, the article (Huy et al., 2021) compared a Transformer-based model with RNNs and demonstrated that the former achieved a MAPE of less than 3% for forecasts extending up to six months ahead.

Finally, Long-Term Load Forecasting (LTLF) constitutes a less prevalent research branch due to its inherently high uncertainty and profound susceptibility to macroeconomic variables. For many years, LTLF primarily relied on simple ANNs (Khuntia et al., 2018) or Transformers. However, unlike STLF and MTLF, which focus predominantly on the accuracy of historical data patterns, the nature of LTLF demands that models not only predict trends but also account for impacts from non-technical factors such as macroeconomic conditions, energy policy shifts, and demographic fluctuations (Lindberg et al., 2019). This complexity imposes significant limitations on traditional methods. Furthermore, the absence of large-scale, standardized benchmarks for LTLF has hindered the establishment of universal performance standards, a common feature in forecasting for other time horizons.

Based on a multi-scale analysis, each level in load forecasting has a distinct focus on prominent models, with the micro-level being evaluated as the most prevalent and widely researched due to its accessible and familiar subjects of study. At this level—which focuses on individual entities like buildings or residential clusters—hybrid models combined with optimization techniques are most used to handle highly noisy and non-linear data characteristics. Meanwhile, at the meso-level for regional power systems, federated learning has emerged as the dominant approach to address distributed data challenges while maintaining privacy. At the macro-level, such as national power systems, research trends concentrate most on advanced DL models integrated with decomposition methods to manage the complexity and large fluctuations in data

The evolution of model families in the field of electric load forecasting clearly reflects the ever-increasing demands for accuracy, flexibility, and the ability to process large-scale data.

In the evolution of load forecasting, basic ML models such as linear regression, KNN, and SVR were foundational in early stages but have since been largely superseded, now mainly serving as benchmarks for comparison. Subsequently, basic DL models—especially RNNs and LSTMs—emerged as the backbone for Short-Term Load Forecasting (STLF), outperforming traditional methods due to their superior ability to capture temporal sequences and non-linear dependencies.

Following this, Advanced DL architectures, such as the Transformer and its variant the Informer, along with Graph Neural Networks (GNNs), have demonstrated significant potential in handling large-scale load data and the uncertainties inherent in today's complex energy environments. Notably, these methods are not only dominant in STLF but are also gradually expanding their application scope to Mid-Term (MTLF) and Long-Term Load Forecasting (LTLF).

Furthermore, Hybrid Models have emerged as a powerful research trend, aiming to synergistically combine various techniques. The integration of decomposition methods such as Singular Spectrum Analysis (SSA), Empirical Mode Decomposition (EMD), and Wavelet Transform with optimization algorithms like Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) has significantly enhanced forecasting accuracy. Hybrid Models effectively address non-linear characteristics and mitigate the limitations of individual techniques.

While not a dominant trend in current research, Soft Computing techniques like fuzzy logic and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) remain highly valuable for handling scenarios with incomplete data, high uncertainty, or significant noise. Their robustness in processing imprecise information ensures their continued relevance in specific, challenging forecasting applications.

Although substantial progress has been achieved in AI-based load forecasting, numerous research gaps persist:

First, probabilistic forecasting is still very limited, especially in ultra-short-term, medium-term, and long-term horizons. Electricity load is heavily influenced by uncertain factors such as weather conditions and customer consumption behaviors. As a result, countless possible electricity usage scenarios may occur at the same time. Probabilistic forecasting provides information about the likelihood of different load levels. This is extremely important for risk management, enabling system operators to design optimal scheduling and operation strategies as well as contingency plans.

Second, the linkage among different forecasting levels remains inconsistent. At present, most studies focus only on a single level rather than forecasting simultaneously across all three levels. Because forecasting models at different scales require different datasets, aggregating micro-level forecasts often produces results inconsistent with macro-level forecasts. Therefore, more research is needed on multi-level forecasting accompanied by the development of a comprehensive framework to integrate the three scales.

Third, socio-economic factors have yet to be incorporated into forecasting models. Electricity load is strongly affected by factors such as urbanization rate, economic growth, and government policies. Integrating socio-economic variables into forecasting is crucial for improving accuracy, especially in medium- and long-term horizons. Doing so would enable system operators to design early strategies and policies for electricity generation planning.

