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RESEARCH ARTICLE

Medium and Long Term Energy Forecasting Methods: A Literature Review

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ABSTRACT Estimating utility demand remains a significant challenge worldwide, being accuracy often compromised by numerous variables involved and limited relevant data available; this compromises models and impacts resource planning, infrastructure, and energy purchases. Energy systems must prioritize efficient resource utilization to address these challenges in the context of technological advances, economic changes, and environmental concerns. This paper conducts a bibliometric and systematic review of energy forecasting methods; the literature review covers the main studies conducted, including the most commonly used variables in forecasting studies, the techniques used, and the forecasting time horizon. As a result, the review presented here will facilitate the selection of the best models, variables, and time horizons for different forecasting applications.

INDEX TERMS Energy demand forecast, energy forecast, medium and long term forecast, energy price.

I. INTRODUCTION

In recent decades, due to the growing concern for the environment associated with climate change, the study of sustainable energy sources and optimization in the use and transmission of energy has driven the study of computational tools for the projection of consumption, projection of price, and target public evaluation within the energy market. Thus, as presented in [5], there is a growing concern for improvements in the development and operation of energy systems through energy forecasting techniques. Demand forecasting plays a fundamentally important role in the management areas of energy utilities, mainly related to resource planning and planning modifications to the working environment system, allowing for better operations management [4].

Forecasting energy consumption is a critical issue for utilities around the world, especially in emerging economies with diverse energy portfolios. Countries such as Brazil, India, Honduras, and South Africa, which rely on hydro, wind, solar, and biomass power, play a pivotal role in the global energy landscape. In these regions, energy sectors often operate in regulated contracting environments, such as Brazil's RCA model, where accurate forecasts are essential for informed energy contracting. Inaccurate forecasts can lead to financial losses, cash flow disruptions and higher tariffs for consumers, underscoring the universal importance of robust forecasting methods.

The Energy Market relies on availability and load information to determine the energy value. These factors, in turn, are defined by various variables: climatic, economic, socio-environmental, and cultural, among others, as well as endogenous factors related to energy companies (generation, transmission, and distribution), such as technical and non-technical losses, and the impact of exogenous variables on them [6]. Given the wide range of relevant factors and variables involved in this issue, it is essential to employ forecasting techniques to provide companies with predictions of energy behavior both at the demand level, which influences

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the amount of energy that will be generated, and the price to establish a market value for energy. These factors are crucial for future planning and the operations of their systems.

Energy demand forecasting models can be categorized as short-term, medium-term, and long-term forecasts. Short-term forecasts predict events that occur only a few hours or days in the future. Medium-term forecasting problems extend to a few weeks or months, while Long-term forecasting can extend into years. The selection of a modeling technique depends on factors such as the quantity of available data and its time horizon. Within this context, various sets of techniques can be identified in the literature and classified into two main groups: those employing regression techniques and those leveraging machine learning algorithms [15], [26]. However, there are often limitations/difficulties in data availability, which affect the results obtained in predictive models. Some methods that are employed to make electrical energy projections will be presented using machine learning and statistical techniques from the literature.

However, given the limitations in data availability, the quality of prediction models is affected. In this case, techniques such as Bayesian Networks allow the creation of scenarios based on technical knowledge for the composition of the model.

A. MOTIVATION AND CONTRIBUTION

The discussion on demand forecasting and energy pricing has become more relevant in recent years, mainly due to the diversification of energy matrices worldwide. This study presents a systematic and bibliometric review on energy demand and energy pricing forecasting, based on the discussion of scientific articles and forecasting studies carried out in different geographical regions in the world, Also focusing on the variables that are used by projection methods for different countries. In this context, the main contributions of this paper can be described as follows:

- **Bibliometric Analysis:** The paper presents a comprehensive bibliometric review of existing studies on demand forecasting, providing an analysis of the evolution of this research and its distribution by country, topic, and keywords. This allows researchers and experts to identify the main countries and fields involved in this area of research.
- **Systematic Review:** The study also conducted a systematic review of existing studies on energy forecasting, performing a critical analysis based on specific research questions. Based on the literature consulted this review will make it possible to identify the main variables, models, and applications in demand forecasting.

Based on the above, since energy demand and supply are factors that exist in electric utilities' daily routines and are currently not considered in their energy market forecasting models, this work has the potential to significantly contribute to the advancement of knowledge on the use of machine learning techniques in medium—and long-term energy market forecasting.

This paper is divided into five sections: Section I presents a brief introduction to the use of computational techniques for forecasting; Section II presents a bibliometric and systematic review of short- and medium-term demand forecasting. Section III contains the final considerations.

II. BIBLIOMETRIC AND SYSTEMATIC REVIEW

A. RESEARCH METHODOLOGY

For the development of the literature review, the work in [27], based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement, was used as a reference [1]. The methodology, shown in Figure 1, includes a bibliometric analysis that aims to map the scientific production, identify the research patterns, and evaluate the influence of the journals and the institutions in the field of medium and long-term forecasting.

First, a bibliometric analysis was performed using the words "energy forecasting" in the SCOPUS search platform, from which a base of 2009 papers was found. For filtering, the articles were limited to the English language. Then, in terms of document type, article, conference, and review were considered. In terms of a subject area, the papers were limited to "Engineering," "Energy," "Computer Science," "Mathematics," "Environmental Science," "Decision Sciences," "Economics, Econometrics and Finance," and "Business Management and Accounting." The papers were also limited to the keywords "forecasting," "energy forecasting," and "machine learning." This resulted in 1332 documents used for the bibliometrics presented in section II-B.

For the literature review, with the aim of answering the research questions posed in Section II-C, a more specific search was conducted. This is because most of the articles found deal only with the short-term horizon, while one of the interests of this study is to identify the variables and approaches used in long-term forecasting studies. The search was conducted on the Scopus platform using the following strings: "neural network" OR "deep learning" OR "machine learning" AND "predict" OR "prediction" OR "forecasting" OR "projection" AND "energy" OR "electricity" AND "price" OR "market" OR "storage" AND "long-term" OR "long-term" OR "mid-term" OR "medium-term." The search yielded 478 documents, which were filtered and limited to studies in engineering, energy, computer science, economics, econometrics, and finance, and the English language, reducing them to 423 scientific articles. From this first filtering, 237 articles, 153 conference papers, 15 conference reviews, 6 article reviews, and ten book chapters are the main articles found.

Similar searches were performed on other platforms, such as IEEE Xplore, SpringerLink, and DirectScience. The Prisma methodology was applied to this database with an individual review of the databases, from which 15 journal articles and 12 international conference papers were selected

