A review of short-term power load and renewable energy generation forecasting based on machine learning

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Abstract: Smart grid is an important development direction in today's energy field. With the rapid development of smart grid technology, the prediction of short-term power load and renewable energy generation has become a key link of smart grid. The prediction of short-term power load, wind energy and solar energy is crucial to the efficient and sustainable operation of power grid. Machine learning, as a powerful data analysis tool, has shown great potential in the field of power system forecasting in recent years. In this context, this paper presents a bibliometric analysis of the literature in this field over the last 15 years and describes some of the machine learning methods used in the literature, which were specifically developed for power load forecasting and power forecasting for wind turbines and solar panels. In addition, this paper compares different machine learning methods and discusses their similarities, with the aim of providing researchers with the choice of machine learning methods. This paper also discusses some of the data sets used in the literature that adapt to their proposed machine learning methods, so that researchers can better choose the appropriate data sets in future work. Finally, the challenges and prospects in the field of short-term power load and renewable energy forecasting are presented.

1. Introduction

The shift of power systems to renewable energy is a significant trend around the world today, as renewable energy responds to national policies around the world to reduce greenhouse gas emissions or other environmental damage. Renewable energy is expected to overtake coal as the dominant form[1] of electricity generation globally by 2025. Renewable energy is made up of a variety of energy sources, including solar, wind, hydro, biomass, geothermal and Marine power, which could meet nearly 40 percent of electricity demand[2] by 2030. This is shown in Figure 1. The white section shows the change in global electricity generation from 2000 to 2019, and the blue section shows the change in global electricity generation from 2019 to 2040 (in the established policy scenario).

Smart grid is an important development direction in today's energy field. The smart technology of power grid and advanced data processing methods enhance the management of renewable energy. In the context of carbon peaking and carbon neutrality, power load is an important part of the dual-carbon target plan, so the accurate prediction of power load is indispensable [3]. In the smart grid, the prediction of short-term power load and renewable energy occupies an important position. Due to the constant change of power demand and the uncertainty of renewable energy, some traditional forecasting methods have been unable to meet the high accuracy of forecasting, and accurate forecasting of power load and renewable energy (photovoltaic power generation and wind power generation) is the focus of the current smart grid. Renewable energy generation and power load can be predicted in a variety of ways, including the traditional statistical method [4], machine learning method [5], deep learning method [6], physical model method [7]. Although there are a variety of methods can be used to predict, but no method is perfect, each method has its advantages and disadvantages. Most of the physical models use solar radiation models and atmospheric dynamics models [8] to forecast, which require a large amount of meteorological data, and are not suitable for short-term forecasting, and the accuracy of the forecast can not meet the expected requirements. Traditional statistical methods include time series models, such as Kalman filter [9], ARIMA[10],

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seasonal autoregression [11], etc. However, due to the complexity of influencing factors, the prediction results of these time series models may not reach the expected results. On the contrary, Traditional machine learning methods include artificial neural network(ANN) [12], support vector machine(SVM) [13], and random forest(RF)[14], the prediction results of machine learning models are often more accurate than physical models and statistical methods, and can better deal with short-term prediction problems. The prediction model based on machine learning has achieved certain results in the prediction of wind speed, power load and solar irradiance. Zeineb Abdmouleh et al., in literature [15], outlined the optimization algorithms used to solve some problems of renewable energy distributed generator sets and the difficulties to be overcome. Finally, the researchers come to the conclusion that Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are the best methods to solve the programming optimization problem. Nursyuhada 'Kamaruzaman et al. outlined solar energy and biomass energy technologies in literature [16], and introduced the advantages of some related technologies, with the aim of providing valuable suggestions to managers of renewable energy. Finally, in order to ensure the efficiency of renewable energy generation, the authors put forward some directions for future development. The study [17] Outlines a number of machine learning methods for determining the size of photovoltaic systems, and concludes that machine learning algorithms can be well applied and optimized for size design, and can be used in remote areas. In reference [18], Zixu Zhao introduced the use of different machine learning models in electrical load prediction, and compared the advantages and disadvantages of each model with different test sets. Finally, it is concluded that the appropriate model should be selected according to the actual situation, and the future research direction is given. The rest of this paper is as follows. Section 2 introduces bibliometric analysis methods and data sources. Section 3 uses the bibliometric method to analyze the short-term power load and renewable energy forecast from 2009 to April 2024. Section 4 summarizes the application of various machine learning methods to short-term power load, wind and solar forecasts. Section 5 discusses the challenges facing the field and the outlook for the future. Section 6 draws conclusions from the discussion.

