data

MDPI

Review

Adaptive Forecasting in Energy Consumption: A Bibliometric Analysis and Review

Manuel Jaramillo [1,*], Wilson Pavón [1] and Lisbeth Jaramillo [2]

[1] Smart Grid Research Group—GIREI, Electrical Engineering Deparment, Salesian Polytechnic University, Quito EC170702, Ecuador; wpavon@ups.edu.ec
[2] Medical School, Pontifical Catholic University of Ecuador, Quito EC200102, Ecuador; lcjaramillo@puce.edu.ec
* Correspondence: mjaramillo@ups.edu.ec

Abstract: This paper addresses the challenges in forecasting electrical energy in the current era of renewable energy integration. It reviews advanced adaptive forecasting methodologies while also analyzing the evolution of research in this field through bibliometric analysis. The review highlights the key contributions and limitations of current models with an emphasis on the challenges of traditional methods. The analysis reveals that Long Short-Term Memory (LSTM) networks, optimization techniques, and deep learning have the potential to model the dynamic nature of energy consumption, but they also have higher computational demands and data requirements. This review aims to offer a balanced view of current advancements and challenges in forecasting methods, guiding researchers, policymakers, and industry experts. It advocates for collaborative innovation in adaptive methodologies to enhance forecasting accuracy and support the development of resilient, sustainable energy systems.

Keywords: bibliometric analysis; adaptive energy forecasting; time series prediction; LSTM-based energy forecasting; optimization in adaptive forecasting

check for updates

Citation: Jaramillo, M.; Pavón, W; Jaramillo, L. Adaptive Forecasting in Energy Consumption: A Bibliometric Analysis and Review. *Data* **2024**, *9*, 13. https://doi.org/10.3390/data9010013

Academic Editor: Irene Finocchi

Received: 20 November 2023
Revised: 29 November 2023
Accepted: 29 December 2023
Published: 11 January 2024

1. Introduction

In today's rapidly changing world of energy and technology, predicting electrical energy consumption patterns has become a significant area of interdisciplinary research. This paper explores adaptive forecasting techniques, which are crucial in addressing the complex challenges of energy consumption patterns and forecasting. The focus is on integrating adaptive techniques that promise precision, efficiency, and responsiveness, aligning with the broader objectives of electrical engineering and energy management.

This paper is based on a comprehensive bibliometric analysis of high-impact publications from the Scopus database from 2015 to the present. This approach ensures the inclusion of the most relevant and contemporary advancements in the field. This paper's methodology involves a rigorous selection, prioritizing publications from Q1 journals renowned for their high standards and rigorous peer review. This filtering layer guarantees the quality and impact of the selected works, identifying over seventy seminal papers that collectively form the backbone of this review.

Central to this endeavor is an algorithm developed to streamline the selection process. It is meticulously crafted to sift through many articles and distill them into a coherent and relevant body of work. This algorithm is a testament to the rigorous methodology used to conduct this review.

Readers will gain insights into influential methodologies, techniques, and findings shaping the future of energy forecasting. The emphasis on adaptive techniques highlights their transformative role in enhancing forecasting models' accuracy and reliability. This exploration is not just confined to theoretical underpinnings but extends to practical applications, showcasing how these advancements are operationalized in real-world scenarios.

This research highlights the upward trend in scholarly publications in this domain, reflecting the field's dynamism and the growing interest in adaptive forecasting methods. This trend underscores the need for continuous innovation and development in this area, which is driven by the challenges and opportunities of the evolving energy sector.

The paper explores various forecasting categories, ranging from electricity demand forecasting, which is crucial for energy efficiency and the integration of renewable sources, to deep learning and neural networks, which are revolutionizing data forecasting. This paper explores machine learning in forecasting, the application of artificial intelligence, and the relevance of time series prediction in various sectors. Discussions on optimization algorithms, environmental and climate considerations, economic factors, and the emergence of hybrid forecasting models further exemplify the multifaceted nature of forecasting.

Moreover, this research identifies and discusses sixteen significant challenges encountered in forecasting, encompassing technical complexities in machine learning algorithms, data governance issues, and the impact of external events like the COVID-19 pandemic. These challenges highlight the necessity for new techniques and approaches to adapt and evolve within this ever-changing landscape.

This paper offers researchers, policymakers, and industry practitioners a comprehensive guide. Providing a balanced perspective on advancements and challenges serves as a vital resource for informed decision making in electrical energy forecasting. The insights and analysis presented here underscore the urgency for continued innovation and collaborative efforts in developing adaptive forecasting methodologies, which are crucial for the future of sustainable and resilient energy systems.

Organization

This paper meticulously dissects the intricate landscape of energy consumption and forecasting, exploring the adaptive methodologies shaping the energy sector's future. A roadmap is provided to guide readers through the exploration.

Section 1—This introduction offers a comprehensive overview of adaptive forecasting in energy, emphasizing its significance, challenges, and evolving methodologies in the field.

Section 2—Bibliometric Exploration: This section explores a comprehensive bibliometric analysis that sheds light on groundbreaking research in the field of energy consumption, featuring adaptive forecasting and valuable insights. It outlines the meticulous selection criteria that guided us in handpicking the most impactful studies in this domain.

Section 3—Methodology: This section outlines the world of bibliometric methodologies to gain a deeper understanding of each technique. The nuances of these methodologies and how they work are explained. The most groundbreaking papers will be highlighted, and their methodologies will be examined to uncover their true essence.

Section 4—State of the Art: Explore the annals of the most influential papers discovered in the bibliometric quest. Each selected paper is analyzed to reveal its objectives, groundbreaking results, and innovative methodologies. Observe the kaleidoscope of approaches utilized by visionary researchers.

Section 5—Discussion and Analysis: This analysis draws on a wide range of literature to distill the most essential insights that define the field. By examining key themes, pressing challenges, and inherent constraints, we can identify future research horizons.

Section 6—Conclusions: As the exploration comes to a close, the encapsulation of the essence of the findings is presented, including the distilled wisdom and revelations uncovered during the research odyssey.

2. Bibliometric Analysis

In the rapidly evolving landscape of electrical engineering, energy forecasting has emerged as a pivotal area of research. The ability to accurately predict energy consumption patterns holds profound implications for designing, operating, and optimizing electrical systems. Integrating adaptive techniques in energy forecasting has ushered in a new era of precision and efficiency, significantly impacting the broader electrical engineering field [1].

The importance of energy forecasting is underscored by the myriad of challenges faced by modern electrical systems, ranging from demand–supply imbalances to the integration of renewable energy sources. Adaptive techniques, which leverage advanced algorithms and methodologies, promise dynamic and responsive forecasting models that can adjust to changing conditions and deliver accurate predictions. An analysis from Scopus based on forecasting techniques from 2015 by considering only high-impact journal publications shows the different keywords associated with forecasting researchers and how these topics are related; this can be seen in Figure 1.

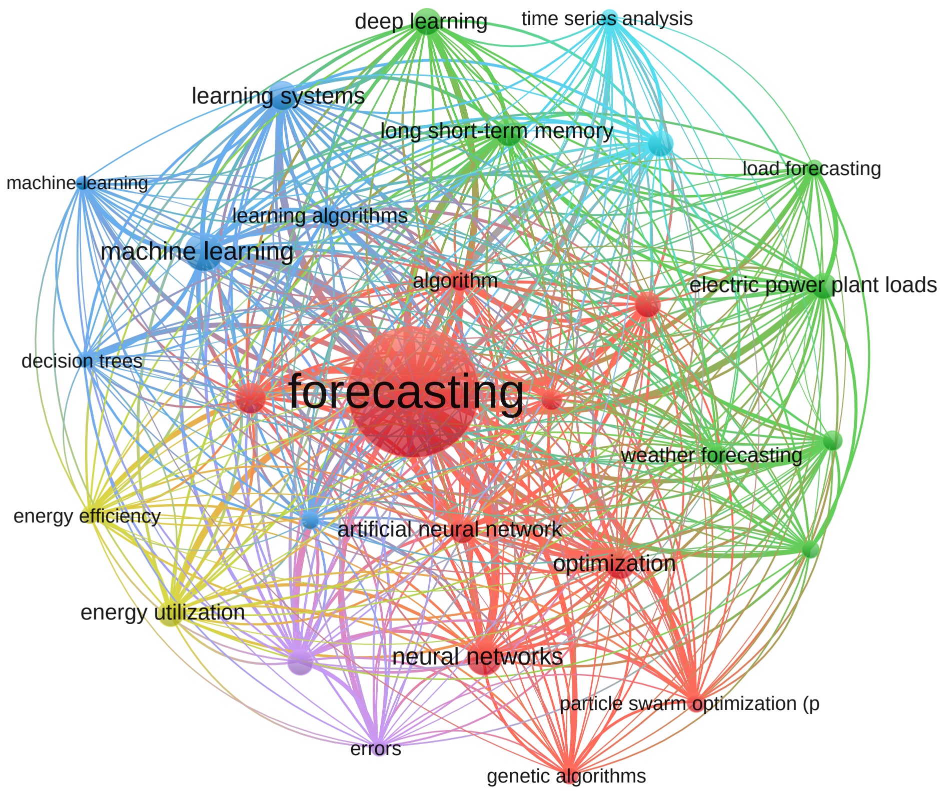

Figure 1. Main keywords associated with forecasting, taken from Scopus database.

An exhaustive literature review was undertaken to provide a comprehensive overview of this domain's current state of the art. The renowned Scopus database served as the primary source for this endeavor. Publications from 2015 to the present were meticulously searched, focusing on keywords such as "energy consumption", "load consumption", and related terms. This approach ensured that the most relevant and recent advancements in the field were captured.

However, an additional filtering layer was applied to ensure the quality and impact of the selected works. Only papers from Q1 journals, recognized for their high standards and rigorous peer review processes, were considered. Furthermore, this subset preferred papers that garnered more citations, indicating their influence and acceptance within the research community. The culmination of this rigorous selection process resulted in more than seventy papers that form the backbone of this state-of-the-art review. This process is further explained in Algorithm 1.

This review will give readers insights into the most influential methodologies, techniques, and findings shaping the future of energy forecasting in electrical engineering. The emphasis on adaptive techniques underscores their significance and transformative role in enhancing forecasting models' accuracy and reliability. Additionally, from the documents extracted, Figure 2 shows the main countries contributing to this research topic.