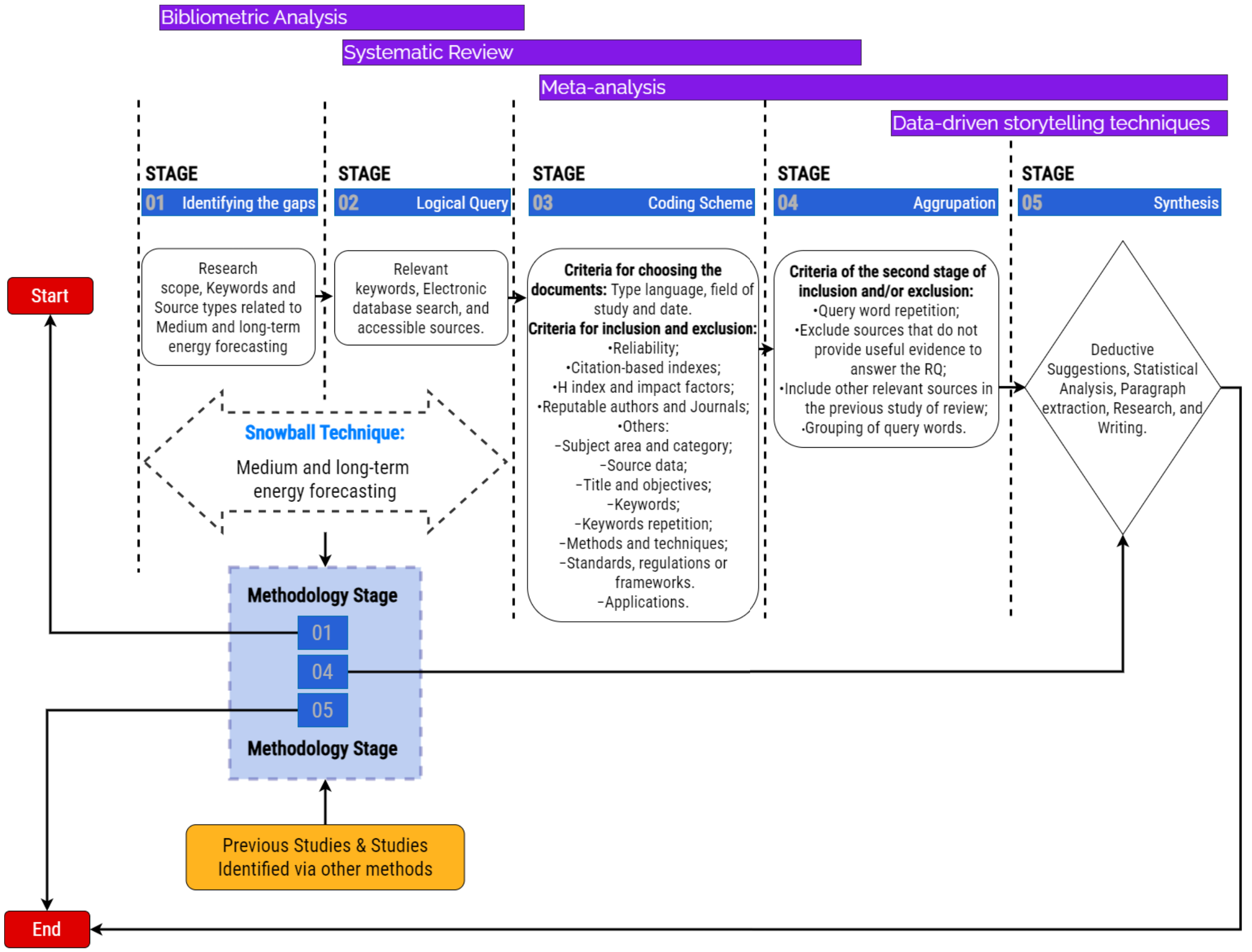

FIGURE 1. Methodology for literature review based on the PRISMA statement.

based on their relevance and application to the proposed study.

Considering that the authors have previously conducted literature reviews on medium and long-term forecasting, a section of previous studies and studies identified through other methods was considered to complement the methodology applied according to the first (1st), fourth (4th), or fifth (5th) methodological step. The snowball method, which consists of using an article's reference list or its citations to identify other articles on the analyzed topic, was also used in this work based on previous studies on the topic. The selected papers are also classified according to the methodological stage to complement the systematic review [3].

The keywords were then updated as a result of filtering the articles, which showed that the main applications for medium- and long-term forecasting, as shown in Table 1, are maintenance planning, energy rationalization, load forecasting for transmission and distribution, and seasonal trend detection. After analyzing the data, a systematic analysis was carried out, separating and grouping them according to the approach used. Finally, techniques for visualizing the synthesized data are used to graphically present the results of the proposed previous study.

To conduct the literature review, the following research questions (RQ) were defined to be answered. 1. RQ1: What variables are used in the literature with the greatest impact on predicting energy prices, consumption, and demand?; 2. RQ2: What are the most commonly used models and how accurate are they for medium- and long-term forecasts?; 3. RQ3: What is the application of neural networks in energy consumption forecasting and which countries have implemented these algorithms in predicting energy consumption? Based on the systematic review, the questions above will be answered in the following sections. 4. RQ4: How do modern hybrid and computational intelligence models improve energy forecasting compared to traditional methods?

B. BIBLIOMETRIC ANALYSIS

A survey of publications related to energy forecasting was conducted over the last 24 years, as shown in Figure 2.

TABLE 1. Main applications for time horizons.

Horizon of Prediction	Limits	Applications
Very short term	One minute to several minutes ahead	Power smoothing; Real-time electricity supply monitoring; Pricing for electricity trading; Photovoltaic storage control.
Short term	An hour to several hours or a day to a week	Economic load dispatch; Operation of energy systems; Real estate market control; Scheduling.
Medium term	One month to several months	Maintenance scheduling
Long term	One year to ten years	Energy rationing; Transmission and distribution; Detection of seasonal trends.

The results show that since 2014, the number of studies analyzing energy forecasting has increased, considering new variables such as renewable generation, especially intermittent generation such as photovoltaic solar energy and wind energy, as the keywords most involved in energy forecasting. In 2023, according to the survey, the largest number of studies on energy forecasting was carried out.

As shown in Figure 3, 55 % are journal articles, 40 % are papers presented at international conferences, and 5 % are reviews of articles related to energy forecasting.

Research on energy forecasting is led by the United States, China, and India, as shown in Figure 4. The United Kingdom, Spain, Germany, Australia, Canada, Italy, and France complete the top 10 countries with the most publications on this topic. According to the survey, Brazil, where this study was carried out, is in 20th place.

Figure 5 shows the fields of study related to energy forecasting. It can be seen that engineering and energy are the dominant fields, with a significant proportion of the research undertaken in the field of computation, but also including other categories such as economics and finance.

The relevant keywords within the analyzed studies are an important analysis based on the collected information. For this purpose, the VOSViewer software was used to generate a thematic map of the keywords according to the number of times they were cited in the studies, as well as the connections with other studies and keywords, as shown in Figure 6. To define and classify the universe of keywords, a clustering process was performed in the software, which resulted in three main areas: Energy Forecasting, Models Used for Energy Forecasting, and Variables Used in the Literature for Energy Forecasting, all of which will be discussed in the systematic review in the following subsections.

C. SYSTEMATIC REVIEW

1) RQ1: WHAT VARIABLES ARE USED IN THE LITERATURE WITH THE GREATEST IMPACT ON PREDICTING ENERGY PRICES, CONSUMPTION, AND DEMAND?

Several variables are used in the literature to predict the price, consumption, and energy demand, covering the economic-social, behavioral, climatic, and environmental spheres. Figure 7 presents a representation of the main variables according to the literature, their prediction horizon, and the main areas of application in which they have been used.

In the economic-social sphere, input variables such as population, GDP, employment rates, immigration rates, urbanization rates, and industrial production indices are often found in long-term projection studies. In addition, variables related to the development of tourism in a region, such as the number of hotels and accommodations, the number of tourists, and occupancy rates in accommodation, as presented in [15], and thus inferring that the level of economic development affects energy consumption [26].

In the behavioral domain, variables are developed that result from a behavioral mode or lifestyle of individual customers and groups of customers. This includes variables such as consumer profile and consumer group typology. In [7], the different requirements of each group of service users are addressed using parameters such as user satisfaction (the difference between the service offered by the company and the user's expectations) and the influence of other users to determine the consumption and sale of electricity.

Climatic conditions have a direct influence on energy consumption. For example, temperature variations impact the demand for cooling or heating environments, so their parameters are important for predictions, especially in the short and medium term. The variables used are temperature, dry bulb temperature, humidity, and wind speed [2], [16].

In the environmental field, the study of the correlation between renewable energy sources and the price of energy

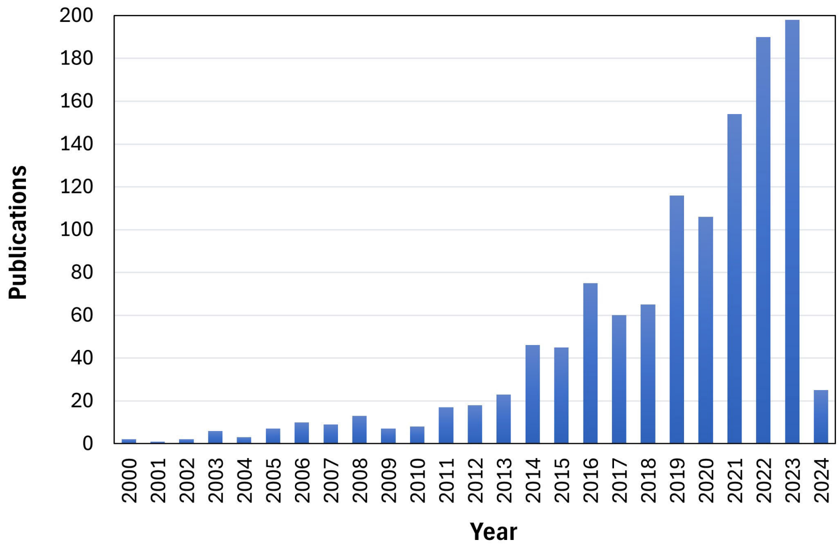

FIGURE 2. Publications related to energy forecasting in recent years.

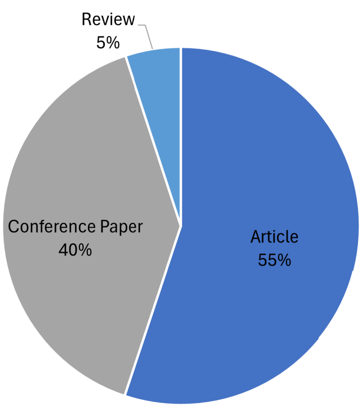

FIGURE 3. Distribution of publications by document type.

is noted, as presented in work [9], which presents the relationship between the consumption and production of renewable energy - such as solar, geothermal and wind - and the retail price of electricity, through which it is observed that with the increase in the price of energy, there is an increase in the adoption of renewable energy, as well as an increase in the rates of purchase of electric vehicles.

The importance of analyzing and identifying the variables that have a direct impact on both energy demand and price has been verified. In the publications, most of the variables used to predict energy demand were the same regardless of the technique used: number of consumers (residential, commercial and industrial), climate issues, especially temperatures, economic issues, losses (technical and non-technical) and energy consumption. In order to forecast energy prices, it is important to first identify the main source of energy generation for the region/country, as this will indicate which variables will contribute to energy price formation. If the main source of energy in a given region is fossil fuels, then the most important variables are economic and energy demand (supply and demand), as they will have a greater impact on the price. However, if the main source of energy generation is hydroelectric or wind power, the variables that have the greatest impact are climatic variables such as: stored natural energy, rainfall, currents, winds, among others.