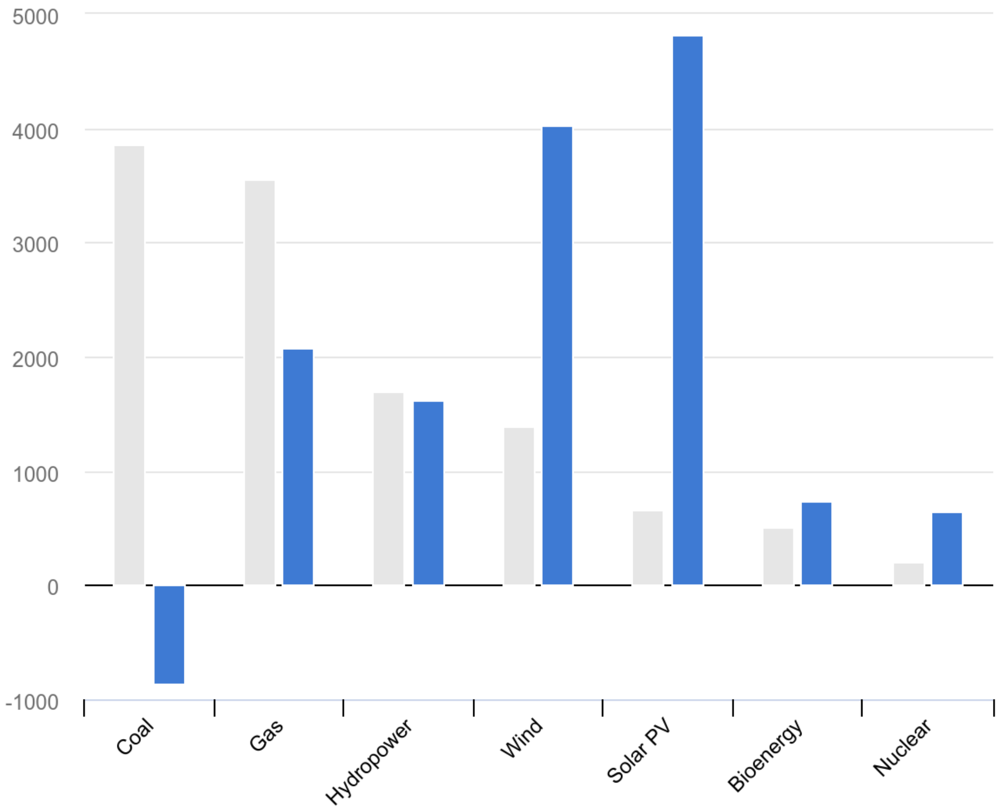

Figure 1 Changes in global electricity generation under established policy scenarios from 2000 to 2040[2]

2. Research Methods

2.1 Data Sources

In order to obtain more accurate research results, in the Web of Science (WoS) database, Enter as "Topic Search (TS) =(short-term load forecasting) OR TS= (photovoltaic power forecasting) OR TS= (wind energy forecasting) is used to search the published academic papers (journal papers + conference papers) all over the world, remove all kinds of irrelevant information and review, and finally get 6000 records, forming a literature database, which can represent the general research direction of this period to a large extent. There are 34 papers published between 2009 and 2014 (0.6%), and 5,966 papers published between 2014 and April 2024 (99.4%). It can be seen that worldwide, the research on distributed energy has been developing continuously since 2014, so we selected 5966 papers published from 2014 to April 2024 as the research data.

2.2 Analysis Methods

By using bibliometrics analysis method, frequency statistics and partial cluster analysis were performed on keywords, institutions and countries of 5966 literatures by CiteSpace software. Combined with literature reading and other methods, the short-term power load, photovoltaic power generation, wind power generation forecast was analyzed.

3. Quantitative analysis

3.1 Country analysis of literature publication

The map of the country cooperation network can clearly reflect the countries in which the literature on distributed energy prediction is particularly published, as well as the links between countries. In CiteSpace, taking country as the node, top30% literature analysis of each time slice (one time slice per year) was selected, and a country cooperative network diagram with 58 nodes and 222 links was obtained, as shown in Figure 2.