Fourth, the interconnection between countries and power systems has been largely neglected in forecasting models. Today’s electricity systems are increasingly interconnected across regions and nations to enhance reliability. Applying AI to long-term load forecasting in multi-system environments therefore represents an important research gap.

Fifth, explainability and time constraints remain major challenges. While AI models can generate highly accurate forecasts, they often cannot explain why certain results are produced. This poses difficulties for planners and policymakers, who need clarity about the factors most influencing electricity demand. Moreover, ultra-short-term and short-term forecasting requires not only accuracy but also rapid prediction to provide timely support to power systems. If a model takes too long to deliver results, the forecasts become outdated and lose practical relevance.

The identified research gaps highlight that AI-based load forecasting still offers substantial opportunities for further investigation. Evidence from the Scopus database indicates that short-term load forecasting (STLF) overwhelmingly dominates the literature, whereas medium-term and long-term forecasting remain significantly underexplored. Consequently, future research could be directed towards developing and refining models for medium- and long-term horizons. Moreover, emerging methodologies such as Federated Learning (FL), Graph Neural Networks (GNN), and Probabilistic Forecasting provide promising avenues for advancement. Expanding the methodological toolkit has the potential to generate transformative contributions to the field. From the perspective of the power sector, AI-driven forecasting models have already demonstrated the ability to improve accuracy, reduce errors, and support the optimal operation of power systems, particularly in addressing short-term load balancing. Nonetheless, the growing demand for electricity, the evolution of energy policies, and the rising share of renewable energy introduces mounting challenges to ensuring long-term system reliability. In this regard, long-term forecasting models are expected to assume a strategic role, equipping policymakers and system operators with evidence-based insights to design robust planning strategies and sound policy frameworks.

5. CONCLUSION

With the number of publications on electric load forecasting using machine learning (ML) based methods being in a period of rapid growth as of 2018–2024, this research field is showing strong potential for future development. In addition, the global dynamic in the research field shows China as a leading country in research output, and a shift of activities towards South Asia with emerging authors in the field. International collaborations exist, although mostly limited to being regional, however, the increasing involvement of South Asia, the Middle East, and Southeast Asia countries suggests opportunities for more global collaboration. This field of research should also be of interest to policymakers, as deep learning and hybrid AI models are found to be of relevance to improving energy management and system reliability.

Regarding the trends in publication, short-term load forecasting (STLF) using deep learning models comprises the majority of the literature, and hybrid models are also gaining interest. However, there is a research gap present in a lack of understanding of longer forecasting horizons. Furthermore, most studies are only for one scale (micro-, meso- or macro-) of forecast rather than simultaneous forecasting across all three levels. This leads to discrepancy between macro-level forecasts and forecasts made by aggregating multiple micro-level forecasts. Moreover, with AI models, there remain limitations with explainability and punctuality. Furthermore, consideration for socio-economic factors and the interconnectedness of systems is lacking in the construction of current models.

As for the future direction of research, there is potential in multi-level forecasting with the development of a comprehensive framework to integrate the three scales of forecast. In this case, research on the integrated framework can form a positive feedback loop for understanding of forecasting on all scales. More research focusing on models for medium- and long-term horizons will help address the current knowledge imbalance with shorter term horizons. Meanwhile, for short-term and especially ultra-short-term forecasting, there is a need to improve punctuality as support for grid digitalization and automation. Furthermore, in-depth research is needed for emerging methodologies such as Federated Learning, Graph Neural Networks, and Probabilistic Forecasting; and soft computing techniques or Adaptive Neuro-Fuzzy Inference Systems should receive further exploration for their use in cases of imprecise information.