In Table 2 the most commonly used variables for forecasting electricity prices and demand, according to the bibliographic references used in this review, as well as those used for forecasting by load level, i.e. by type of consumer, are shown.

Various criteria, such as geographical location, socio-economic factors, politics, and the climate of the region, influence the variables used in demand forecasting. At the residential level, climatic and socio-economic variables stand out as key factors, including population, gross domestic product (GDP) by consumer type, number of subscribers, electrification rate, energy tariff, and historical consumption data. In addition, the region's climate has a different impact depending on the geographical location. In regions where heating is not required in winter, such as much of Latin America, the temperature does not affect consumption, making climate a seasonal variable [12], [15].

At the commercial level, climate is one of the most influential variables, along with GDP. Some studies have also included tourism-related variables for forecasting demand, including the number of hotels, travelers, and average occupancy of hotel rooms per season [15], [26].

At the industry level and overall (including residential, commercial, and industrial sectors), studies such as [2], [7], [16], and [26] have used variables such as the share of

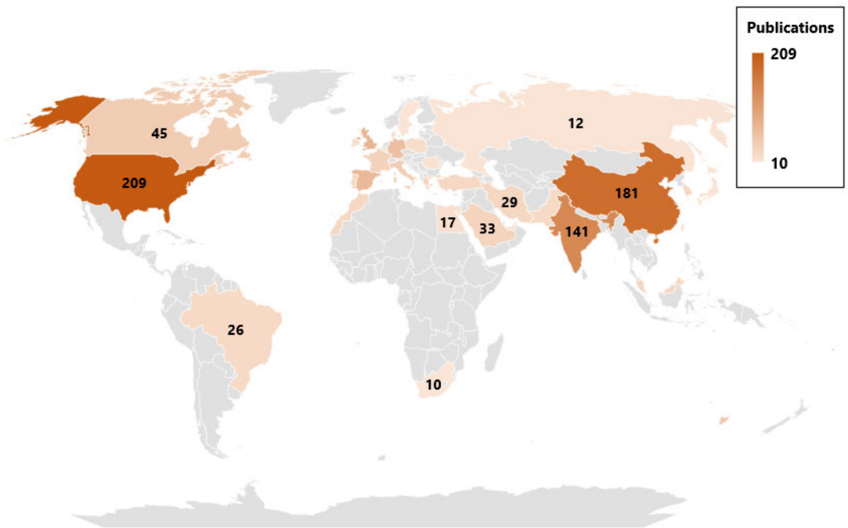

FIGURE 4. Distribution of publications related to energy forecasting worldwide.

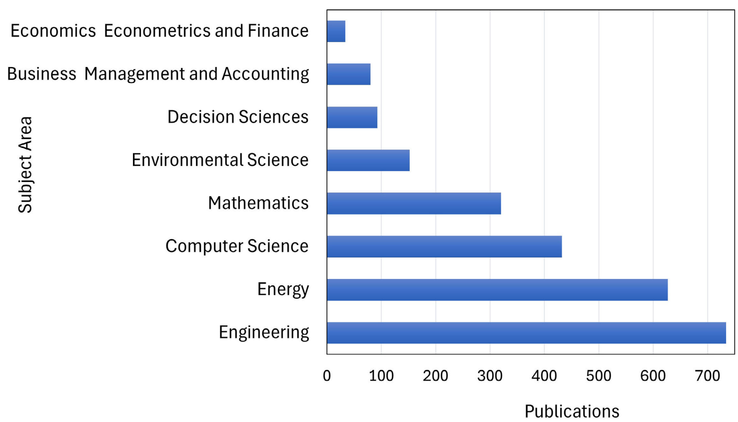

FIGURE 5. Distribution of studies by subject area.

industry, urbanization rate, holiday statistics, year-end population, holiday periods, humidity and wet bulb temperature, which are among the most commonly used.

In conclusion, planners should carefully analyze the variables influencing demand according to geographical, socio-economic, and behavioral aspects to achieve accurate and reliable forecasts.

2) RQ2: WHAT ARE THE MOST COMMONLY USED MODELS AND HOW ACCURATE ARE THEY FOR MEDIUM- AND LONG-TERM FORECASTS?

In [17], three time series forecasting methods are presented: statistical analysis, machine learning, and deep learning. Statistical analysis includes models such as ARIMA, which rely heavily on historical data but are not recommended for long-term forecasting due to the high variability of the data, that is, when the forecast is greater than 5 years it can no longer represent the real behavior of the forecast and begins to have a decreasing prediction curve. Machine learning uses methods such as K-NN (*K-Nearest Neighbors*), SVM (*Support Vector Machine*), and ANN (Artificial Neural Networks). These methods can establish relationships between historical data without considering internal mechanisms. On the other hand, deep learning uses backpropagation and recurrent neural networks to predict time series.

The study in [28] developed an improved ANN model with an Adaptive Backpropagation Algorithm (ABPA). The database used in this study is the monthly energy consumption data between 2011 and 2022 obtained from the Iraqi Ministry of Electricity. Neural networks with Multi-layer Perceptron (MLP) and a Backpropagation Algorithm (BPA) were used to develop the ABPA model to improve the accuracy of models that work with long-term prediction.

A proposed model for predicting monthly electricity prices for five future years is presented in the paper [9]. The analysis is based on a database created by merging data from different

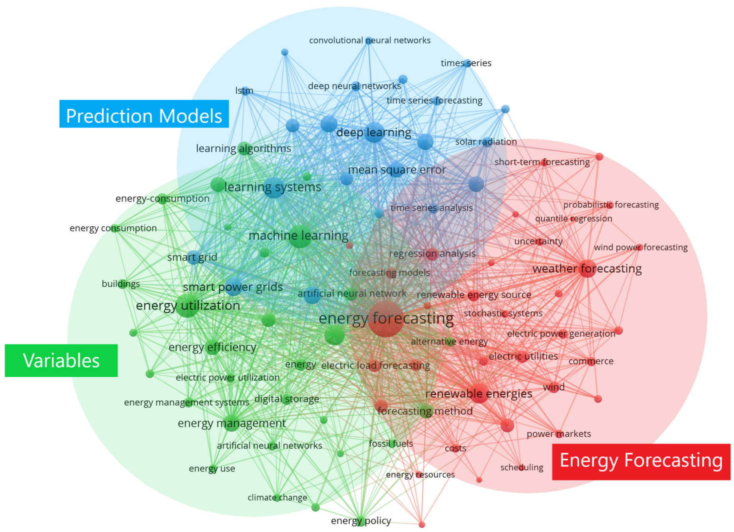

FIGURE 6. Thematic map of keywords separated by relevant categories.

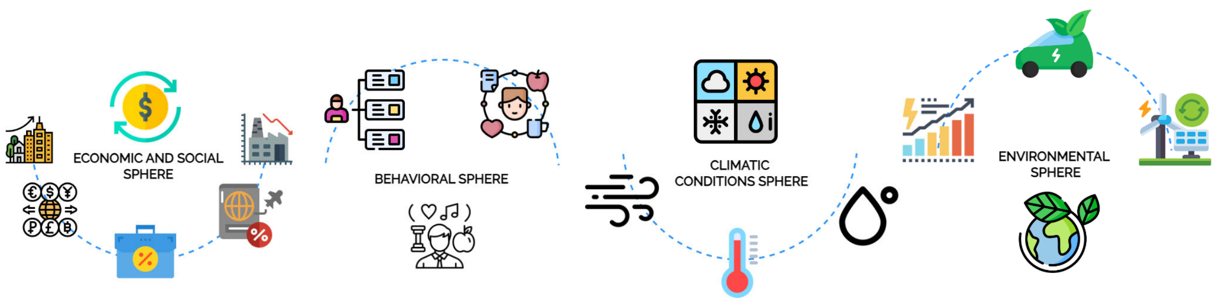

FIGURE 7. Independent variables related to price, consumption and energy demand.

energy companies in California[1] for January 2001 to August 2017. The Pandas Python library was used for data cleaning and two models were developed using the S-ARIMA method to find correlations between variables and electricity prices. The first model was designed to predict future energy prices over three years, using 2001 - 2014 as training data and 2014 - 2017 as test data to predict 2017-2020. The second model aimed at predicting future prices over five years, using 2001 - 2012 as training data, as a test 2012 - 2017, to predict 2017-2022.

An improved time series model using the S-ARIMA method for predicting monthly energy demand in Turkey for 2015-2018 is presented in [8]. The work used data from the Turkish Electricity Transmission Company (TEIAS) containing monthly energy consumption figures from 2002 to 2014. The model was evaluated using the MAE, RMSE (Root Mean Squared Error), and MAPE metrics.