Figure 2 Map of the Distributed Energy Forecast published national cooperative network for 2014-2024

As can be seen from the figure, all countries in the world have conducted researches in this field to a certain extent, and the most published literatures are The People's Republic of China, which indicates that China attaches great importance to the research on distributed energy prediction. Due to the large population base in China, the demand for electricity is increasing year by year. Therefore, many Chinese scholars devote themselves to the study of power load and distributed energy forecasting, constantly improve the accuracy, optimize the forecasting methods, and make outstanding contributions to power generation in the power industry. In addition, the United States, India, Australia, South Korea, Italy, Spain and other countries have also made outstanding contributions to the research in this field.

3.2 Keyword Analysis

Make keyword co-occurrence map in CiteSpace. Keyword co-occurrence graph refers to the formation of a keyword network by analyzing the co-occurrence frequency of keywords in literature in a certain period, reflecting the relationship between keywords, so as to clearly and intuitively see the research hotspots and future trends in this field [19].

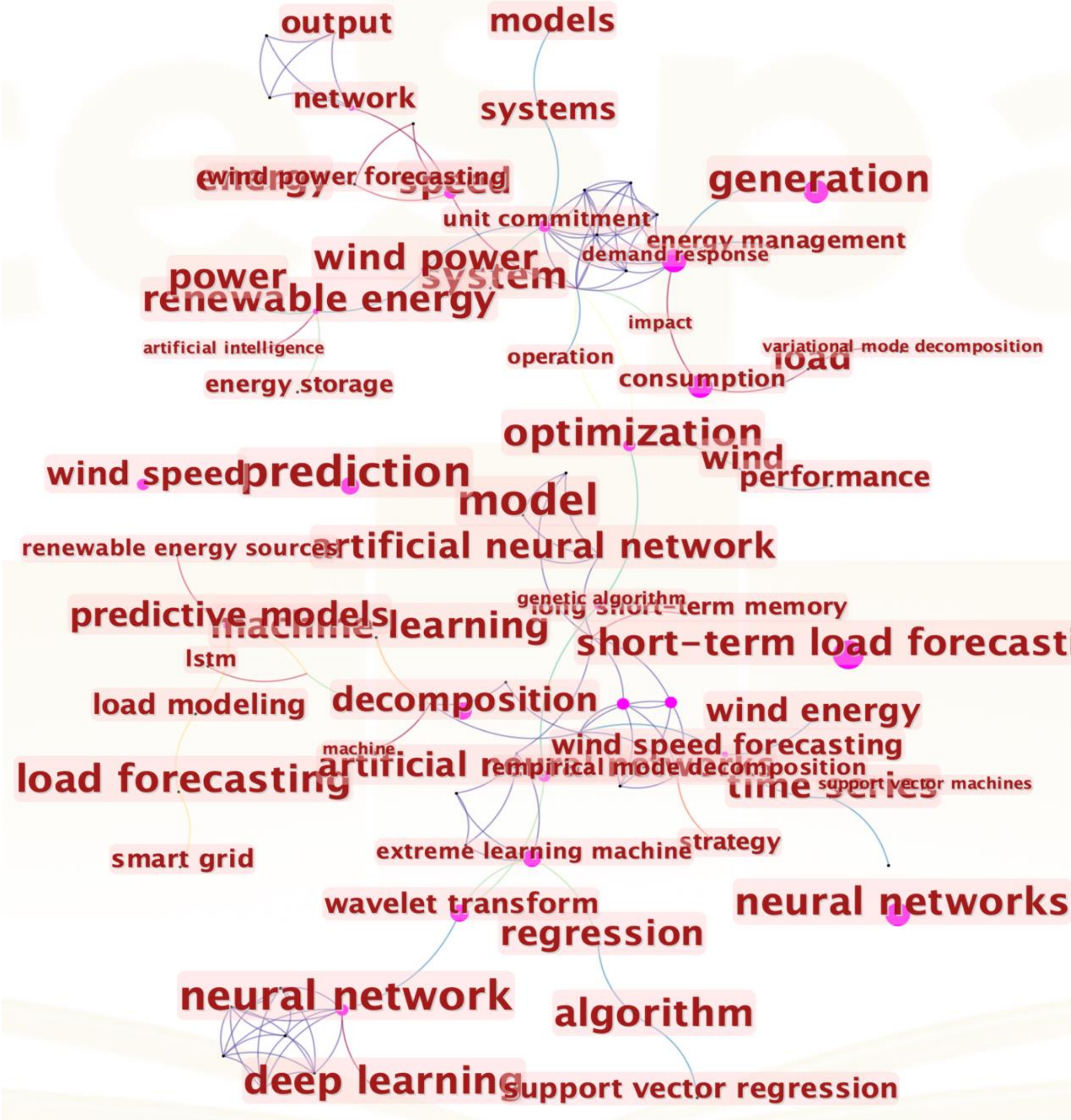

Figure 3. Keyword co-occurrence map of power load and renewable energy forecast from 2014 to 2024

Each year from 2014 to 2024 is taken as a slice to analyze the top 30% keywords, a total of 85. The table is drawn according to the occurrence frequency, intermediary centrality, and initial age. (See Figure 3)

Table 1 Top10 occurrence frequency of hot keywords and their related characteristics

Order Number	Keywords	Centrality	Count	Nascent Year
1	Model	0	986	2014
2	Neural network	0.32	667	2014
3	Load forecasting	0.05	517	2015
4	optimization	0.37	514	2015
5	Deep learning	0	490	2018
6	Short-term forecasting	0.99	401	2014
7	Machine learning	0	375	2018
8	Renewable energy	0.14	330	2015
9	Power	0	306	2015
10	Time series	0.1	301	2015