Algorithm 1 Literature review paper's selection process

Require: Scopus database D, Time frame T = [2015, present], Keywords K = ["energy consumption", "load consumption", ...]
Ensure: Selected papers $P_{selected}$
$papersList \leftarrow \emptyset$
for each $year$ in T **do**
  $papersList \leftarrow papersList \cup \mathrm{Search}(D, year, K)$
$filteredPapers \leftarrow \emptyset$
for each $paper$ in $papersList$ **do**
  if $paper.journal$ is Q1 $\wedge$ $paper.citations$ > threshold **then**
    $filteredPapers \leftarrow filteredPapers \cup paper$
Sort $filteredPapers$ by $paper.citations$ in descending order
$P_{selected} \leftarrow$ top 75 papers from $filteredPapers$
  return $P_{selected}$

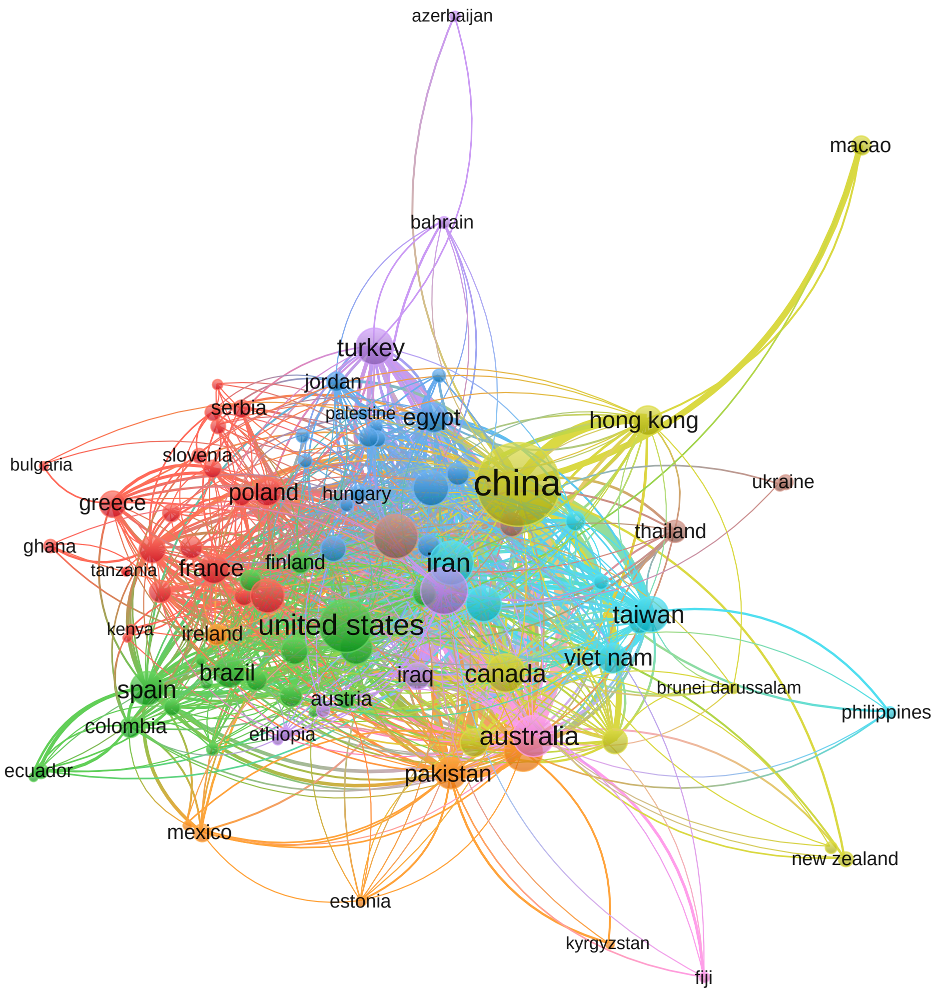

Figure 2. Main countries that have provided key research in energy forecasting.

2.1. Bibliometric Analysis Insights

Based on Algorithm 1, 7913 high-impact articles that meet the required criteria were carefully selected. These articles contain a wealth of information, spanning 13,340 pages. The median citation count per article is 22 with a maximum of 1316 citations. The most critical insights from these articles will be detailed as follows.

2.1.1. Distribution of Publications by Year

In the period spanning from 2015 to 2023, there was a significant upward trend in scholarly publications, according to a comprehensive analysis. The research output started with a modest 299 publications in 2015, but there was a consistent annual increase, reaching a peak of 1647 publications in 2022. This represents a remarkable five-fold growth over just seven years. The year 2023 witnessed a slight dip with 1547 publications. However, this analysis was performed in October 2023, so there is the possibility that this number will increase. The scholarly output surge reflects the field's dynamism and suggests a promising trajectory for future academic endeavors. This trend can be fully seen in Figure 3.

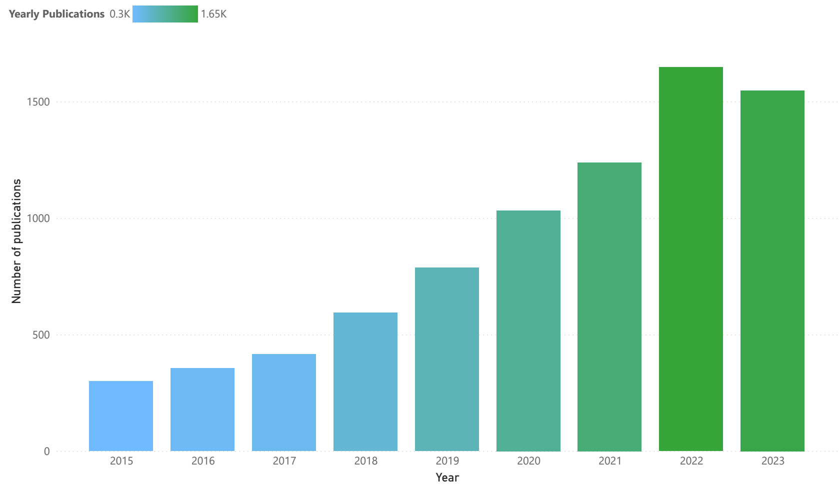

Figure 3. Publications by year related to energy forecasting analysis.

2.1.2. Top 10 Publication Sources

Following the analysis, specific journals and sources have emerged as leading platforms for scholarly discourse. At the forefront is *IEEE Access*, which published 307 papers, demonstrating its pivotal role as a hub for cutting-edge research and technological advancements. *Energy and Buildings* closely follows with 153 publications reflecting the growing emphasis on sustainable and energy-efficient architectural practices. Another noteworthy contributor is *Sustainability (Switzerland)* with 125 publications highlighting the global shift toward sustainable practices and eco-friendly solutions. The prominence of these journals not only signifies the academic community's trust in these platforms but also underscores the contemporary relevance of the subjects they encompass. This data are fully detailed in Figure 4.

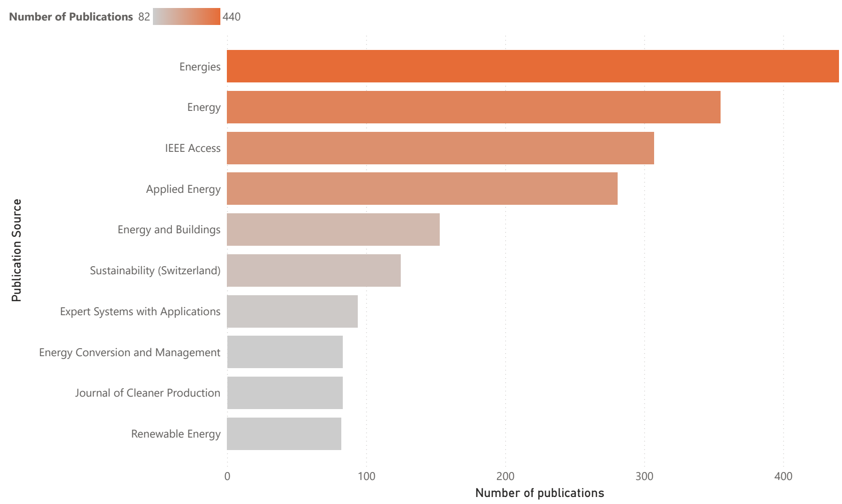

Figure 4. Top 10 publication sources.

2.1.3. Open Access and Non-Open Access Publications

The world of academic publishing is experiencing a noticeable shift toward open access, reflecting a global commitment to make knowledge more accessible. A closer analysis of publications from 2015 to 2018 reveals several categories of open access each with unique characteristics and prevalence.

- **Gold Open Access**: This is the most common model with 1311 publications. In this model, articles are freely accessible from the outset, which are typically funded by article processing charges paid by authors or their institutions. This approach emphasizes the importance of the immediate and widespread dissemination of research findings.
- **Bronze Open Access**: Offers a more flexible yet less defined open access avenue with 293 publications. This model provides free-to-read articles provided by publishers without a specific license.
- **Green Open Access**: With 478 publications, this term refers to the self-archiving of either pre-peer-review or post-peer-review versions of the work in online repositories, ensuring a broader reach without immediate open publication.
- **Hybrid Gold Open Access**: With 154 publications, it combines open and closed-access articles. In this model, journals offer authors an open access option after an article processing charge, while other content remains subscription-based.

These diverse open-access models highlight the multifaceted strategies adopted by the academic community. It is a testament to the evolving nature of research dissemination, aiming to cater to both the researchers' need for visibility and the public's right to access. A detailed analysis of open-access vs. non-open-access publications is shown in Figure 5, in this figure around 4% of the analyzed articles were not classified and included in the figure because the type of publication access was not well stated.

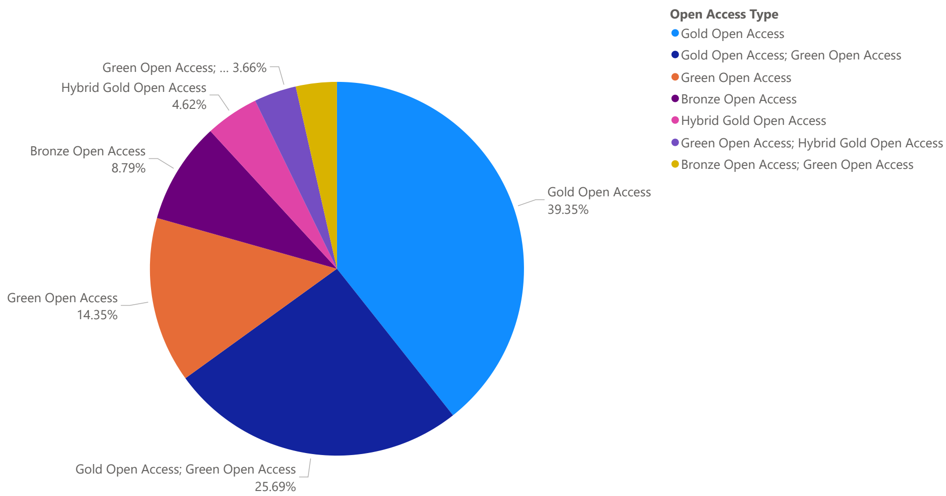

Figure 5. Open access vs. non-open access publications distributions.