The work in [18] presents the models *Recurrent Neural Network* (RNN), *Long Short-Term Memory* (LSTM) and *Gated Recurrent Unit* (GRU). Three types of variables are used. The *top-down* variables involve predicting energy use for groups, including data related to the economy, population, migration, and temperature. Bottom-up variables include data such as changes in energy load, distribution of energy resources, vehicle adoption rates, and active power demand from previous years.

In [24], SVM, DT (*Decision Tree*), ANN, GBDT (*Gradient Boosting Decision Tree*), GPR (*Gaussian Process Regression*), and MLR (*Multiple Linear Regression*) methods were applied to data from the Hong Kong Census and Statistics Department[2] and the Ministry of Housing and Urban-Rural Development in China, which were compared using MAPE, *Adjusted R-Square*, NMBE (*Normalized Mean Bias Error*), and CV-RMSE (*Coefficient of Variance Root Mean Squared Error*) metrics to select the model with the best performance for predicting residential and commercial demand.

The research carried out in [25]presents an approach to long-term electricity load forecasting in the state of Uttarakhand using Artificial Neural Networks (ANN). The model was developed to forecast electricity demand

[1] https://data.ca.gov/

[2] https://www.censtatd.gov.hk/hkstat/sub/so90. jsp

TABLE 2. Forecasting variables used in literature according to the specific sector.

Reference	Variable	Type of Load
[12]	a) Population; b) Gross Domestic Product; c) total number of subscribers (residential, commercial, industrial); d) Weather.	Mainly residential (67 %)
[15]	a) Historical load realization data for each type of load; b) Gross Domestic Product (GDP) for each type of load; c) The number of customers for each type of load; d) Inflation and economic growth as indicators of economic conditions; e) The tariff for each type of load; f) The electrification index, which is the ratio of households using electricity to the total number of households in a city or region; g) Electricity plan for new or existing customers; h) Tourism variables, number of hotels, number of travelers, number of occupied hotel rooms.	Industrial, Residencial and Comercial (Tourism).
[26]	a) Share of secondary industry (SR); b) Urbanization rate (UR); c) GDP. d) Population at the end of the year (POP) will have a significant impact on the total peak electrical load, based on previous studies.	Industrial Loads
[7], [29]	a) Combination of electricity sales data; b) Users' electricity consumption data; c) Electricity price information; d) weather data and vacation statistics.	Mix of Residential, Commercial and Industrial sectors.
[2]	a) Month index; b) Temperature; c) Relative humidity; d) Wind speed.	Mix of Residential, Commercial and Industrial sectors.
[16]	a) Variables were calendar (date, months of the year, non-working days per month); b) Weather factors (relative humidity and wet bulb temperature).	Mix of Residential, Commercial and Industrial sectors.

from 2021 to 2030, incorporating input variables such as socioeconomics (state GDP), population growth, historical load data, climatic factors, and new factors such as electric vehicle infrastructure and renewable energy sources. The dataset was divided into 2011-2015 training, 2016-2018 validation, and 2019-2020 testing. The artificial neural network approach proved more accurate and adaptable than traditional models, especially when incorporating modern variables such as electric vehicles and renewable energy. The research provides a robust predictive model to guide energy policies and infrastructure investments to meet future demand.

The study in [10] presents an MLR model for predicting energy demand based on economic indicators and analyzing future trends. The input data collected covers 36 years from various government sources. This study highlights the importance of the forecasting process for developing and planning energy distribution and shows the relevance of economic data for energy demand.

The article [33], introduces the Heteroscedastic Temporal Convolutional Network (HeTCN), an advanced model for electricity price forecasting in the day-ahead market. The proposed framework integrates an encoder-decoder architecture with methodologies designed to capture heteroscedastic uncertainties. The Temporal Convolutional Network (TCN) is employed to extract long-term temporal patterns, price cycles, and complex dependencies, while a Deep Neural Network (DNN) incorporates the TCN's output to generate both point forecasts and uncertainty estimations. Furthermore, the heteroscedastic output layer simultaneously predicts the mean and variance of electricity prices, effectively addressing uncertainty in volatile market conditions. To classify methods and applications, Table 3 shows the main models and variables used in the literature, its forecast horizon, and the location where it is used worldwide.

3) RQ3: WHAT IS THE APPLICATION OF NEURAL NETWORKS IN ENERGY CONSUMPTION FORECASTING, AND WHICH COUNTRIES HAVE IMPLEMENTED THESE ALGORITHMS IN PREDICTING ENERGY CONSUMPTION?

The paper by [21] uses four types of neural networks - Feedforward: Neural Network (FFNN), Long Short-Term Memory Neural Network (LSTM), Bidirectional LSTM Neural Network (Bi LSTM), and Gated Recurrent Unit (GRU) Neural Network for the prediction of energy consumption for 10 and 20 days into the future. The 2014-2018 data used were collected from the ADMIE (Independent Electricity Transmission Operator), located in Greece.[3] RMSE (Root Mean Square Error) and MAPE (Mean Absolute Percentage Error) were used to evaluate these models. In addition, chaos

[3] www.admie.gr

TABLE 3. Summary of articles published between 2019 and 2022 related to energy forecasting.

Time Horizon	Literature Survey and Insights	Model	Independent Variables	Location
Next-Day Energy Spot Price Forecast	The literature review highlights the evolution of electricity price forecasting methods, emphasizing the integration of machine learning and deep learning techniques. It discusses advanced models, such as deep neural networks and long-term memory networks, alongside traditional methods, such as support vector machines (SVM) and autoregressive moving average (ARMA) models. The review notes the limitations of static models and the importance of feature selection techniques to improve prediction accuracy. It also highlights recent innovations, including hybrid models and improved grid search algorithms, which have shown significant improvements in forecasting performance compared to traditional methods [31]	LSTM-IGS	Holidays, Significant Events, and Historical Series of Energy Prices	Australian
Electricity consumption forecast for the next 24 hours	Develop improved versions of DeepAR that can reduce error propagation in long-term forecasts and incorporate climate, socioeconomic, and behavioral data to enrich forecasts [48]	LSTM, DeepAR and K-means	Energy consumption	Dortmund - Germany
Energy price forecast for the next 48 hours	Using a parameterized Gaussian distribution to model electricity prices simplifies the underlying complexity, which may limit the model's accuracy. Future research should explore a wider range of probabilistic distributions to represent real-world data better [33]	Heteroscedastic Temporal Convolutional Network (HeTCN)	Electricity prices, historical generation forecasts and historical load forecasts	Datasets: Nord Pool, PJM, EPEX-BE, EPEX-FR, and EPEX-DE
14-day future energy demand prediction	The article identifies several challenges in load forecasting methodologies, particularly the lack of consideration of internal physical factors such as occupancy and internal system efficiency, which can increase energy demand in older infrastructure; possible changes in power system layouts, such as the redistribution of transmission losses, may require a re-evaluation of forecasting methods. It points to future research to improve forecasting models, including incorporating electric vehicles and the variation of electricity prices in consumption patterns [20]	LSTM	National demand projection, wind generation projection, transmission demand projection and solar generation projection	United Kingdom
Electrical load forecast next week and next month horizons	Future work could explore long-term forecasts, and include variables such as holidays and population growth that can impact energy load [34]	LSTM	Meteorological and historical load	Odisha - Indian
Energy load prediction for ten days and 20 days in the future	The article addresses the challenge of accurately forecasting electricity load in Greece, as there are areas with abrupt changes in load values. It highlights the chaotic behavior of load time series and the limitations of traditional forecasting methods	FNN, LSTM, Bi LSTM and GRU	Electricity load per hour	Greece

TABLE 3. *(Continued.)* Summary of articles published between 2019 and 2022 related to energy forecasting.

Time Horizon	Literature Survey and Insight	Model	Independent Variables	Location
	in capturing these dynamics. A new approach is proposed that combines deep learning recurrent neural networks with chaos theory, specifically using Lyapunov time to improve forecast accuracy. Further research is needed on the stability and adaptability of models in long-term forecasting in dynamic environments [21]			
Monthly peak load prediction	The article highlights that future research on electricity load forecasting in Cambodia should focus on developing more sophisticated models incorporating a wider range of influencing factors, such as economic indicators and consumer profiles. There is a need for comparative studies between machine learning-based forecasting methods and traditional statistical approaches to identify the most effective techniques for different contexts. Finally, the article points out that while neural networks are promising, there is a lack of widespread application and validation of these models in the Cambodian context [16]	Linear Regression and ANN	Days, month of the year, relative humidity, dry bulb temperature, rest days	Kingdom of Cambodia
Monthly Forecast of Electricity Spot Prices	The study shows that the spot price of energy is very volatile and that the linear regression method is unable to represent the relationship between the variables, especially in the medium and long term, which is why the trend is to use hybrid methods to obtain more accurate results [32]	Linear Regression and Neural Network	Historical Series of Electricity Prices	Shanxi
Forecast of Electricity Consumption for the Next 2 Months	The article's literature review highlights the importance of time series forecasting models for understanding energy consumption patterns. It emphasizes the need for comparative studies that evaluate different forecasting models under similar conditions, as existing research has not extensively explored models that incorporate multiple factors, such as temperature and price. The review also discusses the limitations of previous work, which has generally focused on exploring a single variable for prediction, but without exploring how models behave with additional parameters, such as holidays, that can affect performance. Exploring the integration of renewable energy sources into forecasting models is another important direction for future research. The study shows that the spot price of energy varies greatly and that the linear regression method is not able to represent the relationship between the variables, especially in the medium and long term, so the tendency is to use hybrid methods to obtain more accurate results [29]	Random Forest, XGBoost, SARIMAX, FB Prophet and CNN	Historical Profiles of Load, External Temperature and Prices	Sweden
Monthly prediction in 4 future months	The article highlights the challenges of forecasting periodic energy consumption, emphasizing that traditional forecasting methods often ignore the periodicity of time series data. It discusses the	LSTM	Data from cooling equipment	China