References

Askari, M., & Keynia, F. (2020). Mid-term electricity load forecasting by a new composite method based on optimal learning MLP algorithm. *IET Generation, Transmission and Distribution*, *14*(5), 845-852. 10.1049/iet-gtd.2019.0797

Aslam, S., Ayub, N., Farooq, U., Alvi, M. J., Albogamy, F. R. H., Rukh, G., Haider, S. I., Azar, A. T., & Bukhsh, R. (2021). Towards electric price and load forecasting using cnn-based ensemble in smart grid. *Sustainability (Switzerland)*, *13*(22). 10.3390/su132212653

Bin Kamilin, M. H., & Yamaguchi, S. (2024). Resilient Electricity Load Forecasting Network with Collective Intelligence Predictor for Smart Cities. *Electronics*. MDPI. 10.3390/electronics13040718

Bin Kamilin, M. H., & Yamaguchi, S. (2024). Resilient Electricity Load Forecasting Network with Collective Intelligence Predictor for Smart Cities †. *Electronics (Switzerland)*, *13*(4). 10.3390/electronics13040718

Chahkoutahi, F., & Khashei, M. (2017). A seasonal direct optimal hybrid model of computational intelligence and soft computing techniques for electricity load forecasting. *Energy*, *140*, 988-1004. 10.1016/j.energy.2017.09.009

Chen, J., Do, Q., Nguyen, T. A., & Doan, T. T. H. (2018). Forecasting monthly electricity demands by wavelet neuro-fuzzy system optimized by heuristic algorithms. *Information (Switzerland)*, *9*(3).

Cui, Y., Li, Z., Wang, Y., Dong, D., Gu, C., Lu, X., & Zhang, P. (2024). Informer model with season-aware block for efficient long-term power time series forecasting. *Computers and Electrical Engineering*, *119*. 10.1016/j.compeleceng.2024.109492

Dursun, B., Aydın, F., Zontul, M., & Sener, S. (2014). Modelling and estimating of load demand of electricity generated from hydroelectric power plants in Turkey using machine learning methods. *Advances in Electrical and Computer Engineering*, *14*(1), 121-132. 10.4316/AECE.2014.01019

Fekri, M. N., Patel, H., Grolinger, K., & Sharma, V. (2020). Deep learning for load forecasting with smart meter data: Online Adaptive Recurrent Neural Network. *Applied Energy*, *282*. 10.1016/j.apenergy.2020.116177

Gama, J. M.P., & Pereira Rodrigues, P. P. (2007). Stream-based electricity load forecast. *Lecture Notes in Computer Science*, *4702 LNAI*, 446-453. 10.1007/978-3-540-74976-9_45

Gao, T., Niu, D., Ji, Z., & Sun, L. (2022). Mid-term electricity demand forecasting using improved variational mode decomposition and extreme learning machine optimized by sparrow search algorithm. *Energy*, 125328.

Ghadimi, N., Akbarimajd, A., Shayeghi, H., & Abedinia, O. (2018). Two stage forecast engine with feature selection technique and improved meta-heuristic algorithm for electricity load forecasting. *Energy*, *161*, 130-142. 10.1016/j.energy.2018.07.088

Gholizadeh, N., & Musílek, P. (2022). Federated learning with hyperparameter-based clustering for electrical load forecasting. *Internet of Things (The Netherlands)*, *17*. 10.1016/j.iot.2021.100470

Giap, H. Q., Nguyen, Q. T. T., Trinh, H. T., & Nguyen, T. K. (2024). Toward Enhancing Mid-Term Load Forecasting: RNN-Based Models vs Transformer-Based Models. *GMSARN International Journal*.

Guo, Z., Zhou, K., Zhang, X., & Yang, S. L. (2018). A deep learning model for short-term power load and probability density forecasting. *Energy*, *160*. 10.1016/j.energy.2018.07.090

Habbak, H., Mahmoud, M., Metwally, K., Fouda, M. M., & Ibrahem, M. I. (2023). Load Forecasting Techniques and Their Applications in Smart Grids. *Energies*, 1480.

Hahn, H., Meyer-Nieberg, S., & Pickl, S. (2009). Electric load forecasting methods: Tools for decision making. *European Journal of Operational Research*, 902-907.

Hamed, C., Shaker, H., Zareipour, H., Wood, D. H., & Amjady, N. (2015). Short-term electricity load forecasting of buildings in microgrids. *Energy and Buildings*, *99*, 50-60. 10.1016/j.enbuild.2015.04.011

Han, J., & Zeng, P. (2024). Short-term power load forecasting based on hybrid feature extraction and parallel BiLSTM network. *Computers and Electrical Engineering*, *119*. ScienceDirect. 10.1016/j.compeleceng.2024.109631

Hasan, S., Khosravi, A., & Jaafar, J. B. (2015). Training of interval type-2 fuzzy logic system using extreme learning machine for load forecasting. *IMCOM '15*. Research Gate. 10.1145/2701126.2701177