2.1.4. Publications Citations Analysis

- **Top 10 Publications with the Highest Number of Citations**: Table 1 comprises the most notable publications based on their citation count, which signifies the impact and recognition these works have garnered in the academic community.
- **Publications with Zero Citations**: A considerable portion of the research, which amounts to 1176 publications, has not received any citations. This could be due to the research being very recent, limited to a specific niche, or not yet attracting enough attention from the academic community.
- **Publications with Citations Above the Average**: Around 27% of the research papers have citations higher than the average of 22.11. This implies that a small portion of the publications are responsible for most of the citations, which is a common phenomenon in the academic world referred to as the Pareto principle or the 80/20 rule.

Table 1. Top 10 most cited papers.

No.	Publication Title	Citations
1	"Short-Term Residential Load Forecasting Based on LSTM Recurrent Neural Network" [2]	1316
2	"Statistical and Machine Learning forecasting methods: Concerns and ways forward" [3]	656
3	"Remote sensing for agricultural applications: A meta-review" [4]	653
4	"Trees vs Neurons: Comparison between random forest and ANN for high-resolution prediction of building energy consumption" [5]	565
5	"Optimal deep learning LSTM model for electric load forecasting using feature selection and genetic algorithm: Comparison with machine learning approaches" [6]	484
6	"Back propagation neural network with adaptive differential evolution algorithm for time series forecasting" [7]	462
7	"A short-term building cooling load prediction method using deep learning algorithms" [8]	448
8	"A deep cnn-lstm model for particulate matter (Pm2.5) forecasting in smart cities" [9]	419
9	"Empirical Mode Decomposition based ensemble deep learning for load demand time series forecasting" [10]	344
10	"Smart multi-step deep learning model for wind speed forecasting based on variational mode decomposition, singular spectrum analysis, LSTM network and ELM" [11]	337

After a thorough analysis, it is clear that some publications have much higher citation counts than others. However, many publications have not been cited, which was possibly due to factors such as the research's originality, the topic's pertinence, or the publication's visibility. Furthermore, the fact that only a quarter of the publications have citation counts above the average highlights the cutthroat nature of academic publishing and the importance of producing impactful research. A histogram showing the number of papers citations distribution is shown in Figure 6.

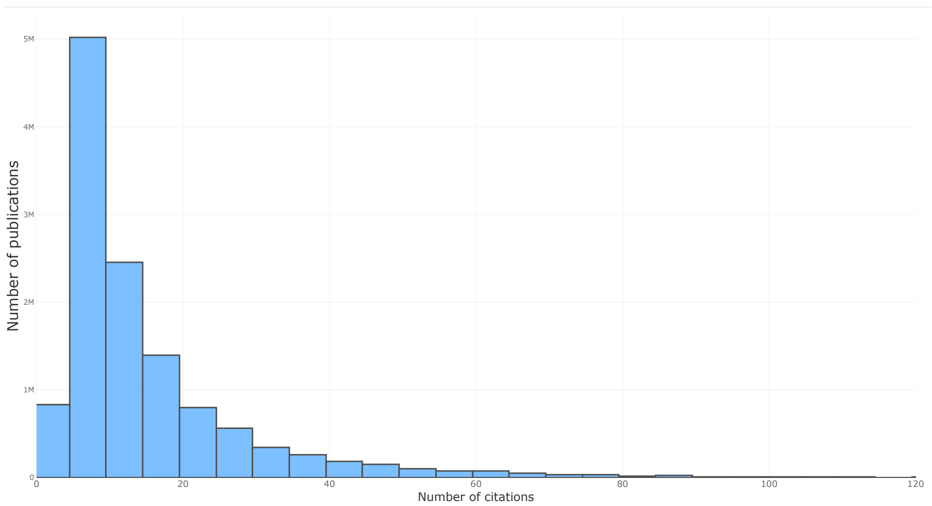

Figure 6. Histogram distribution of paper's citations.

3. Methodology

Energy, load, and electricity consumption is a research field that has employed a variety of methodologies to tackle different challenges and explore new frontiers. Sixteen predominant methodologies were identified in the literature review that this paper focuses its efforts on, as shown in Figure 7. These methodologies range from advanced machine learning techniques, including LSTM-based approaches and Generative Adversarial Networks (GANs), to more traditional methods, such as regression analysis and optimization techniques. Each methodology offers unique advantages and is suited for specific types of tasks.

For instance, LSTM-based approaches are particularly effective in handling sequence prediction problems, making them ideal for time series forecasting. On the other hand, comparative analysis serves as a tool to evaluate and compare the performance of various algorithms, models, or techniques in specific scenarios.

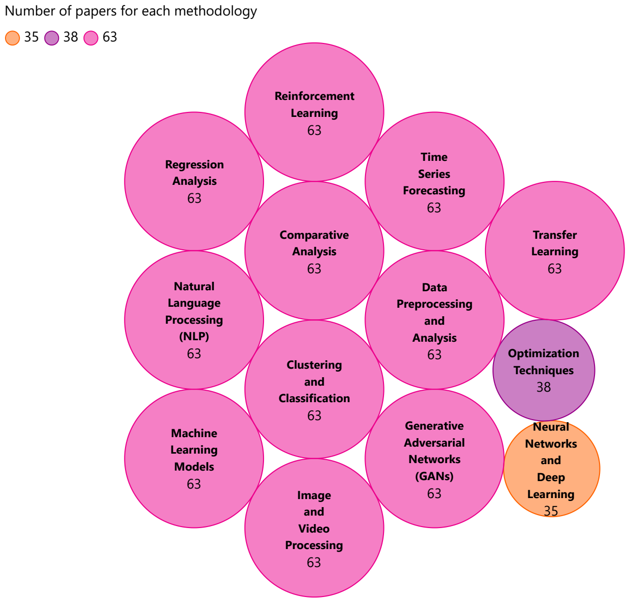

Figure 7. Main methodologies identified in the state-of-art review.

Moreover, integrating methodologies like Natural Language Processing (NLP) and Image and Video Processing indicates the interdisciplinary nature of modern electrical engineering research. It bridges the gap between textual and visual data processing.

Table 2 provides a detailed breakdown of each methodology, the number of papers that employed each methodology (from the state-of-the-art SoTA), the main papers that use each methodology, a brief description, and their typical usage in research. This overview aims to offer readers a comprehensive understanding of the current methodological landscape in electrical engineering research.

Table 2. Principal methodologies applied for adaptive forecasting.

Methodologies	Number of Papers	Description	How It Was Applied
LSTM-Based Approaches [2,9,11–22]	14	Long Short-Term Memory (LSTM) is a type of Recurrent Neural Network (RNN) architecture suited for sequence prediction.	Used for time series forecasting, sequence prediction, and tasks with temporal dependencies.
Comparative Analysis [2,3,6,11–13,16,17,19,22–35]	63	Involves comparing multiple techniques to determine their effectiveness.	Evaluate and compare the performance of various algorithms, models, or techniques in specific applications.
Neural Networks and Deep Learning [2,9,11–13,16–19,23,31,33,35–44]	35	Neural Networks are computational models inspired by the human brain; deep learning uses multi-layered neural networks.	Focuses on designing, implementing, and optimizing deep neural network architectures.
Optimization Techniques [19,24,32,34,35,40,45–47]	38	Aims to find the best solution from possible solutions.	Uses optimization algorithms to enhance electrical systems' performance, improve algorithm efficiency, or solve specific problems.
Feature Extraction and Selection [6,9,11–13]	34	Identifying and selecting the most relevant input variables or features.	Discusses methods to extract meaningful features from raw data and techniques to select the most relevant task features.
Time Series Forecasting [2,3,6,11,12]	63	Predicting future values based on previously observed values in a time sequence.	Focuses on forecasting in domains like energy consumption, stock prices, or weather using various algorithms.
Data Preprocessing and Analysis [2–4,6,9]	63	Cleaning, transforming, and analyzing raw data for computational tasks.	Discusses techniques for handling missing data, outliers, noise, and methods to transform and analyze data.
Machine Learning Models [3,4,6,9,11]	63	Training computational models on data to make predictions or decisions.	Explores various machine learning algorithms, from regression and classification to clustering.
Regression Analysis [2–4,6,9]	63	A statistical method to examine the relationship between variables.	Uses regression techniques to model and analyze relationships in various applications.

Table 2. *Cont.*

Methodologies	Number of Papers	Description	How It Was Applied
Clustering and Classification [2–4,6,9]	63	Clustering groups data points based on similarity, while classification assigns predefined labels.	Discusses clustering and classification algorithms and their applications in segmenting or categorizing data.
Natural Language Processing (NLP) [2–4,6,9]	63	Interaction between computers and human language.	Techniques and models for tasks like sentiment analysis, machine translation, and text summarization.
Image and Video Processing [2–4,6,23]	63	Techniques to process, analyze, and interpret visual information.	Algorithms and techniques for tasks like image recognition, video analysis, and visual data compression.
Reinforcement Learning [3,6,9,11,23]	63	A type of machine learning where an agent learns to behave in an environment.	Application in optimizing electrical systems, controlling devices, and making decisions in dynamic environments.
Generative Adversarial Networks (GANs) [2,23–25,48]	63	A class of machine learning models where two networks are trained together.	Design and application of GANs in tasks like data generation, image synthesis, and anomaly detection.
Transfer Learning [2–4,6,9]	63	Using knowledge gained while solving one problem for a different, related problem.	Techniques to transfer knowledge from one domain or task to another.
Functional Data Analysis [49–55]	63	Functional Data Analysis (FDA) is an advanced statistical method focusing on analyzing data that functions, curves, or shapes can represent.	Researchers treat time series data, like hourly electricity prices or demand, as continuous functions rather than discrete points, enabling a more nuanced analysis and prediction.
Applications and Use Cases [2–4,6,11]	20	Focus on the practical applications of the methodologies.	Real-world examples and case studies of how various methodologies are applied in practice.

4. State of the Art

This section analyzes the most influential papers selected from the bibliometric analysis through Algorithm 1. For each document, objectives, methodologies, and principal results are highlighted. This section has been divided according to the main thematics that papers have employed in their corresponding analysis. Papers are classified into Deep learning approaches, Renewable energy approaches, Environmental and agricultural applications, Economic and price forecasting, Advanced methodologies and comparisons, and Other approaches.

4.1. Deep Learning Approaches

The rapid advancements in artificial intelligence and machine learning have paved the way for innovative solutions across various domains. Researchers harness the power of deep learning techniques, from energy consumption to health management, to address complex challenges. Here is a concise summary of some notable research papers in this realm:

Numerous studies have shown that sophisticated neural network models are increasingly relied upon to enhance accuracy in energy forecasting. For instance, ref. [2] focuses on short-term residential load forecasting using an LSTM-based framework. In contrast, ref. [11] introduces a novel wind speed prediction model employing advanced techniques like VMD, SSA, LSTM, and ELM. Similarly, ref. [16] discusses using deep neural network algorithms for short-term load forecasting in smart grid systems.