TABLE 3. *(Continued.)* **Summary of articles published between 2019 and 2022 related to energy forecasting.**

Time Horizon	Literature Survey and Insight	Model	Independent Variables	Location
	limitations of existing models, such as autoregressive moving average (ARMA) and autoregressive fractional integrated moving average (ARFIMA), which do not adequately capture the periodic nature of energy consumption data. It mentions the need to include other variables in addition to the target, as well as the importance of using autocorrelation graphs to extract hidden characteristics. The paper emphasizes that future research will focus on developing a hybrid model that combines the LSTM with other forecasting models, aiming to take advantage of the strengths of different models to improve forecasting accuracy and reliability, since the LSTM has limited behavior with missing data. And to investigate other variables that directly affect energy consumption [17]			
Prediction of 6 future months	In the method proposed in this work, there is a risk of the algorithm getting stuck in local bounds, so the hyperparameters should be analyzed. Future research could focus on refining the method for calculating the rotation rate in the electricity market to improve the prediction of the number of users. Investigating the integration of more complex algorithms beyond simple neural networks and linear regression could improve the detection of complex patterns in sales data and explore the impact of external factors, such as economic changes and user behavior, on electricity sales forecasting, which could provide important insights [7]	Deep Trust Network	Electricity sales in kWh, User energy consumption, peak time price, normal price, variation in energy prices, maximum temperature, minimum temperature, average temperature, rainfall, day of the week, holiday symbol	China
Monthly energy demand for 10 future months	The traditional Back-Propagation Algorithm (BPA) struggles with long-term prediction because the optimal weights obtained during training become less representative over time, especially when future data sets exhibit different behavior than the trained data sets, especially during unprecedented events such as the COVID-19 outbreak. The Adaptive Backpropagation Algorithm (ABPA), on the other hand, requires significant differences in behavior between training data sets, which may not always be present in real-world scenarios [28]	ANN-ABPA	Monthly energy consumption	Iraq
Monthly prediction over 1 year	Several forecasting methods have been used, including econometric methods, autoregressive models, and regression models, with artificial neural networks (ANNs) being used for their ability to model nonlinear problems, indicating that ANNs outperform traditional methods such as regression and ARIMA in forecasting accuracy, especially for seasonal data. However, in some cases, ANNs struggle to detect seasonal patterns in forecasts. There is a lack of research on the impact of	ANN and S-ARIMA	Monthly energy consumption	Turkey

TABLE 3. *(Continued.)* **Summary of articles published between 2019 and 2022 related to energy forecasting.**

Time Horizon	Literature Survey and Insight	Model	Independent Variables	Location
	external factors, such as economic indicators or demographic changes, on electricity demand forecasting. Comparison with SARIMA is limited, and further exploration of hybrid models combining ANN with other forecasting methods may be beneficial [8]			
Prediction of energy load within 1 year in the future	The study highlights how future research could explore the integration of renewable energy sources into load demand forecasting models, taking into account their characteristics that may influence load patterns. Investigate the impact of tourism, economic and population growth variables on demand forecasting, as these variables contribute to an increase in electricity consumption [15]	LSTM-RNN, MLR	Energy load consumption for each type of consumer, GDP, number of customers per type of consumption, savings indicators, tariff per type of consumption, ratio between the number of households consuming and the total number of households, existing electricity plans and tourism-related variables	Bali Province
Prediction of peak monthly energy load one year in the future	The article shows that the linear regression model produces large errors, suggesting a limitation in its ability to accurately predict peak loads compared to the neural network model, which accounts for non-linear relationships. The performance of the neural network model, although satisfactory, could be improved with more training and test data, indicating a potential weakness in the robustness of the model due to limited data availability. Another point is to investigate the impact of economic and demographic factors on load forecasting, which may provide a more comprehensive understanding of electricity demand patterns [2]	ANN	Month, temperature, relative humidity and wind speed	Oman
Seasonal energy load prediction in 1 future year	The study points out that there is a potential for overfitting in the models, especially when using deep learning techniques, which can lead to poor generalization in unseen data. The training algorithms used can require significant computational resources and time, especially for complex models, which can be a limitation in practical applications. The performance of the models can be influenced by the choice of the activation functions of the training algorithms, and the process of selecting this function, as well as the hyperparameters, is complex and computationally expensive. It is worth investigating the impact of additional variables, such as economic indicators and consumer behavior patterns, on load forecasting models, which could improve forecasting results [19]	MLP	Day of the week, time of day, dew point, dry bulb temperature and day of the month	New York
Energy load prediction for 1 and 3 years ahead	The article uses advanced sequence prediction models, specifically Long-Term Memory (LSTM) and Closed Recurrent Unit (GRU), to improve prediction accuracy by capturing the sequential characteristics of multi-year data. The two models	LSTM and GRU	Economy, population, temperature, changes in energy loads, adoption of electric vehicles and demand from the previous year	Canada

TABLE 3. *(Continued.)* Summary of articles published between 2019 and 2022 related to energy forecasting.

Time Horizon	Literature Survey and Insight	Model	Independent Variables	Location
	produce similar results, so consideration should be given to developing other hybrid methods with other forecasting techniques, as both hit and miss the same points and do not complement each other. Research could also focus on refining temperature normalization procedures, exploring more economic characteristics, and using renewable energy [18]			
Weekly Energy Forward Curve over 2 years	The article highlights the complexity of setting contract prices in the Brazilian energy market, where the PLD is insufficient to value long-term contracts due to the influence of various factors such as energy balance, tariff projections and marginal expansion costs. It notes the lack of standardized comparison between different forecasting methodologies due to different forecasting horizons and data sets. The study highlights that none of the models effectively predicted significant price fluctuations, indicating the need to include exogenous variables to improve forecasting accuracy [14]	SARIMAX, LSTM, GRU, CNN-LSTM	Weekly Energy Forward Curve	Brazil
Energy demand prediction for three future years	Traditional Grey models have limitations, particularly their inability to predict complex sequences due to fixed forms of accumulation accurately. The model proposed in this paper has limitations in accurately predicting electricity consumption during unprecedented events such as the COVID-19 pandemic, which caused significant deviations between actual and predicted values. This indicates a potential weakness in the model's adaptability to sudden external changes [23]	Discrete Grey Model	Monthly electricity consumption	Hubei, China
Monthly electricity price prediction for 3 and 5 years ahead	In this region, there are extremely influential factors such as the political-economic climate, changes in international policy that cannot be predicted, and weather patterns that significantly affect electricity prices on a daily basis. A fundamental limitation of the forecasting technique used in this work is the inability to account for these unpredictable external influences [9]	S-ARIMA	Natural gas consumption, monthly generated energy, net energy generation, net energy imports, GDP, renewable energy	California
Prediction of energy consumption for 4 future years	One of the main weaknesses of the approach is the potential for overfitting, which is a common problem when using deep learning techniques, especially convolutional neural networks. The complexity of multivariate time series data can pose challenges in accurately capturing the underlying patterns, especially when seasonality and non-linear characteristics are present. Future research could explore other variables, such as economic and climatic, to improve the analysis of electricity consumption trends [11]	CNN-SVM	Energy consumption per minute	France

TABLE 3. *(Continued.)* Summary of articles published between 2019 and 2022 related to energy forecasting.