Hong, T., & Fan, S. (2016). Probabilistic electric load forecasting: A tutorial review. *International Journal of Forecasting*. ScienceDirect. 10.1016/j.ijforecast.2015.11.011

Huang, N., Lu, G., & Xu, D. (2016). A permutation importance-based feature selection method for short-term electricity load forecasting using random forest. *Energies*, *9*(10). 10.3390/en9100767

Huang, N., Lu, G., & Xü, D. (2016). A permutation importance-based feature selection method for short-term electricity load forecasting using random forest. *Energies*, *9*(10). 10.3390/en9100767

Huy, P. C., Nguyen, M. Q., Tien, N. D., & Anh, T. T. Q. (2021). Short-Term Electricity Load Forecasting Based on Temporal Fusion Transformer Model. *IEEE Access*, *10*, 106296-106304. 10.1109/ACCESS.2022.3211941

Jetcheva, J. G., Majidpour, M., & Chen, W. (2014). Neural network model ensembles for building-level electricity load forecasts. *Energy and Buildings*, *84*, 214-223. 10.1016/j.enbuild.2014.08.004

Jha, N., Prashar, D., Rashid, M., Gupta, S. K., & Saket, R. K. (2021). Electricity load forecasting and feature extraction in smart grid using neural networks. *Computers and Electrical Engineering*, *96*. 10.1016/j.compeleceng.2021.107479

Jumaa, S. S. (2023). Studying Electricity Load Forecasting and Optimizing User Benefits with Smart Metering. *Journal of Applied Data Sciences*, *4*(4), 490. 10.47738/jads.v4i4.147

Khuntia, S. R., Rueda, J. L., & Meijden, M. A.M.M. v. d. (2018). Long-Term Load Forecasting Considering Volatility Using Multiplicative Error Model. *Energies*. MDPI. 10.3390/en11123308

Kong, W., Dong, Z. Y., Jia, Y., Hill, D. J., Xu, Y., & Zhang, Y. (2019). Short-Term Residential Load Forecasting based on LSTM Recurrent Neural Network. *IEEE Transactions on Smart Grid*. ResearchGate. 10.1109/TSG.2017.2753802

Koprinska, I., Rana, M., & Agelidis, V. G. (2015). Correlation and instance based feature selection for electricity load forecasting. *Knowledge-Based Systems*, *82*, 29-40. 10.1016/j.knosys.2015.02.017

Koprinska, I., Rana, M., & Vassilios G., A. (2015). Correlation and instance based feature selection for electricity load forecasting. *Knowledge-Based Systems*, *82*, 29-40. Science Direct. 10.1016/j.knosys.2015.02.017

Koprinska, I., Sood, R., & Agelidis, V. G. (2010). Variable selection for five-minute ahead electricity load forecasting. *Proceedings - International Conference on Pattern Recognition*. IEEE. 10.1109/ICPR.2010.711

Li, L., Meinrenken, C. J., & Modi, V. (2021). Short-term apartment-level load forecasting using a modified neural network with selected auto-regressive features. *Applied Energy*, *287*, 116509. 10.1016/j.apenergy.2021.116509

Lin, J. (2022). Short-term load forecasting based on LSTM networks considering attention mechanism. *International Journal of Electrical Power and Energy Systems*, *137*. 10.1016/j.ijepes.2021.107818

Lindberg, K.B., Seljom, P., Madsen, H., Fischer, D., & Korpås, M. (2019). Long-term electricity load forecasting: Current and future trends. *Utilities Policy*. ScienceDirect. 10.1016/j.jup.2019.04.001

Luo, S., Wang, B., Gao, Q., Wang, Y., & Pang, X. (2024). Stacking integration algorithm based on CNN-BiLSTM-Attention with XGBoost for short-term electricity load forecasting. *Energy Reports*, *12*, 2676-2689. 10.1016/j.egyr.2024.08.078

Madrid, E. A., & Antonio, N. (2021). Short-term electricity load forecasting with machine learning. *2021*, *12*(2), 1-21. 10.3390/info12020050

Madrid, E. A., & Antonio, N. (2021). Short-term electricity load forecasting with machine learning. *Information (Switzerland)*, *12*(2), 1-21. 10.3390/info12020050

Majida, K., Khan, H. R., Lubaba, Bin Khalid, M. H., & Qazi, S. A. (2022). Threefold Optimized Forecasting of Electricity Consumption in Higher Education Institutions. *Computers, Materials and Continua*, *73*(2), 2351-2370. 10.32604/cmc.2022.026265

Misiurek, K., Olkuski, T., & Zysk, J. (2025). Review of Methods and Models for Forecasting Electricity Consumption. *Energies*, 4032.