In the field of environmental forecasting, ref. [9] introduces APNet, which predicts PM2.5 concentrations using a CNN-LSTM combination. The study emphasizes the importance of measuring air quality in smart city management. Additionally, ref. [12] presents models for photovoltaic power forecasting, which is essential for addressing the unpredictability of solar energy.

Various studies focus on forecasting in human-centric and environmental contexts. For instance, using machine learning, ref. [25] adopts a novel approach to thermal comfort modeling. In contrast, refs. [27,56] focus on water quality prediction using various modeling approaches such as ANFIS and advanced denoising techniques. Ref. [31] emphasizes water quality monitoring by predicting variables like dissolved oxygen and chlorophyll-a in lakes using deep learning models.

In the healthcare sector, ref. [28] presents a comparative analysis of machine learning techniques for predicting COVID-19 outbreaks, highlighting the limitations of standard epidemiological models.

Lastly, various studies exhibit the versatility and effectiveness of deep learning frameworks in diverse forecasting scenarios. From wind speed prediction [14,26] and residential load forecasting [36] to electricity price prediction [37], traffic signal control [38], and solar photovoltaic power [57], these studies demonstrate the broad application of neural networks and machine learning in various forecasting tasks.

Collectively, these studies showcase the transformative potential of deep learning techniques across various sectors, emphasizing their capability to address complex challenges and drive innovation.

4.2. Renewable Energy Approaches

Over the years, energy research has made significant progress with innovative ideas such as solar irradiance and microgrid technologies. Significant advances have been made in this field with groundbreaking research conducted in various aspects of energy generation, consumption, and optimization:

Various approaches have been presented in various research papers in renewable energy forecasting and optimization. For instance, ref. [48] explores the potential of text mining in solar irradiance and photovoltaic power forecasting literature. Meanwhile, ref. [45] develops a hybrid optimization algorithm for a solar and wind energy system. Furthermore, ref. [40] proposes an ADP-based approach for economic dispatch in microgrids with distributed generations. In addition, ref. [58] introduces a seasonal gray model for electricity consumption forecasting in China's primary industries. Similarly, ref. [59] presents an energy management system for a grid-connected microgrid with renewable resources. Lastly, ref. [60] focuses on predicting future power consumption in Beijing while considering global warming effects.

Research papers such as [46,61] provide insights into optimizing and managing energy use in microgrid technologies and real-time demand-side management. For instance, ref. [61] proposes a decentralized real-time demand-side management system for microgrids, integrating renewable energy sources, EVs, and ESSs. On the other hand, ref. [46] explores using Data-driven Model Predictive Control to optimize building energy usage, emphasizing its scalability and robustness.

Finally, various forecasting challenges and solutions in the energy sector are discussed in research papers such as [30,32,34,47,62,63]. For example, ref. [47] presents a hybrid model combining IEMD, ARIMA, and WNN for short-term electricity load prediction. Similarly, ref. [30] introduces AI techniques for predicting building heating loads. In addition, ref. [62] discusses wind speed forecasting using a comprehensive system. Meanwhile, ref. [32] integrates a sheep-flocking behavior-inspired evolutionary algorithm with a neural network for load forecasting. Furthermore, ref. [63] introduces a regional hybrid short-term load forecasting model for Assam, India. Lastly, ref. [34] proposes a novel forecasting model integrating the firefly algorithm for industrial energy systems.

The following papers are mainly considered Deep Learning approaches. However, they also focus on renewable energy. Paper [12] addresses the challenges posed by the unpredictability, intermittency, and randomness of solar energy for accurate photovoltaic power forecasting. Ref. [13] introduces a novel wind speed prediction model in the wind energy sector. Ref. [29] emphasizes the significance of predictive analytics in managing decentralized energy systems, specifically in predicting the energy output of a solar thermal collector system. Ref. [14] presents a wind speed prediction model that combines Wavelet Packet Decomposition (WPD) with Convolutional Neural Network (CNN) and Convolutional Long Short Term Memory Network (CNNLSTM). Ref. [64] discusses a hybrid deep learning model for enhancing the accuracy of photovoltaic power prediction. Ref. [65] presents a hybrid model, EMD-mRMR-FOA-GRNN, for short-term load forecasting in the deregulated electric power market. Ref. [57] creates GAN and CNN-based models for solar photovoltaic power forecasting.

4.3. Environmental and Agricultural Applications

Integrating advanced technologies in various sectors has paved the way for innovative solutions and methodologies that address complex challenges. From utilizing remote sensing in agriculture to applying machine learning in building energy systems and water quality prediction, researchers are harnessing the power of technology to drive forward-thinking approaches in diverse fields. Here is a brief overview of some notable studies in this domain:

Two papers, refs. [4,6], focus on remote sensing's role in agriculture. Both studies highlight the significance of remote sensing data in different agricultural applications, such as crop breeding, yield forecasting, and understanding ecosystem services. Ref. [6] is particularly noteworthy for its comprehensive approach, blending empirical and deterministic methods and covering both the technical and practical applications of remote sensing in agriculture.

Two other papers, refs. [66,67], delve into distinct but related areas. Ref. [66] investigates the environmental implications of urban development, using qualitative and quantitative methods to inform sustainable urban planning practices. On the other hand, ref. [67] explores machine learning's role in building energy system modeling and analysis, emphasizing its importance in energy-efficient operations and building analytics.

Finally, ref. [39] analyzes the application of artificial intelligence methods, such as ANN, SVM, and GMDH, in predicting water quality components of the Tireh River in Iran. The study compares various models and concludes that the SVM model is the most accurate in predicting water quality components.

Although the following papers mainly use deep learning techniques, they can also be classified into this category. Ref. [68] discusses the significance of precise forecasting in the agricultural industry, focusing on soybean and wheat prices. Ref. [31] predicts water quality variables, namely dissolved oxygen (DO) and chlorophyll-a (Chl-a), in the Small Prespa Lake in Greece using deep learning models.

4.4. Forecasting Based on Functional Data Analysis

Two studies, namely [53,54], address the issue of short-term electricity demand forecasting. Ref. [54] uses the Functional Auto Regressive with Exogenous Variables (FARX) model to enhance the forecasting accuracy in the Nord Pool electricity market. Meanwhile, ref. [53] proposes a Functional vector autoregressive State Space Model (FSSM) to enhance the accuracy of electricity demand forecasting in the French electricity market. Both studies demonstrate that specialized functional models can significantly enhance forecasting accuracy compared to traditional methods.

Moving on to electricity price forecasting, refs. [49,50] provide insights into this field. Ref. [49] highlights various techniques and their evolution in response to the dynamics of liberalized power markets, focusing on hybrid methods. Ref. [50], on the other hand, proposes a novel approach that combines Functional Data theory with neural networks to enhance forecasting models for functional time series in electricity markets.

Regarding advanced computational models for short-term electrical load forecasting, we have [51,55]. Ref. [51] assesses modern linear and non-linear parametric modeling techniques and concludes that the ANN-LM model with one hidden layer outperforms others. Meanwhile, ref. [55] uses Long Short-Term Memory (LSTM) networks for forecasting, demonstrating their superiority over traditional machine learning methods in handling sequential time series data.

Finally, ref. [52] presents a two-stage distributionally robust optimization model for Community-Integrated Energy Systems (CIES) to manage uncertainties in renewable energy generation. This study highlights the effectiveness of data-driven models in balancing economic operation and robustness, outperforming traditional methods in operational economy and computational efficiency.

4.5. Economic and Price Forecasting

Two research papers, refs. [24,69], address the use of advanced forecasting techniques but in different scenarios. Ref. [24] describes the difficulties of predicting crude oil prices and proposes using a new model combining support vector regression (SVR) with a wrapper-based feature selection approach to capture the non-linear properties of crude oil time series with greater precision. In contrast, ref. [69] provides an overview of machine learning techniques in energy economics and finance, identifying popular techniques and suggesting areas for future research. Both papers emphasize the significance of advanced computational models to tackle complicated forecasting issues in dynamic markets.

Similarly, refs. [22,70] focus on forecasting in the energy sector but with different objectives. Ref. [70] explores electricity demand forecasting in Australia's National Electricity Market, comparing the effectiveness of various data-driven techniques such as MARS, SVR, and ARIMA models. The study highlights the correlation between the effectiveness of these models and their forecasting horizons. On the other hand, ref. [22] introduces a new model, SSA-FAGM-SVR, to predict carbon emissions for the G20 nations, demonstrating superior accuracy and adaptability compared to mainstream algorithms.

Although the following papers mainly use deep learning techniques, they can also be classified into this category. Ref. [68] focuses on forecasting soybean and wheat prices using regression ensembles. Ref. [16] discusses the importance of load forecasting for the reliability of smart grid systems and introduces a deep neural network algorithm for short-term load forecasting (STLF). Ref. [37] shows a hybrid model called WT-Adam-LSTM for predicting electricity prices. Ref. [70] presents an accurate electricity demand forecasting model in Australia's National Electricity Market (NEM).

4.6. Advanced Methodologies and Comparisons

The rapid evolution of technology and methodologies in various fields has led to groundbreaking research and insights. From the intricacies of time series forecasting and the potential of quantum computing to the vast realm of Big Data and the complexities of urban planning, researchers are continuously pushing the boundaries to understand and address contemporary challenges. Here is a brief overview of some of the notable research in these domains:

The papers [3,71] investigate advanced methodologies for data analysis but in different contexts. Paper [3] compares traditional statistical and machine learning methods for time series forecasting, highlighting the superiority of traditional methods in certain cases. On the other hand, ref. [71] explores the potential of Big Data in deciphering socio-economic patterns and emphasizes the need for a robust architecture that integrates non-traditional data sources.

Regarding quantum computing, papers [72,73] focus on quantum algorithms. Both studies aim to understand and evaluate the performance of quantum algorithms compared to classical ones. Paper [72] undertakes a rigorous literature review and experimental evaluation, while [73] uses a comparative approach to highlight the efficiency and potential advantages of quantum algorithms. Collectively, these papers offer insights into the current state and future trajectory of quantum computing.

Lastly, paper [74] presents a study in urban planning, aiming to combine traditional knowledge with contemporary technological advances. This research uses a combination of qualitative and quantitative approaches to develop a framework that enhances urban development and quality of life.

Additionally, although the following papers can be mainly categorized into other categories, they can also be classified into this category. Ref. [73] presents an examination of the field of quantum computing, focusing on quantum algorithms and their potential applications, while [67] shows machine learning techniques employed in building load prediction.