As can be seen from Table 1, model is the keyword with the highest frequency, because the prediction of short-term load, solar power generation and wind power all need to use model as a forecasting tool. Neural network, deep learning and machine learning are all the methods used for prediction in the current era. The machine learning method with the highest frequency is Neural network, including time series, which is also its component. The emergence of optimization is because the accuracy of prediction is low for a single machine learning method. When the optimization algorithm is used, the accuracy of prediction will be greatly improved.

3.3 Cluster analysis

Cluster analysis refers to the grouping of information objects based on the information found in the data describing objects and their relationships. CiteSpace provides the function of dividing the network into clusters and automatically labeling clusters [20] This paper uses CiteSpace to perform cluster analysis on keywords. Figure 4 shows 10 clusters. Modularity (Q value) of 0.7939 will generally be within the range of [0, 1]. If Q>0.3, this will indicate that the cluster structure will be significant [21]. In addition, Weighted Mean Silhouette's S value will be 0.9806. In addition, weighted mean Silhouette will be 0.7. The clustering is significant and S-values above 0.5 are considered to be reasonable. Q value and S value are the basis to judge whether the clustering is significant. It can be seen that the clustering divided in this paper is efficient and convincing.

Table 2 Specific information of ten clusters and their typical literature

Cluster	Size	Silhouette	Key Words	Typical Papers
0	11	0.987	deep learning; photovoltaic power forecasting; short-term memory; energy management; demand response;	Value of price responsive load for wind integration in unit commitment; Photovoltaic power forecasting with a long short-term memory autoencoder networks;
1	9	1	short-term load forecasting; artificial neural network; feature selection; partial mutual information; weather variables | deep learning;	An image inpainting approach to short-term load forecasting; A new hybrid approach of clustering based probabilistic decision tree to forecast wind power on large scales
2	7	0.969	heat demand solar power forecasting; data re-sampling; short-term building energy; signal decomposition	Els-net: a new approach to forecast decomposed intrinsic mode functions of electricity load; Multivariate ensemble forecast framework for demand prediction of anomalous days