Moradzadeh, A., Moayyed, H., & Mohammadi-ivatloo, B. (2022). Short-term electricity demand forecasting via variational autoencoders and batch training-based bidirectional long short-term memory. *Sustainable Energy Technologies and Assessments*, *52*. 10.1016/j.seta.2022.102209

Moradzadeh, A., Moayyed, H., Zare, K., & Mohammadi-ivatloo, B. (2022). Short-term electricity demand forecasting via variational autoencoders and batch training-based bidirectional long short-term memory. *Sustainable Energy Technologies and Assessments*, *52*(102209). 10.1016/j.seta.2022.102209

Navneet Kumar, S., Singh, A. K., & Manoj, T. (2012). Selection of hidden layer neurons and best training method for FFNN in application of long term load forecasting. *Journal of Electrical Engineering*, *63*(3), 153-161. 10.2478/v10187-012-0023-9

Ömer, F. E. (2016). Forecasting electricity load by a novel recurrent extreme learning machines approach. *International Journal of Electrical Power and Energy Systems*. Science Direct. 10.1016/j.ijepes.2015.12.006

Oreshkin, B. N., Dudek, G., Pełka, P., & Turkina, E. (2021). N-BEATS neural network for mid-term electricity load forecasting. *Applied Energy*, *293*. 10.1016/j.apenergy.2021.116918

Pai, P. F., & Hong, W. C. (2005). Support vector machines with simulated annealing algorithms in electricity load forecasting. *Energy Conversion and Management*, *17*, 2669-2688. 10.1016/j.enconman.2005.02.004

Pallonetto, F., Jin, C., & Mangina, E. E. (2022). Forecast electricity demand in commercial building with machine learning models to enable demand response programs. *Energy and AI*.

Qingyong, Z., Chen, J., Xiao, G., He, S., & Deng, K. (2023). Transform Graph: A novel short-term electricity net load forecasting model. *Energy Reports*, *9*, 2705-2717. 10.1016/j.egyr.2023.01.050

Sergio, S., Nebot, A., Mugica, F., & Avellana, N. (2015). Hybrid methodologies for electricity load forecasting: Entropy-based feature selection with machine learning and soft computing techniques. *Energy*, *86*, 276-291.

10.1016/j.energy.2015.04.039

Sharma, M., Namita, M., Mishra, A., & Gupta, A. (2023). Machine Learning-Based Electricity Load Forecast for the Agriculture Sector. *International Journal of Software Innovation*, *11*(1). 10.4018/IJSI.315735

Shirzadi, N., Nizami, A., Khazen, M., & Nik-Bakht, M. (2021). Medium-term regional electricity load forecasting through machine learning and deep learning. *Designs*, *5*(2). 10.3390/designs5020027

Singh, S. N. K., Singh, A. K., & Tripathy, M. (2012). Journal of Electrical Engineering. *63*, *3*, 152-161. 10.2478/v10187-012-0023-9

Smyl, S. (2020). A hybrid method of exponential smoothing and recurrent neural networks for time series forecasting. *International Journal of Forecasting*. ScienceDirect. 10.1016/j.ijforecast.2019.03.017

Solyali, D. (2020). A comparative analysis of machine learning approaches for short-/long-term electricity load forecasting in Cyprus. *Sustainability (Switzerland)*, *12*(9). 2020. 10.3390/SU12093612

Stratigakos, A., Bachoumis, A., & Vita, V. (2021). Short-term net load forecasting with singular spectrum analysis and lstm neural networks. *Energies*, *14*. MDPI. 10.3390/en14144107

Tong, C., Li, J., Lang, C., Kong, F., Niu, J., & Rodrigues, J. J.P.C. (2018). An efficient deep model for day-ahead electricity load forecasting with stacked denoising auto-encoders. *Journal of Parallel and Distributed Computing*, *117*, 267-273.