4.7. Other Approaches

Ref. [25] discusses a new approach to thermal comfort modeling, focusing on predicting individual thermal comfort responses. Ref. [28] explores the potential of machine learning techniques in predicting COVID-19 outbreaks.

In [15], the authors introduce a hybrid deep learning model that aims to enhance the accuracy of photovoltaic power prediction. This model combines short-term memory and Convolutional Neural Networks to capture temporal and spatial data characteristics. The authors assert the superior performance of this model compared to other models and highlight its effectiveness in integrating solar energy into existing energy systems. Additionally, the model's ability to capture temporal and spatial data characteristics makes it a reliable tool for predicting photovoltaic power.

Paper [75] explores quantum computing, specifically quantum algorithms and their applications. The research aims to determine the feasibility of quantum algorithms in solving complex problems that classical algorithms find challenging. The methodology involves theoretical analysis and practical experimentation for a comprehensive understanding. The ultimate objective is to open doors for a new era of computing with quantum technology; quantum algorithms play a crucial role in addressing challenges presently deemed insurmountable by classical standards.

Although the following papers mainly use deep learning techniques, they can also be classified into this category. Ref. [61] presents research on integrating microgrid technologies with renewable energy sources, electric vehicles (EVs), and energy storage systems (ESSs). Ref. [61] presents integrating microgrid technologies with renewable energy sources, electric vehicles (EVs), and energy storage systems (ESSs) for decentralized real-time demand-side management. Ref. [44] presents the use of cyber–physical–social systems (CPSS) in the industrial Internet of Things (IIoT) for bearing RUL prediction.

5. Discussion and Analysis

5.1. Principal Topics Identified in the State-of-the-Art Review

Forecasting has become crucial in the ever-changing world of research and technology, guiding decisions and strategies across multiple industries. The art and science of prediction have evolved, resulting in specialized categories that address unique challenges and utilize innovative methodologies. This document explores several critical forecasting categories, ranging from the complexities of electricity demand to the latest advancements in artificial intelligence and deep learning. Each category represents a distinct aspect of forecasting and emphasizes the interdisciplinary nature of this field. As we delve into these categories, we will discover the depth and breadth of forecasting and its significant role in shaping the future.

- **Electricity Demand Forecasting:**
  Predicting electricity consumption is an essential aspect for energy providers and policymakers. Accurate forecasting in this domain ensures efficient energy distribution, minimizes waste, and supports the integration of renewable energy sources. As the world moves toward sustainable energy, the precision and efficiency of electricity demand forecasting have become critical.
- **Deep Learning and Neural Networks:**
  Deep learning, a subfield of machine learning, has revolutionized data forecasting. Neural networks, modeled after the human brain, provide advanced models that adapt and learn from data, successfully applied in various sectors from finance to healthcare.
- **Machine Learning in Forecasting:**
  The adaptive algorithms of machine learning have revolutionized how we forecast. By analyzing historical data, these algorithms can predict future events with incredible accuracy. Their ability to improve themselves over time ensures that predictions become more accurate, making machine learning an essential tool for modern forecasting.
- **Renewable Energy and Forecasting:**
  Forecasting renewable energy production is crucial for grid stability and efficiency

in a global shift toward sustainable energy sources. However, predicting energy production from inherently variable sources like wind and solar energy is challenging.

- **Artificial Intelligence in Forecasting:**
  Integrating AI into forecasting has brought about significant improvements in prediction capabilities. With vast datasets and advanced algorithms, AI can accurately forecast events that were once thought impossible to predict. Its applications range from predicting stock market trends to anticipating natural disasters.
- **Time Series Prediction:**
  Time series forecasting is a classical statistical method that predicts future values based on previously observed values. It has been widely used in various fields, such as economics, weather forecasting, and stock market predictions. Despite the emergence of AI, its enduring relevance speaks to its effectiveness and reliability.
- **Optimization Algorithms in Forecasting:**
  Refining forecasting models is pivotal. Tweaking parameters and processes ensures accurate predictions, enhancing efficiency.
- **Environmental and Climate Considerations:**
  Forecasting in environmental contexts has become crucial due to pressing climate change concerns. Accurate prediction of climatic patterns, sea-level rises, and temperature fluctuations can aid in mitigation and adaptation strategies.
- **Economic Factors in Forecasting:**
  Economic forecasting is crucial for policymakers, investors, and businesses. Stakeholders can make informed decisions by predicting market trends, inflation rates, and employment patterns, ensuring economic stability and growth.
- **Hybrid Forecasting Models:**
  Hybrid models combine forecasting techniques to improve accuracy, leveraging individual strengths and compensating for weaknesses.

Table 3 displays the count of papers classified under each identified topic.

Table 3. Number of papers associated with each topic category.

Topic	Number of Papers
Electricity Demand Forecasting	10
Deep Learning and Neural Networks	65
Machine Learning in Forecasting	65
Renewable Energy and Forecasting	63
Artificial Intelligence in Forecasting	65
Time Series Prediction	66
Optimization Algorithms in Forecasting	63
Environmental and Climate Considerations	64
Economic Factors in Forecasting	65
Hybrid Forecasting Models	63
Probabilistic Forecasting	65
Energy Storage and Forecasting	63
Data-Driven Forecasting	65
Technological Advancements in Forecasting	65
Grid Integration and Forecasting	63
Statistical Methods in Forecasting	65

5.2. Principal Problems Identified in the Review

This comprehensive review identifies sixteen significant issues that span from technical complexities in machine learning algorithms to broader concerns encompassing data governance and the unforeseen impact of external events. These problems underscore the multifaceted nature of the field and highlight the need to develop new techniques to keep pace with its ever-evolving demands.

The challenge of achieving accuracy and reliability in forecasting, particularly in metrics such as electric load and wind speed, is frequently mentioned. Traditional methods are often found to be limited, necessitating more advanced or innovative approaches. The complexity and non-linearity of various datasets, including electric load and water quality, pose significant challenges. Data-related issues like inconsistent patterns, noisy data, and preprocessing needs are shared. Machine learning challenges include overfitting, vanishing gradients in RNNs, and issues with algorithms like LSTM. The influence of environmental and external factors like weather and climate on predictions is also noted, along with scalability and practical implementation challenges, particularly in emerging fields like quantum computing. The limitations and challenges of specific technologies such as neural networks, deep learning, and traditional econometrics are criticized, while concerns about the reproducibility and validation of results from studies are raised. Discussions also centered around the black-box nature of specific models, challenges in capturing long-term dependencies, and the necessity for model updates. Economic and financial implications, domain-specific challenges, hardware and infrastructure limitations, data governance and privacy concerns, limitations in decomposition and signal processing techniques, and the impact of external events like the COVID-19 pandemic are also highlighted as significant barriers.

- **Accuracy and Reliability:** Forecasting accurate and reliable energy metrics, such as electric load and wind speed, remains a challenge, according to many papers.
- **Limitations of Traditional Methods:** Several papers discuss the limitations of traditional forecasting or modeling methods and emphasize the need for more advanced or innovative approaches.
- **Complexity and Non-Linearity:** The complexity and non-linearity of various datasets, such as electric load or water quality, are often cited as challenges.
- **Data Challenges:** Data-related issues commonly include inconsistent patterns, noisy data, and the need for preprocessing.
- **Machine Learning Challenges:** Several papers highlight issues with specific machine learning techniques, such as overfitting, vanishing gradients in RNNs, and challenges with algorithms like LSTM.
- **Environmental and External Factors:** The impact of external factors like weather and climate on prediction is common.
- **Scalability and Practical Implementation:** Some papers discuss the gap between theoretical advancements, practical implementations, and scalability issues in domains such as quantum computing.
- **Challenges with Specific Technologies:** Neural networks, deep learning, and traditional econometrics are often criticized for their limitations and challenges.
- **Reproducibility and Validation:** The challenge of replicating results from studies and ensuring the validity and reproducibility of findings is mentioned in several papers.
- **Modeling Challenges:** Discussions around modeling often center on the black-box nature of certain models, the challenge of capturing long-term dependencies, and the need for model updates.
- **Economic and Financial Implications:** The potential financial losses due to forecasting errors, the economic implications of energy consumption, and other economic factors are highlighted in some papers.
- **Challenges Specific to Domains:** Certain problems are specific to particular domains, such as challenges in agriculture, traffic signal systems, or urbanization-related issues.
- **Hardware and Infrastructure Limitations:** Some papers discuss limitations related to specific hardware, such as quantum hardware, or challenges with infrastructure like smart grids.
- **Data Governance and Privacy:** Issues related to data governance, privacy concerns, and handling unstructured data are mentioned in some papers.
- **Challenges with Decomposition and Signal Processing:** Empirical Mode Decomposition (EMD) is criticized for its limitations in certain contexts.
- **Challenges Due to External Events:** External events, such as the COVID-19 pandemic, are highlighted as introducing deviations or biases in certain datasets or forecasts.

From Section 4, the number of papers that have faced each of the problems identified is shown in Figure 8.

By further analyzing the problems that authors have faced, the five most common problems, the five most common curious behaviors, the five most common unique thematics, and the five most common trends related to the problems found in Section 4 have been identified. They are shown in Table 4.

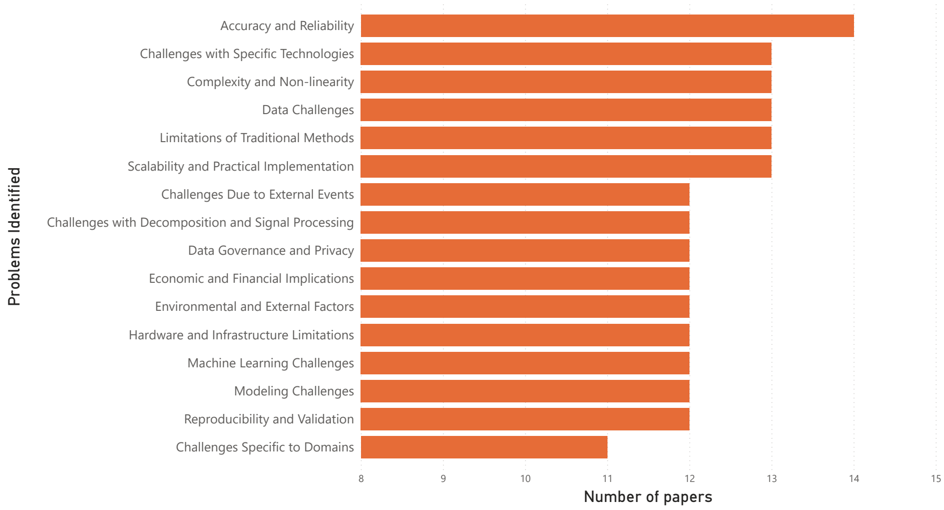

Figure 8. Number of papers into each problem category.