Time Horizon	Literature Survey and Insight	Model	Independent Variables	Location
Prediction of energy demand for future decades	The paper shows how the existing literature does not adequately address the impact of socio-economic development on electricity demand over long time periods. Future research should focus on investigating the uncertainties associated with different representative concentration pathways, global circulation models, and socio-economic development pathways that can help improve forecast reliability. Analyze updating the hyperparameters of the gradient boosting decision tree algorithm to improve forecast accuracy [24]	SVM, DT, ANN, GBDT, GPR and MLR	Monthly energy consumption by sector (commercial and residential) and climate data	China
Prediction of energy load for future decades	The model does not explicitly account for unexpected or extreme events, such as natural disasters, abrupt economic fluctuations, or global energy crises, which can significantly affect the long-term forecast. Future research will combine artificial neural networks with deep learning techniques such as CNNs or LSTMs to try to capture seasonal patterns and long-term trends [25]	ANN	Socio-Economics, Historical Load Data, Electric Vehicles and Renewables	Uttarakhand - Indian
Energy demand prediction for the years 2022 to 2032	The reliance on certain input parameters, such as GDP, population, and historical load, may not capture all factors that influence electricity demand. The study does not address how external factors, such as economic fluctuations or changes in consumer behavior, may affect the model's long-term projections. Future research could focus on analyzing load requirements in various sectors beyond the scope of the current study. This could include sectors such as transportation and energy consumption patterns. Investigating the impact of emerging technologies, such as electric vehicles and their charging infrastructure, on electricity demand could provide valuable information [22]	ANN	Electricity demand, GDP, population growth, number of consumers and demand projection for the years 2025 to 2030	India
Energy consumption forecast 2019 - 2028	Investigating the impact of different neural network architectures, such as varying the number of layers and hidden neurons, could lead to better forecasting results. In addition, the integration of more diverse data sets, including external data such as weather patterns, economics, and both technical and non-technical losses, could help improve the robustness of electricity consumption forecasts. Finally, comparative studies between ANN and other emerging forecasting methods can provide information on their relative effectiveness, leading to hybrid methods [13]	ANN	Energy consumption, number of customers, GDP and population	Indonesia
Demand Forecast for the next 11 years	Future research should focus on comparing parametric regression and ARIMA models with non-parametric methods, such as artificial neural networks and fuzzy logic, for long-term load forecasting, as this comparison aims to evaluate the effectiveness and accuracy of different forecasting techniques. In addition, further analysis can explore the integration of more advanced machine learning techniques and data-driven approaches to improve forecasting performance [30]	Multiple Linear Regression, ARIMA	Population, Gross Domestic Product, Oil Price, Renewable Energy Generation, and Temperature	Jordan

TABLE 3. *(Continued.)* Summary of articles published between 2019 and 2022 related to energy forecasting.

Time Horizon	Literature Survey and Insight	Model	Independent Variables	Location
Prediction of energy demand for the years 2011-2025	In addition to the proposed multiple regression model, future studies may explore using artificial intelligence or stochastic methods to improve the accuracy of electricity demand forecasts. This could increase the accuracy of estimates and provide a broader understanding of electricity consumption patterns. Investigate the impact of variables such as GDP, commercial and industrial growth patterns, and climate variables [10]	MLR	Total population, per capita energy use and fossil fuel consumption	Pakistan
Prediction of consumption between 2016 and 2040	There is potential to explore the integration of socio-economic variables that may influence electricity consumption patterns in Uganda and similar regions. In addition, studies could examine the impact of policy changes on electricity consumption trends that directly affect projections [12]	PSO-ABC and ANN	Energy consumption, population, GDP, number of consumers (residential, commercial and industrial) and average energy load from 1990 to 2016	Uganda
Prediction of various factors for the years 2015 to 2060	The study focuses mainly on the relationship between temperature and energy consumption and ignores other important factors that influence electricity demand, such as economic development and urbanization. Future research could focus on the regional impacts of climate change on electricity demand, as most existing studies analyze this at the national level, leaving a gap in regional analysis. Investigate the long-term effects of urbanization and population dynamics on energy consumption under different socio-economic pathways, as this can provide important information [26]	Linear Regression	Energy consumption, temperature, urbanization rate, PBI, total annual population	Beijing, China

theory was used to define the prediction time horizon with the highest possible accuracy.

In [19], a Deep-Feed Forward Neural Network (Deep-FNN) with sigmoid transfer function and Rectified Linear Unit (ReLu) activation function is presented for predicting energy load over the seasons. As a database, it is used information on energy load between 2010 and 2018 collected by NYISO,[4] which highlights the variables of temperature, time of day (*Time Effects*) and peak times (*Effect of Load*) and how they affect the amount of energy used.

In [11], the complexity of working with data with seasonal and non-linear characteristics is highlighted, given that when considering the challenge of optimal forecasting, the seasonal treatment can be expected to be very important for short-term forecasting, more specifically forecasting for a horizon of less than one year. In this first phase, the data from the multivariate series are transformed into a multichannel image using Convolutional Neural Networks (CNN), due to the need to encode the non-visual data so that it mimics the properties of visual data before using the Convolutional Neural Networks (CNN) method to facilitate visual recognition and classification. In the second phase, the modified data is input for the hybrid CNN-SVM model, which can work with multivariables. Then, in the third phase, key features are extracted from the trained model to make predictions with new inputs.

In [22], the energy demand analysis for a period of 10 future years (2022 - 2032) is presented through the use of ANN, using as input data the energy load, PBI, population growth, number of energy consumers, energy demand forecast between the years 2025 and 2030. The model was developed using MATLAB[5] (*Matrix Laboratory*) platform and evaluated using the MAPE metric. This is similar to the work that also uses input variables related to population, energy consumption, and demand for an ANN model that come from various sources such as *Uganda Bureau of Statistics*.,[6] *Electricity Regulatory*[7] Authority and the World Bank API's, from which data on population[8] and GDP[9] were obtained.

[4]ttps://www.nyiso.com/load-data

[5]www.mathworks.com

[6]http://www.ubos.org/publications/statistical-abstract

[7]http://www.era.or.ug/index.php/statistics-tariffs/tariffs

[8]http://api.worldbank.org/v2/en/indicator/SP.POP.TOTL?downloadformat=excel

[9]http://api.worldbank.org/v2/en/indicator/NY.GDP.MKTP.CD?downloadformat=excel

In [2]'s work, linear regression and neural network models are developed to predict monthly peak energy capacity using historical and climatic data from 2006 to 2010 from the Mazoon Electricity Company (MZEC), Omã. Two methods are compared in the work, using 2006 to 2009 as training data to predict monthly energy load for 2010 and finally validated using MSE and MAE metrics. These methods were calculated using the MATLAB tool.

The paper [15] presents a proposal to replace the current regression model (*Multiple Linear Regression*) used to develop the electrical infrastructure plan with LSTM (*Long Short Term Memory*) used in deep learning. Unlike *Standard Feedforward Neural Networks*, it has feedback connections and the ability to process single data points and temporal data sequences and is an improvement on RNN (*Recurrent Neural Network*).

The [16] study was developed based on data obtained from the department of the *National Control Center* (NCC) and the *Electricité Du Camdodge* (EDC), which is Cambodia's largest electricity company responsible for the generation, transmission, and distribution of energy. At the same time, the climate data came from *NASA Prediction of Worldwide Energy Resources*. The study aims to predict future year's monthly transmission peak load indices. Using MATLAB software, linear regression and neural networks are used as models to analyze peak load variations for the years 2010 and 2019. MAE and MAPE metrics are used to evaluate and compare the models.

In [20], a system for detecting high energy demand events at the national level is proposed. The system has been developed in two stages, the first performing energy demand forecasting using LSTM and the second performing dynamic filtering of potential energy demand peaks. The national demand forecast, the wind generation forecast, the transmission demand forecast, and the solar generation forecast were used as inputs, from which the Christmas weekends and holidays (December 23 to February 2) were removed.

The state of Odisha in India also used the LSTM algorithm to forecast the electricity load in the short term horizon in the range of one week to one month. The historical series of load data was collected from the Odisha Dispatch Center and the meteorological variables such as temperature, relative humidity, dew point, wet bulb temperature and wind speed were collected from the NASA database. The LSTM-based model was found to be highly effective, outperforming comparative methods and providing a robust solution for power system load forecasting. Future work could explore longer-term forecasting and include variables such as holidays that can affect power load [34].

The article [12] begins with a case study of Uganda, a country in a region that relies primarily on traditional forms of biomass energy (wood and charcoal) for heating and cooking. The energy load required is estimated to increase in the coming decades. In this sense, for the energy forecasting, the model used was a hybrid method of particle swarm optimization (PSO) and artificial bee colony (ABC), which performs better in global exploration. To select the variables, R-squared and p-values were used to find the significance of the independent variables in predicting the dependent variable. The data set was divided into two parts: the training set used to improve the model coefficients and the validation set used to evaluate the prediction performance using the MAPE and *R-squared* metrics.

In [13] it is shown through the prediction with the use of Artificial Neural Networks that with the growth of the population and the economic growth there is an increase in energy consumption and the number of customers. The developed model exhibits good prediction accuracy during the learning phase, however, in terms of the accuracy of the prediction results with the input variables determined, it did not show a satisfactory prediction using artificial neural networks when compared with the consumption estimated by the PLN RUPTL (*Electricity Supply Business Plan*) 2019-2028, which is carried out by the Department of Energy and Mineral Resources of the Province of West Java.

In [23], a prediction method is presented that is a variation of a (*Discrete Grey Model*) (DGM) for fractional seasonal data. Monthly electricity consumption data from 2010 to 2019, collected by the Hubei Provincial Bureau of Statistics, are used. The data is divided into four groups according to the season: Q1 (March to May), Q2 (June to August), Q3 (September to November) and Q4 (December to February). Throughout the paper, however, it will be noted that the projections for 2019-2020 differ significantly from the actual values due to the impact of the COVID-19 outbreak on energy consumption, particularly in the period between December 2019 and February 2020.