Wang, G., Wang, X., Wang, Z., Ma, C., & Song, Z. (2022). A VMD-CISSA-LSSVM Based Electricity Load Forecasting Model. *Mathematics*, *10*. MDPI. 10.3390/math10010028

Wang, J., Xing, Q., Zeng, B., & Zhao, W. (2022). An ensemble forecasting system for short-term power load based on multi-objective optimizer and fuzzy granulation. *Applied Energy*, 120042.

Wang, L., Wang, X., & Zhao, Z. (2024). Mid-term electricity demand forecasting using improved multi-mode reconstruction and particle swarm-enhanced support vector regression. *Energy*, 132021.

Wang, Y., Jiang, W., Wang, C., Song, Q., Zhang, T., Dong, Q., & Li, X. (2023). An electricity load forecasting model based on multilayer dilated LSTM network and attention mechanism. *Frontiers in Energy Research*, 11.

Weron, R. (2014). Electricity price forecasting: A review of the state-of-the-art with a look into the future. *International Journal of Forecasting*. ScienceDirect. 10.1016/j.ijforecast.2014.08.008

Wu, C., Tzeng, G. H., & Lin, R. (2009). A Novel hybrid genetic algorithm for kernel function and parameter optimization in support vector regression. *Expert Systems with Applications*, *36*(3 PART 1), 4725-4735. 10.1016/j.eswa.2008.06.046

Wu, D., Wang, B., Precup, D., & Boulet, B. (n.d.). Boosting Based Multiple Kernel Learning and Transfer Regression for Electricity Load Forecasting. *Lecture Notes in Computer Science*, *10536 LNAI*, 39-51. 10.1007/978-3-319-71273-4_4

Xia, Y., Wang, J., Wei, D., & Zhang, Z. (2023). Combined framework based on data preprocessing and multi-objective optimizer for electricity load forecasting. *Engineering Applications of Artificial Intelligence*, *119*. 10.1016/j.engappai.2022.105776

Xu, X., Chen, Y., Goude, Y., & Qiwei, Y. (2021). Day-ahead probabilistic forecasting for French half-hourly electricity loads and quantiles for curve-to-curve regression. *Applied Energy*, *301*. Science Direct. 10.1016/j.apenergy.2021.117465

Yang, Z., Li, J., Liu, C., & Wang, H. (2025). Forecasting very short-term power load with hybrid interpretable deep models. *Systems Science & Control Engineering*. 10.1080/21642583.2025.2486136

Yaslan, Y., & Bican, B. (2017). Empirical mode decomposition based denoising method with support vector regression for time series prediction: A case study for electricity load forecasting: Journal of the International Measurement Confederation. *Measurement: Journal of the International Measurement Confederation*, *103*, 52-61. 10.1016/j.measurement.2017.02.007

Yousaf, A., Asif, R. M., Shakir, M., Rehman, A. U., & Adrees, M. S. (2021). An improved residential electricity load forecasting using a machine-learning-based feature selection approach and a proposed integration strategy. *Sustainability (Switzerland)*, *13*(11). 10.3390/su13116199

Zahid, M., Ahmed, F., Javaid, N., Abbasi, R. A., & Kazmi, H. S. Z. (2019). Electricity price and load forecasting using enhanced convolutional neural network and enhanced support vector regression in smart grids. *Electronics (Switzerland)*, *8*(2). 10.3390/electronics8020122

Zhang, F., Deb, C., Lee, S. E., Yang, J., & Shah, K. W. (2016). Time series forecasting for building energy consumption using weighted Support Vector Regression with differential evolution optimization technique. *Energy and Buildings*, *126*, 94-103. 10.1016/j.enbuild.2016.05.028

Zhou, D., Ma, S., Jiarui, H., Han, D., Huang, D., Yan, S., & Li, T. (2020). An electricity load forecasting model for Integrated Energy System based on BiGAN and transfer learning. *Energy Reports*, *6*, 3446-3461. 10.1016/j.egyr.2020.12.010

Zhou, F., Zhou, H., Li, Z., & Zhao, K. (2022). Multi-Step Ahead Short-Term Electricity Load Forecasting Using VMD-TCN and Error Correction Strategy. *Energies*, *15*(15). MDPI. 10.3390/en15155375