Table 4. Five most common problems, curious behaviors, unique thematic, and trends found in the problems analyzed in the SoAT.

Categories	1	2	3	4	5
Most Common Occurrences	Forecasting challenges in various domains.	Limitations and challenges of machine learning models.	Data-related issues, including quality, preprocessing, and noise.	Environmental factors affecting predictions and models.	Complexity and accuracy challenges in modeling.
Most Common Curios Behaviors	Over-reliance on a single data source or time series for evaluations.	Neural networks being deemed unsuitable or criticized for their "black-box" nature.	Challenges in replicating results from certain studies.	The gap between theoretical advancements and practical implementations in quantum computing.	The "curse of dimensionality" in dynamic programming.
Most Common Unique Thematic	Quantum computing challenges, including decoherence and scalability.	Challenges specific to renewable energy sources, such as wind and solar.	Issues related to urbanization, such as loss of green spaces and waste management.	The impact of external events, like the COVID-19 pandemic, on forecasting and modeling.	Challenges in integrating AI techniques into traditional traffic signal systems.
Most Common Trends	A shift toward more advanced machine learning techniques, such as deep learning and neural networks.	Emphasis on environmental sustainability and the challenges it presents.	The increasing importance of accurate forecasting in various sectors, from energy to agriculture.	The growing recognition of the limitations of traditional models and the need for more adaptive and dynamic models.	The integration of AI and machine learning into various domains, indicating a trend toward automation and data-driven decision making.

5.3. Principal Constraints the Researchers Have Faced

Continuing with the analysis, after the principal problems were identified, it is equally important to identify the constraints. They play a crucial role in scientific research by shaping the outcomes of studies. The literature review identified various limitations, such as data availability and technological barriers, that can affect the validity and applicability of their findings. Most of the time constraints may be classified as obstacles; however, they also define the scope and context of a study. Recognizing and addressing these limitations ensures the research's integrity and provides a comprehensive understanding of the challenges inherent in the field. Furthermore, by acknowledging these limitations, researchers can pave the way for future studies to address and overcome these challenges. Understanding constraints is essential as it offers a realistic perspective on the findings, ensuring that conclusions are robust and relevant to real-world scenarios. The following Section 4 highlights the primary constraints, and Figure 9 shows the number of papers and their distribution based on different constraints.

- **Data Availability and Quality:** Many papers emphasized the need for high-quality, real-world data for training and testing, including the availability, quality, and size of datasets.
- **Model Limitations:** Traditional statistical and machine learning methods have limitations when dealing with complex and non-linear energy data.
- **Computational Challenges:** Several papers have highlighted the high computational demands, particularly for deep learning models, and emphasized the necessity of access to advanced computing resources.
- **Environmental and External Factors:** Climatic conditions, human behavior, and environmental sustainability are crucial in energy forecasting.
- **Technical Challenges:** Recurrent themes included overfitting, noisy data, and challenges in training RNNs.
- **Real-time Forecasting:** Several research papers have highlighted the significance of real-time forecasting in practical scenarios.
- **Hardware and Technological Limitations:** Constraints related to quantum hardware, the need for extremely low temperatures for quantum operations, and the limitations of current remote sensing techniques were mentioned.
- **Economic and Financial Constraints:** Budget constraints, electricity price volatility, and proprietary algorithms were highlighted in the energy industry.
- **Socio-Political and Regulatory Challenges:** Several papers discussed regulatory, policy, socio-cultural, and socio-political challenges in urban planning.
- **Geographical and Topographical Constraints:** Geographic constraints in urban development, unique environmental contexts of certain regions, and limited land availability were mentioned.

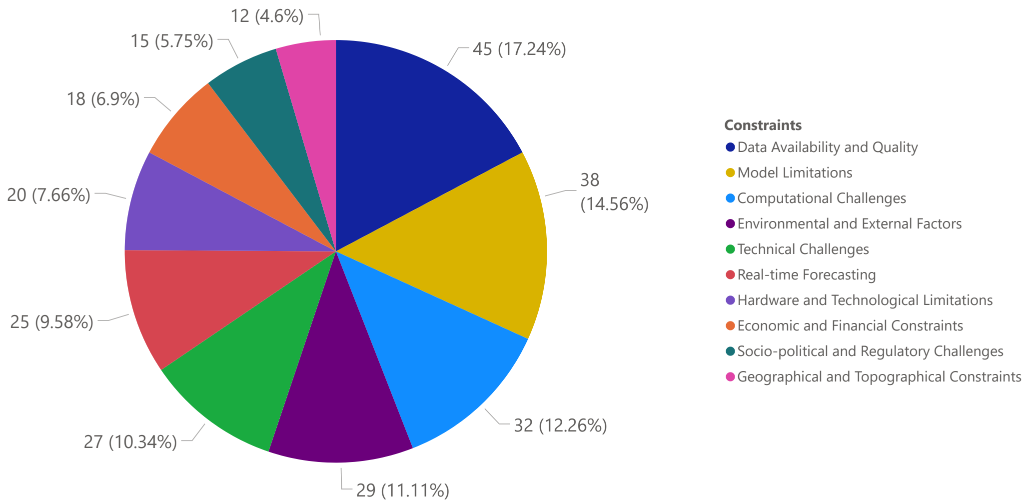

Figure 9. Number of papers into each category for constraints found in the review.

The challenges faced by researchers in energy forecasting are multifaceted and complex. The emphasis on "Data Availability and Quality" highlights the critical role of robust and representative datasets in shaping accurate and reliable forecasting models. The constraints related to "Model Limitations" and "Computational Challenges" suggest that while advancements in machine learning and statistical methods have propelled the field forward, a pressing need remains to address the complexities inherent in energy data. The mention of "Environmental and External Factors" and "Technical Challenges" underscores the dynamic nature of energy forecasting, where externalities such as climatic conditions and technical issues like overfitting can significantly influence outcomes.

Moreover, the constraints related to "Hardware and Technological Limitations" and "Economic and Financial Constraints" shed light on the practical challenges researchers and industry professionals face. The need for specialized hardware, especially for quantum operations, and the economic implications of electricity price volatility emphasize the intersection of technological innovation and economic realities in energy forecasting. The constraints about "Socio-Political and Regulatory Challenges" and "Geographical and Topographical Constraints" highlight the broader societal and geographical contexts in which energy forecasting operates. These constraints paint a comprehensive picture of the energy forecasting landscape, emphasizing the need for interdisciplinary approaches and collaboration to address the myriad challenges and drive the field forward.

5.4. Potential Future Directions Analysis

One primary direction for future research is expanding the scope of studies beyond current limitations. Present research often focuses on specific locations or short-term predictions, which restricts the generalizability and applicability of the findings. Future studies should aim to broaden their scope to encompass a wider range of environments and extend prediction horizons to cover longer periods. This approach will enable a more comprehensive understanding of the methods' effectiveness and applicability across various settings. Another critical area is emphasizing the real-world applicability of theoretical models and simulations. It is vital for future research to prioritize real-world testing and validation to ensure that theoretical models are practical and applicable in actual scenarios. This shift from theory to practice is crucial for realizing these models' value and applicability.

Additionally, the analysis underscores the importance of harnessing technological innovations and advancements. Some studies indicate that specific methodologies possess an untapped potential that could surpass current standards if further refined. Therefore, a direction toward leveraging technological innovations is essential for future research. The challenges of deep learning models, particularly regarding data quality, preprocessing requirements, and training time, are also highlighted. Addressing these challenges to make deep learning models more efficient and accurate is crucial for future studies. Furthermore, the potential of bio-inspired algorithms, inspired by natural behaviors, shows promise but requires testing for scalability and applicability in diverse datasets. Lastly, addressing significant data challenges, including privacy concerns, data heterogeneity, and potential biases when relying on non-traditional data sources, is imperative for advancing energy forecasting research.

This "Future Directions Analysis" sets the stage for the next wave of innovations in energy forecasting, and the most relevant strategies are listed as follows:

- **Expanding Scope of Studies:** Although there have been some promising results in the field, the current research often has a limited scope, focusing on specific locations or short-term predictions. To further validate the methodologies, future research should broaden its scope to encompass a wider range of environments and extend the prediction horizons to cover longer periods. Doing so makes it possible to gain a more comprehensive understanding of the effectiveness and applicability of the methods used in this study area.
- **Emphasis on Real-World Applicability:** While theoretical models and simulations certainly have their place in research, several academic papers have emphasized the importance of real-world testing and validation. These models' actual value and applicability can be fully realized only through practical applications. Thus, future research must prioritize real-world testing to ensure that theoretical models are applicable in practice.
- **Technological Innovations:** Some studies suggest that specific methodologies have untapped potential to surpass current standards with further refinement, indicating a direction toward harnessing technological innovations and advancements in future research.
- **Challenges of Deep Learning Models:** Deep learning models are currently being widely used and researched. However, they pose several challenges, especially regarding data quality, preprocessing requirements, and training time. It is crucial for future research to focus on addressing these challenges, aiming to make deep learning models more efficient and accurate.

- **Bio-Inspired Algorithms:** The potential of bio-inspired algorithms, derived from behaviors observed in nature, shows promise for future research. However, these algorithms require testing for scalability and applicability in diverse datasets.
- **Addressing Big Data Challenges:** Future research must prioritize addressing privacy concerns, data heterogeneity, and potential biases when relying on non-traditional data sources.

6. Conclusions

The paper highlights the criticality of electrical energy forecasting in facilitating efficient and dependable power system operations. The review accentuates the revolutionary impact of adaptive techniques in augmenting the precision and dependability of forecasting models. With the integration of adaptive techniques, there is a new wave of precision and efficiency in energy forecasting, which has significantly transformed the entire electrical engineering domain.

A comprehensive bibliometric analysis evaluated academic contributions from 2015 to 2023. The results of this study aided in recognizing the most important journals for research in the field and classifying them into open-access and non-open-access categories. The analysis also highlighted the growing research interest in adaptive forecasting techniques, significantly increasing scholarly publications. Additionally, the research paper offers valuable insights into the most cited works, demonstrating the influence and recognition of specific studies in the academic community.

The paper delves into forecasting energy, load, and electricity consumption and identifies sixteen predominant methodologies. These methodologies vary from advanced machine learning techniques, including LSTM-based approaches and Generative Adversarial Networks (GANs), to more traditional methods such as regression analysis and optimization techniques. Each methodology has unique advantages with LSTM-based approaches efficiently forecasting time series. The paper provides a comprehensive understanding of the different techniques used in this field and their strengths.