The work in [14] focuses on forecasting the forward curve of electricity prices in Brazil, using four forecasting models: SARIMAX (*Seasonal Autoregressive Integrated Moving Average*), LSTM (*Long Short Term Memory*), GRU (*Gated Recurrent Unit*), and the hybrid model CNN-LSTM (*Convolutional Neural Networks*). The data used for the price projection are the spot price, the PLD (Difference Settlement Price) and the forward price curve provided by Dcide. Historical data from the weekly energy price series from 2012 to 2016 were used to train the models, and the years 2017 and 2018 were used for testing. Forecasting is done on a weekly basis for both years. In this way, weekly forecasts of future energy price series with maturities ranging from 0 to 4 weeks (A+[0 - 4]) were made. In the end, the best models for each week of maturity were: the SARIMAX model for maturity forecasts (A+0 and A+4), the LSTM for maturity (A+1) and the CNN-LSTM for maturity (A+2, A+3). It can be seen that for large variations in future prices, none of the models was able to predict.

The article about [29] focuses on predicting energy consumption in Kalmar, Sweden, for the study different techniques for energy forecasting were analyzed such as Random Forest, XGBoost, SARIMAX, FB Prophet and CNN. The methodology aims to provide robust models that can accurately predict energy consumption, facilitating effective management in commercial environments. To increase the accuracy of the predictions, a multivariate time series forecasting problem approach was used, which allows for a comprehensive analysis by integrating different data sources such as historical load profiles, outdoor temperature profiles, and price profiles. The results of the forecasting methods were carried out over a two-month horizon, and the CNN model outperformed the others in terms of forecasting accuracy and flexibility.

The study by [30] approaches long-term demand forecasting in Jordan using statistical methods, i.e. a hybrid model that combines multiple linear regression (MLR) and autoregressive integrated moving average (ARIMA) techniques, to improve the long-term forecasting rate. The input data used are population, gross domestic product, price of barium oil, and renewable energy production. The historical training data covers 1990 to 2022, and the model forecasts demand for 2024 to 2035. Specifically, the ARIMA forecasting method proved superior to the MLR model in terms of time series adjustment, indicating greater forecasting accuracy. The forecasting results were divided into normal, optimistic, and pessimistic scenarios. Some important points were verified, such as extreme weather conditions significantly affecting electricity demand, refugee influx rapidly affecting demand growth, and stresses the infrastructure and public service sectors. Thus, the comparison between the MLR and ARIMA models shows that although ARIMA performs better, it can still be sensitive to the choice of orders and model parameters, which can affect the accuracy of the forecasts.

In [31] A hybrid model using long-term memory techniques (LSTM) based on an improved network search algorithm (IGS) is proposed for forecasting electricity prices. The algorithm (IGS) enhances the efficiency of hyper-parameter tuning and allows a systematic and precise selection of the ideal parameters for the LSTM model by integrating exogenous factors such as holidays and significant events into the forecasting model, thereby significantly improving the reliability and accuracy of price forecasting in the wholesale market. The very short-term (1-day) energy price forecasting was performed using LSTM-IGS, which proved to be superior to traditional methods such as LSTM, FFNN and their variations. Thus, exogenous variables directly affect energy market prices.

The article [48] presents a methodology for predicting demand and classifying electricity consumers based on the coincidence factor (CF), with the aim of optimizing tariff planning and demand management. Two neural network models, LSTM and DeepAR, were used to predict consumer behavior, taking into account temporal and seasonal characteristics. In addition, the K-means clustering algorithm was applied, integrated with internal and external CFs, to analyze long-term behavior and its impact on system load peaks.

In research conducted on [32] studies the forecasting of electricity prices in Shanxi Province. For forecasting, multi-model modeling was used, which includes regression, neural networks and added gray theory modeling. The model predicts the monthly spot price of energy, which helps new companies (which don't have much influence in the sector) to make transaction decisions. For short-term forecasting, regression and neural network algorithms were used, which proved to have a good accuracy rate. To improve things even further, gray theory modeling and triple exponential smoothing were added, which improved the reliability of the forecast results by allowing the treatment of extreme electricity prices that neural networks cannot handle.

A summary of the models according to time horizon, elaborated from the literature consulted in this study in Table 1, is presented in Figure 8. It can be observed that most of the existing models have been used in long-term horizon forecasting studies, while the number of models used for the short and medium term is reduced, mainly due to their effectiveness.

4) RQ4: HOW DO MODERN HYBRID AND COMPUTATIONAL INTELLIGENCE MODELS IMPROVE ENERGY FORECASTING COMPARED TO TRADITIONAL METHODS?

Over the years, energy forecasting has become increasingly challenging due to the high variability introduced by the growth of renewable energy sources. Traditionally, forecasting relied on physical methods—primarily mathematical models representing the dynamics of variables associated with renewable energy, such as climate. Statistical and deep learning approaches have also played significant roles. More recently, hybrid methods have gained prominence by combining and leveraging the strengths of these traditional techniques, thereby reducing prediction errors for specific applications. To identify trends in energy forecasting, a thematic map of leading models was created using the keywords "ENERGY FORECASTING" and "MODELS" on the SCOPUS platform, with the analysis conducted via VosViewer software. Figure 9 illustrates the primary models employed in studies, with a focus on those utilized from 2014 to 2024.

Machine learning (ML) and deep learning (DL) continue to dominate forecasting applications, with diverse methodologies tailored to specific objectives, such as predicting electrical load and energy consumption. For example, in [35], the authors focus on short-term load forecasting for a university campus in Canada, using regression models and historical consumption data from January 2016 to March 2020, identifying Gaussian process models as the most accurate. In contrast, [36] examines monthly electricity consumption in four European countries using Fuzzy Nearest Neighbor Regression (FNNR), demonstrating competitive performance against traditional methods such as ARIMA.

Furthermore, [37] provides a comparative overview of forecasting methods, highlighting the effectiveness of probabilistic approaches such as DeepAR and Any-Quantile Exponential Smoothing Recurrent Neural Network (AQ-ESRNN) in calibrating forecast intervals, though without delving

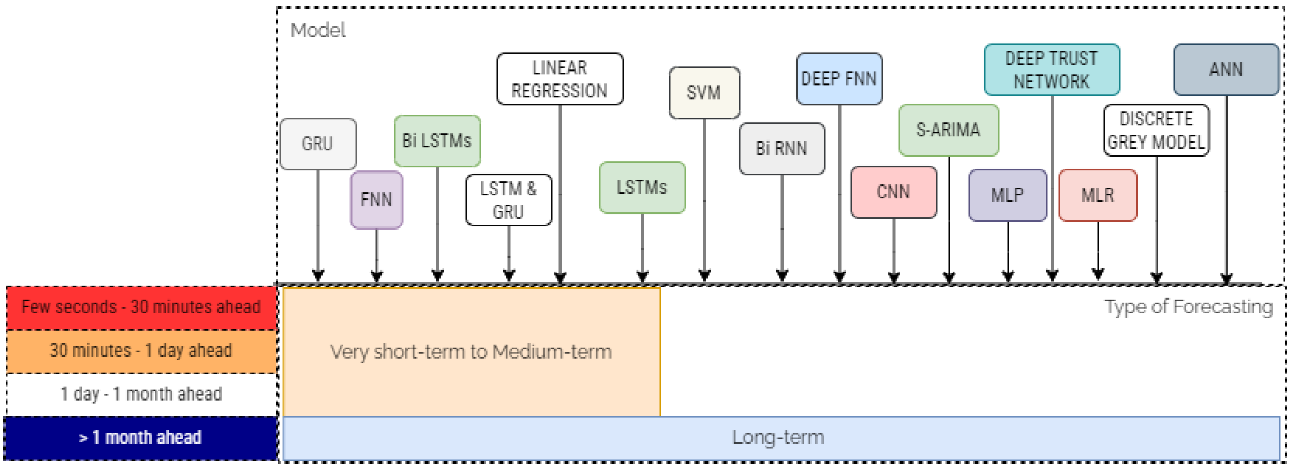

FIGURE 8. Time horizons models used in Literature according to the type of forecasting.