Finally, this research offers an extensive review of the latest methodologies and findings shaping the future of electrical energy adaptive forecasting. Highlighting the significance of adaptive strategies and conducting a bibliometric analysis provides a comprehensive view of the current research landscape. Furthermore, the paper suggests promising avenues for future exploration in electrical energy forecasting.

Author Contributions: M.J.: conceptualization, methodology, validation, writing—review and editing, data curation, formal analysis. W.P.: methodology, validation, writing—review and editing. L.J.: writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by Universidad Politécnica Salesiana and GIREI—Smart Grid Research Group.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data supporting this article are openly available from the Scopus data Base repository at [https://www.scopus.com/search/form.uri#basic] (accessed on 30 November 2023).

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

LSTM	Long Short-Term Memory (a type of recurrent neural network architecture)
AI	Artificial Intelligence (The simulation of human intelligence in machines)

ML	Machine Learning (a type of AI that allows software applications to predict outcomes)
CNN	Convolutional Neural Network (a class of deep neural networks for visual imagery)
VMD	Variational Mode Decomposition (a method for signal processing)
SSA	Singular Spectrum Analysis (a non-parametric spectral estimation method)
ELM	Extreme Learning Machine (a type of feedforward neural network)
SVR	Support Vector Regression (a type of support vector machine for regression)
PCS	Personal Communication Service (or other meanings depending on context)
ANN	Artificial Neural Network (a computing system inspired by biological neural networks)
ANFIS	Adaptive Neuro-Fuzzy Inference System (a neural network based on the Takagi–Sugeno system)
GWO	Gray Wolf Optimizer (an optimization algorithm)
SIR	Susceptible, Infected, Recovered (a model used in epidemiology)
SEIR	Susceptible, Exposed, Infected, Recovered (an extension of the SIR model)
MPC	Model Predictive Control (a type of control in process systems)
DPC	Digital Power Control (or other meanings depending on context)
IEMD	Improved Empirical Mode Decomposition (a method for signal processing)
ARIMA	Autoregressive Integrated Moving Average (a forecasting method)
WNN	Wavelet Neural Network (a type of artificial neural network)
FOA	Fruitfly Optimization Algorithm (a nature-inspired optimization algorithm)
DRL	Deep Reinforcement Learning (a combination of deep learning and reinforcement learning)
GOA	Grasshopper Optimization Algorithm (a nature-inspired optimization algorithm)
SVM	Support Vector Machine (a supervised machine learning algorithm)
SDA	Stochastic Diffusion Search (or other meanings depending on context)
CPSS	Continuous Power System Simulation (or other meanings depending on context)
IIoT	Industrial Internet of Things (a subcategory of IoT)
LCR	Load Control Relay (or other meanings depending on context)
FA	Firefly Algorithm (a nature-inspired optimization algorithm)
EKC	Environmental Kuznets Curve (a relationship between environmental quality and economy)

References

1. Jaramillo, M.; Carrión, D. An Adaptive Strategy for Medium-Term Electricity Consumption Forecasting for Highly Unpredictable Scenarios: Case Study Quito, Ecuador during the Two First Years of COVID-19. *Energies* **2022**, *15*, 8380. [CrossRef]
2. Kong, W.; Dong, Z.Y.; Jia, Y.; Hill, D.J.; Xu, Y.; Zhang, Y. Short-Term Residential Load Forecasting Based on LSTM Recurrent Neural Network. *IEEE Trans. Smart Grid* **2019**, *10*, 841–851. [CrossRef]
3. Al-Abri, E.S.; Spiliotis, E. Statistical and Machine Learning forecasting methods: Concerns and ways forward. *PLoS ONE* **2016**, *13*, e0194889.
4. Weiss, M.; Jacob, F.; Duveiller, G. Remote sensing for agricultural applications: A meta-review. *Remote Sens. Environ.* **2020**, *236*, 111402. [CrossRef]
5. Ahmad, M.W.; Mourshed, M.; Rezgui, Y. Trees vs. Neurons: Comparison between random forest and ANN for high-resolution prediction of building energy consumption. *Energy Build.* **2017**, *147*, 77–89. [CrossRef]
6. Bouktif, S.; Fiaz, A.; Ouni, A.; Serhani, M.A. Optimal deep learning LSTM model for electric load forecasting using feature selection and genetic algorithm: Comparison with machine learning approaches. *Energies* **2018**, *11*, 1636. [CrossRef]
7. Wang, L.; Zeng, Y.; Chen, T. Back propagation neural network with adaptive differential evolution algorithm for time series forecasting. *Expert Syst. Appl.* **2015**, *42*, 855–863. [CrossRef]
8. Fan, C.; Xiao, F.; Zhao, Y. A short-term building cooling load prediction method using deep learning algorithms. *Appl. Energy* **2017**, *195*, 222–233. [CrossRef]
9. Huang, C.J.; Kuo, P.H. A deep cnn-lstm model for particulate matter (Pm2.5) forecasting in smart cities. *Sensors* **2018**, *18*, 2220. [CrossRef]
10. Qiu, X.; Ren, Y.; Suganthan, P.N.; Amaratunga, G.A. Empirical Mode Decomposition based ensemble deep learning for load demand time series forecasting. *Appl. Soft Comput. J.* **2017**, *54*, 246–255. [CrossRef]
11. Liu, H.; Mi, X.; Li, Y. Smart multi-step deep learning model for wind speed forecasting based on variational mode decomposition, singular spectrum analysis, LSTM network and ELM. *Energy Convers. Manag.* **2018**, *159*, 54–64. [CrossRef]
12. Wang, K.; Qi, X.; Liu, H. A comparison of day-ahead photovoltaic power forecasting models based on deep learning neural network. *Appl. Energy* **2019**, *251*, 113315. [CrossRef]

13. Chen, J.; Zeng, G.Q.; Zhou, W.; Du, W.; Lu, K.D. Wind speed forecasting using nonlinear-learning ensemble of deep learning time series prediction and extremal optimization. *Energy Convers. Manag.* **2018**, *165*, 681–695. [CrossRef]
14. Liu, H.; Mi, X.; Li, Y. Smart deep learning based wind speed prediction model using wavelet packet decomposition, convolutional neural network and convolutional long short term memory network. *Energy Convers. Manag.* **2018**, *166*, 120–131. [CrossRef]
15. Wang, K.; Qi, X.; Liu, H. Photovoltaic power forecasting based LSTM-Convolutional Network. *Energy* **2019**, *189*, 116225. [CrossRef]
16. Kuo, P.H.; Huang, C.J. A high precision artificial neural networks model for short-Term energy load forecasting. *Energies* **2018**, *11*, 213. [CrossRef]
17. Li, Y.; Zhu, Z.; Kong, D.; Han, H.; Zhao, Y. EA-LSTM: Evolutionary attention-based LSTM for time series prediction. *Knowl. Based Syst.* **2019**, *181*, 104785. [CrossRef]
18. Somu, N.; M R, G.R.; Ramamritham, K. A hybrid model for building energy consumption forecasting using long short term memory networks. *Appl. Energy* **2020**, *261*, 114131. [CrossRef]
19. Wang, Z.; Hong, T.; Piette, M.A. Building thermal load prediction through shallow machine learning and deep learning. *Appl. Energy* **2020**, *263*, 114683. [CrossRef]
20. He, F.; Zhou, J.; Feng, Z.K.; Liu, G.; Yang, Y. A hybrid short-term load forecasting model based on variational mode decomposition and long short-term memory networks considering relevant factors with Bayesian optimization algorithm. *Appl. Energy* **2019**, *237*, 103–116. [CrossRef]
21. Qu, J.; Liu, F.; Ma, Y.; Fan, J. A Neural-Network-Based Method for RUL Prediction and SOH Monitoring of Lithium-Ion Battery. *IEEE Access* **2019**, *7*, 87178–87191. [CrossRef]
22. Zhang, Y.; Li, X.; Zhang, Y. A novel integrated optimization model for carbon emission prediction: A case study on the group of 20. *J. Environ. Manag.* **2023**, *344*, 118422. [CrossRef] [PubMed]
23. Hewamalage, H.; Bergmeir, C.; Bandara, K. Recurrent Neural Networks for Time Series Forecasting: Current status and future directions. *Int. J. Forecast.* **2021**, *37*, 388–427. [CrossRef]
24. Karasu, S.; Altan, A.; Bekiros, S.; Ahmad, W. A new forecasting model with wrapper-based feature selection approach using multi-objective optimization technique for chaotic crude oil time series. *Energy* **2020**, *212*, 118750. [CrossRef]
25. Kim, J.; Zhou, Y.; Schiavon, S.; Raftery, P.; Brager, G. Personal comfort models: Predicting individuals' thermal preference using occupant heating and cooling behavior and machine learning. *Build. Environ.* **2018**, *129*, 96–106. [CrossRef]
26. Bedi, J.; Toshniwal, D. Deep learning framework to forecast electricity demand. *Appl. Energy* **2019**, *238*, 1312–1326. [CrossRef]
27. Najah Ahmed, A.; Binti Othman, F.; Abdulmohsin Afan, H.; Khaleel Ibrahim, R.; Ming Fai, C.; Shabbir Hossain, M.; Ehteram, M.; Elshafie, A. Machine learning methods for better water quality prediction. *J. Hydrol.* **2019**, *578*, 124084. [CrossRef]
28. Ardabili, S.F.; Mosavi, A.; Ghamisi, P.; Ferdinand, F.; Varkonyi-Koczy, A.R.; Reuter, U.; Rabczuk, T.; Atkinson, P.M. COVID-19 outbreak prediction with machine learning. *Algorithms* **2020**, *13*, 249. [CrossRef]
29. Ahmad, M.W.; Reynolds, J.; Rezgui, Y. Predictive modelling for solar thermal energy systems: A comparison of support vector regression, random forest, extra trees and regression trees. *J. Clean. Prod.* **2018**, *203*, 810–821. [CrossRef]
30. Le, L.T.; Nguyen, H.; Dou, J.; Zhou, J. A comparative study of PSO-ANN, GA-ANN, ICA-ANN, and ABC-ANN in estimating the heating load of buildings' energy efficiency for smart city planning. *Appl. Sci.* **2019**, *9*, 2630. [CrossRef]
31. Barzegar, R. Short-term water quality variable prediction using a hybrid CNN – LSTM deep learning model. *Stoch. Environ. Res. Risk Assess.* **2020**, *34*, 415–433. [CrossRef]
32. Singh, P.; Dwivedi, P. Integration of new evolutionary approach with arti fi cial neural network for solving short term load forecast problem. *Appl. Energy* **2018**, *217*, 537–549. [CrossRef]
33. Wu, J.; Hu, K.; Cheng, Y.; Zhu, H.; Shao, X.; Wang, Y. Data-driven remaining useful life prediction via multiple sensor signals and deep long short-term memory neural network. *ISA Trans.* **2020**, *97*, 241–250. [CrossRef] [PubMed]
34. Zhu, Z.; Zhou, M.; Hu, F.; Wang, S.; Ma, J.; Gao, B.; Bian, K. A day-ahead industrial load forecasting model using load change rate features and combining FA-ELM and the AdaBoost algorithm. *Energy Rep.* **2023**, *9*, 971–981. [CrossRef]
35. Afzal, S.; Ziapour, B.M.; Shokri, A.; Shakibi, H.; Sobhani, B. Building energy consumption prediction using multilayer perceptron neural network-assisted models; comparison of different optimization algorithms. *Energy* **2023**, *282*, 128446. [CrossRef]
36. Sajjad, M.; Khan, Z.A.; Ullah, A.; Hussain, T.; Ullah, W.; Lee, M.Y.; Baik, S.W. A Novel CNN-GRU-Based Hybrid Approach for Short-Term Residential Load Forecasting. *IEEE Access* **2020**, *8*, 143759–143768. [CrossRef]
37. Chang, Z.; Zhang, Y.; Chen, W. Electricity price prediction based on hybrid model of adam optimized LSTM neural network and wavelet transform. *Energy* **2019**, *187*, 115804. [CrossRef]
38. Ma, X.; Mei, X.; Wu, W.; Wu, X.; Zeng, B. A novel fractional time delayed grey model with Grey Wolf Optimizer and its applications in forecasting the natural gas and coal consumption in Chongqing China. *Energy* **2019**, *178*, 487–507. [CrossRef]
39. Haghiabi, A.H.; Nasrolahi, A.H.; Parsaie, A. Water quality prediction using machine learning methods. *Water Qual. Res. J.* **2018**, *53*, 3–13. [CrossRef]
40. Shuai, H.; Fang, J.; Ai, X.; Tang, Y.; Wen, J.; He, H. Stochastic optimization of economic dispatch for microgrid based on approximate dynamic programming. *IEEE Trans. Smart Grid* **2019**, *10*, 2440–2452. [CrossRef]
41. Zhang, R.; Chen, Z.; Chen, S.; Zheng, J.; Büyüköztürk, O.; Sun, H. Deep long short-term memory networks for nonlinear structural seismic response prediction. *Comput. Struct.* **2019**, *220*, 55–68. [CrossRef]

42. Sengupta, S.; Basak, S.; Saikia, P.; Paul, S.; Tsalavoutis, V.; Atiah, F.; Ravi, V.; Peters, A. A review of deep learning with special emphasis on architectures, applications and recent trends. *Knowl. Based Syst.* **2020**, *194*, 105596. [CrossRef]
43. Cui, Z.; Wu, J.; Lian, W.; Wang, Y.G. A novel deep learning framework with a COVID-19 adjustment for electricity demand forecasting. *Energy Rep.* **2023**, *9*, 1887–1895. [CrossRef]
44. Ren, L.E.I.; Sun, Y. Prediction of Bearing Remaining Useful Life With Deep Convolution Neural Network. *IEEE Access* **2018**, *6*, 13041–13049. [CrossRef]
45. Zhang, W.; Maleki, A.; Rosen, M.A.; Liu, J. Sizing a stand-alone solar-wind-hydrogen energy system using weather forecasting and a hybrid search optimization algorithm. *Energy Convers. Manag.* **2019**, *180*, 609–621. [CrossRef]
46. Smarra, F.; Jain, A.; de Rubeis, T.; Ambrosini, D.; D'Innocenzo, A.; Mangharam, R. Data-driven model predictive control using random forests for building energy optimization and climate control. *Appl. Energy* **2018**, *226*, 1252–1272. [CrossRef]
47. Zhang, J.; Wei, Y.M.; Li, D.; Tan, Z.; Zhou, J. Short term electricity load forecasting using a hybrid model. *Energy* **2018**, *158*, 774–781. [CrossRef]
48. Yang, D.; Kleissl, J.; Gueymard, C.A.; Pedro, H.T.; Coimbra, C.F. History and trends in solar irradiance and PV power forecasting: A preliminary assessment and review using text mining. *Sol. Energy* **2018**, *168*, 60–101. [CrossRef]
49. Cerjan, M.; Krželj, I.; Vidak, M.; Delimar, M. A literature review with statistical analysis of electricity price forecasting methods. *IEEE Eurocon.* **2013**, *2013*, 756–763. [CrossRef]
50. González, J.P.; Roque, A.M.S.; Pérez, E.A. Forecasting functional time series with a new hilbertian ARMAX model: Application to electricity price forecasting. *IEEE Trans. Power Syst.* **2018**, *33*, 545–556. [CrossRef]
51. Javed, U.; Ijaz, K.; Jawad, M.; Ansari, E.A.; Shabbir, N.; Kütt, L.; Husev, O. Exploratory data analysis based short-term electrical load forecasting: A comprehensive analysis. *Energies* **2021**, *14*, 5510. [CrossRef]
52. Li, Y.; Han, M.; Shahidehpour, M.; Li, J.; Long, C. Data-driven distributionally robust scheduling of community integrated energy systems with uncertain renewable generations considering integrated demand response. *Appl. Energy* **2023**, *335*, 120749. [CrossRef]
53. Nagbe, K.; Cugliari, J.; Jacques, J. Short-term electricity demand forecasting using a functional state space model. *Energies* **2018**, *11*, 1120. [CrossRef]
54. Shah, I.; Jan, F.; Ali, S. Functional Data Approach for Short-Term Electricity Demand Forecasting. *Math. Probl. Eng.* **2022**, *2022*, 6709779. [CrossRef]
55. Torres, J.F.; Martínez-Álvarez, F.; Troncoso, A. A deep LSTM network for the Spanish electricity consumption forecasting. *Neural Comput. Appl.* **2022**, *34*, 10533–10545. [CrossRef] [PubMed]
56. Lu, H.; Ma, X. Hybrid decision tree-based machine learning models for short-term water quality prediction. *Chemosphere* **2020**, *249*, 126169. [CrossRef]
57. Wang, F.; Zhang, Z.; Liu, C.; Yu, Y.; Pang, S.; Duić, N.; Shafie-khah, M.; Catalão, J.P. Generative adversarial networks and convolutional neural networks based weather classification model for day ahead short-term photovoltaic power forecasting. *Energy Convers. Manag.* **2019**, *181*, 443–462. [CrossRef]
58. Wang, Z.X.; Li, Q.; Pei, L.L. A seasonal GM(1,1) model for forecasting the electricity consumption of the primary economic sectors. *Energy* **2018**, *154*, 522–534. [CrossRef]
59. Luo, L.; Abdulkareem, S.S.; Rezvani, A.; Miveh, M.R.; Samad, S.; Aljojo, N.; Pazhoohesh, M. Optimal scheduling of a renewable based microgrid considering photovoltaic system and battery energy storage under uncertainty. *J. Energy Storage* **2020**, *28*, 101306. [CrossRef]
60. Hongyu, Z.; Bo, C.; Ying, L.; Junwei, G.; Cong, L.; Wenyi, Z.; Haobo, Y. ScienceDirect Research on medium- and long-term electricity demand forecasting under climate change. *Energy Rep.* **2022**, *8*, 1585–1600. [CrossRef]
61. Tushar, M.H.K.; Zeineddine, A.W.; Assi, C. Demand-Side Management by Regulating Charging and Discharging of the EV, ESS, and Utilizing Renewable Energy. *IEEE Trans. Ind. Inform.* **2018**, *14*, 117–126. [CrossRef]
62. Liu, Z.; Jiang, P.; Zhang, L.; Niu, X. A combined forecasting model for time series: Application to short-term wind speed forecasting. *Appl. Energy* **2020**, *259*, 114137. [CrossRef]
63. Barman, M.; Choudhury, N.B.D.; Sutradhar, S. A regional hybrid GOA-SVM model based on similar day approach for short-term load forecasting in Assam, India. *Energy* **2018**, *145*, 710–720. [CrossRef]
64. Peng, L.; Liu, S.; Liu, R.; Wang, L. Effective long short-term memory with differential evolution algorithm for electricity price prediction. *Energy* **2018**, *162*, 1301–1314. [CrossRef]
65. Liang, Y.; Niu, D.; Hong, W.C. Short term load forecasting based on feature extraction and improved general regression neural network model. *Energy* **2019**, *166*, 653–663. [CrossRef]
66. Ghimire, S.; Deo, R.C.; Raj, N.; Mi, J. Deep solar radiation forecasting with convolutional neural network and long short-term memory network algorithms. *Appl. Energy* **2019**, *253*, 113541. [CrossRef]
67. Zhang, L.; Wen, J.; Li, Y.; Chen, J.; Ye, Y.; Fu, Y.; Livingood, W. A review of machine learning in building load prediction. *Appl. Energy* **2021**, *285*, 116452. [CrossRef]
68. Ribeiro, M.H.D.M.; dos Santos Coelho, L. Ensemble approach based on bagging, boosting and stacking for short-term prediction in agribusiness time series. *Appl. Soft Comput. J.* **2020**, *86*, 105837. [CrossRef]
69. Ghoddusi, H.; Creamer, G.G.; Rafizadeh, N. Machine learning in energy economics and finance: A review. *Energy Econ.* **2019**, *81*, 709–727. [CrossRef]

70. Al-Musaylh, M.S.; Deo, R.C.; Adamowski, J.F.; Li, Y. Short-term electricity demand forecasting with MARS, SVR and ARIMA models using aggregated demand data in Queensland, Australia. *Adv. Eng. Inform.* **2018**, *35*, 1–16. [CrossRef]
71. Blazquez, D.; Domenech, J. Technological Forecasting & Social Change Big Data sources and methods for social and economic analyses. *Technol. Forecast. Soc. Chang.* **2018**, *130*, 99–113. [CrossRef]
72. GBD 2017 SDG Collaborators. Measuring progress from 1990 to 2017 and projecting attainment to 2030 of the health-related Sustainable Development Goals for 195 countries and territories: A systematic analysis for the Global Burden of Disease Study 2017. *Lancet* **2018**, *392*, 2091–2138. [CrossRef] [PubMed]
73. Touzani, S.; Granderson, J.; Fernandes, S. Gradient boosting machine for modeling the energy consumption of commercial buildings. *Energy Build.* **2018**, *158*, 1533–1543. [CrossRef]
74. Zhu, H.; Xiao, X.; Huang, X.; Rao, C.; Xiang, X. Time-lead nonlinear grey multivariable prediction model with applications. *Appl. Math. Model.* **2023**, *123*, 464–483. [CrossRef]
75. Song, J.; Wang, J.; Lu, H. A novel combined model based on advanced optimization algorithm for short-term wind speed forecasting. *Appl. Energy* **2018**, *215*, 643–658. [CrossRef]