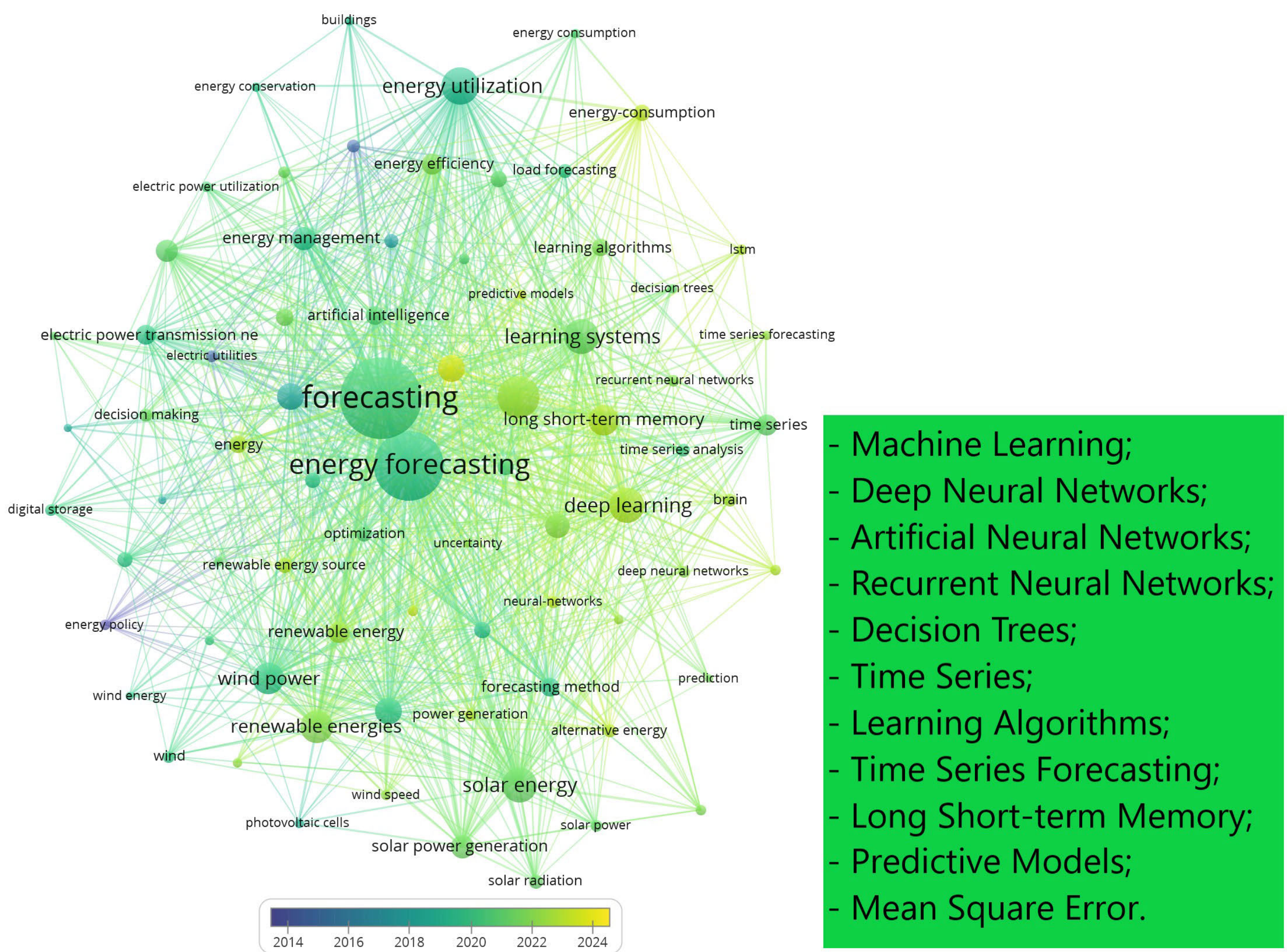

FIGURE 9. Forecasting models used in literature for energy forecasting for 2014-2024.

into specific datasets. These studies exemplify the diversity of approaches in electric load forecasting, ranging from regression models to advanced probabilistic techniques while underscoring the critical role of accuracy in energy planning.

Recent research in [38] and [39] highlights the effectiveness of hybrid models for energy load forecasting across varying time horizons and methodologies. In [38], medium-term forecasting for the Greek power system employs an ensemble approach combining Orthogonal Matching Pursuit (OMP) and Huber Regressor (HR), with evaluations spanning over 435 regression schemes and 64 feature modifications. This study underscores the significance of multivariate configurations and the inclusion of energy production data, resulting in marked improvements in prediction accuracy. In contrast, [39] investigates short-term single-step predictions using a voting regressor, which averages outputs from multiple base models. Based on 15-minute interval data from the CERTH-ITI smart home in Greece, this research emphasizes the impact of incorporating exogenous factors, such as weather conditions, on prediction performance. While both studies affirm the effectiveness of hybrid and ensemble methods, their focus differs, with [38] exploring a broader range of regression schemes and [39] emphasizing a specific voting regression approach.

Computational intelligence (CI) methods, including artificial neural networks (ANNs), genetic algorithms (GAs), fuzzy logic, and hybrid models, have gained traction due to their ability to manage nonlinear and complex data relationships [40], [41]. For instance, ANNs are extensively utilized for load forecasting and energy demand estimation [42], [43], [44] while GAs optimize forecasting models and parameters [45]. Fuzzy logic excels in short-term load forecasting by accommodating uncertainty and imprecision in the data [36], [46]. Hybrid models, which integrate multiple methodologies, demonstrate significant potential in enhancing forecast accuracy by harnessing the strengths of complementary approaches.

Hybrid methods have become increasingly prominent in energy forecasting problems, especially when multiple variables are used as model inputs. This approach combines complementary methods, as seen in [49], where time series decomposition and exponential smoothing methods are used for energy consumption forecasting. In [50], a set of neural network techniques is used for energy demand forecasting. The approach combines three different ANN models, each designed to capture different aspects of the time series. The results show that the proposed method outperforms traditional approaches such as multiple linear regression, SARIMAX, and conventional neural networks. The research of [51] also demonstrates the trend of using hybrid methods for time series forecasting. Although traditional techniques such as LSTM and neural networks are widely used, their combination complements each other, resulting in significantly better results.

Comparative studies consistently show that CI methods outperform traditional statistical techniques such as ARIMA, especially in nonlinear or discontinuous data scenarios. Hybrid models that combine CI techniques with statistical methods achieve superior performance metrics, such as lower root mean square error (RMSE) and mean absolute percentage error (MAPE), compared to standalone statistical models. [47]. These results highlight the limitations of traditional methods in capturing complex energy consumption patterns.

In conclusion, the comparative analysis of forecasting techniques shows that while traditional models such as ANNs and decision trees have advantages, hybrid and ensemble models that utilize feature importance and multivariate configurations offer superior performance. As the energy sector evolves, the adoption of these advanced forecasting methods will be essential to optimize energy management and ensure a sustainable energy future.

III. FINAL CONSIDERATIONS

Demand forecasting and energy price forecasting remain significant energy market challenges for experts. This paper's main goal has been to present a bibliometric and systematic review of studies related to medium—and long-term demand forecasting, focusing on identifying the main variables and models used in the literature worldwide for such applications. The bibliometric review allowed the authors to observe the growing number of studies related to demand forecasting and the main countries carrying out this type of research.

The systematic literature review, on the other hand, revealed that the independent variables in this study revolve around four spheres: socioeconomic, behavioral, climatic, and environmental, all of which influence price, consumption, and energy demand.

Electricity forecasting is a multidisciplinary field that requires the integration of multiple factors that interact in complex ways. The quality of data, the choice of modeling techniques, and the ability to capture and incorporate the most relevant variables determine the accuracy of forecasts. Accurate and reliable forecasts are more critical than ever in a global energy transition scenario The literature review shows that and increasing penetration of renewable energy sources.

The bibliometric analysis showed that research on energy prices and demand has grown in recent years. This is due to global climate issues and the high penetration of uncontrollable sources in electrical systems, which requires more flexibility in planning the expansion of electrical system generation and transmission. A variety of techniques for forecasting energy prices and demand in the short, medium, and long term have been reviewed in the literature. These techniques include statistical methods and machine learning techniques that are currently widely used, especially convolutional neural networks. It has also been shown which techniques are most commonly used for short-, medium-, and long-term energy forecasting. This shows that some techniques, when it comes to long-term forecasting, are not able to represent/generalize this forecast, so they use combinations of techniques, as shown in the literature.

Finally, the survey also showed that in many countries, energy price and demand forecasting takes into account several variables, not only the target energy variables (price and demand). This shows that the country's main source of energy generation is influential, i.e., in countries where the main source of energy generation is based on hydroelectric, solar, and wind power, climate variables are taken into account as they are directly influential. If the main source of energy generation is fossil fuels, GDP, population size, and other factors are taken into account, as shown in the literature.

Despite the aspects evaluated in this study, it is clear that some points still need to be explored, such as: carrying out a more in-depth investigation of the factors that affect the volatility of electricity prices; carrying out a detailed analysis of the impact of the climate variable temperature in relation to energy demand and prices. Most of the studies reviewed use neural network models, but as shown in some of them, these techniques have difficulties in dealing with outlier data, providing opportunities for research by analyzing other pattern recognition models for making predictions.

When it comes to long-term forecasting of electricity demand and prices, it is known to be a complex and challenging task, as it considers various variables with their historical series and patterns. We believe that flexible factors should be taken into account in the forecasts, such as the analyst's knowledge when performing a prediction. In other words, techniques that allow for this inference should be utilized to achieve increasingly accurate results.

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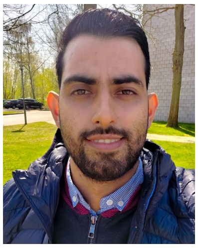

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