3	7	0.976	Wind power forecasting; multidimensional data | deep learning; photovoltaic power forecasting; solar energy;	A benchmarking framework for performance evaluation of statistical wind power forecasting models; Assessment of critical parameters for artificial neural networks based short-term wind generation forecasting
4	3	0.994	deep learning; fluctuating pattern; multiple time series; sensitivity analysis | neural network; energy storage system; multiple time series	Ensemble residual networks for short-term load forecasting; Dynamic hybrid model for short-term electricity price forecasting;
5	8	1	wind turbines; wind energy conversion systems; multiple time series; trim aggregation | wind speed forecasting;	A self-adaptive evolutionary fuzzy model for load forecasting problems on smart grid environment; The study and application of a novel hybrid forecasting model - a case study of wind speed forecasting in China
6	6	0.939	load forecasting; statistical-dynamical downscaling; signal decomposition | predictive models; recurrent neural networks;	Ensemble residual networks for short-term load forecasting; A comparative analysis of neural networks and enhancement of elm for short term load forecasting
7	6	0.967	short-term memory; convolutional neural network; electric energy consumption; | wind speed forecasting; multi-objective optimization	A self-adaptive hybrid approach for wind speed forecasting; A hybrid forecasting model with parameter optimization for short-term load forecasting of micro-grids
8	5	1	renewable energy; energy storage system; electricity markets; distribution system; | wind energy; time series; wind power plants;	Battery Ess planning for wind smoothing via variable-interval reference modulation and self-adaptive soc control strategy; Recent trends in variable generation forecasting and its value to the power system;
9	5	0.959	wind energy; probability distribution; energy sustainability | wind speed forecasting; fuzzy inference; fuzzy type ii inference system; forecasting accuracy	Medium-term wind speeds forecasting utilizing hybrid models for three different sites in Xinjiang, China; A hybrid wind speed forecasting model based on phase space reconstruction theory and Markov model: a case study of wind farms in northwest China

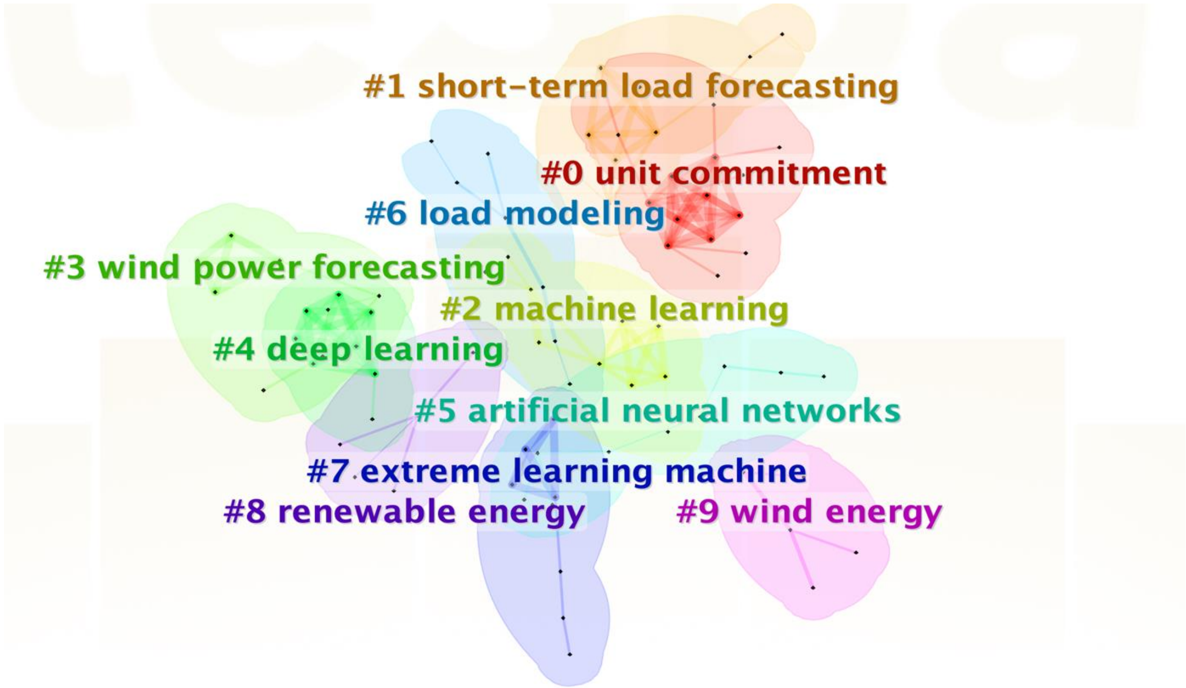

Figure 4 Keyword cluster analysis of power load and renewable energy forecast from 2014 to 2024

Table 2 shows the details of the 10 clusters.

The size of Cluster#0 is the largest, which indicates that short-term memory in deep learning and K-nearest neighbor algorithm in machine learning are most commonly used in the study of energy management and load management, and the proportion of PV power prediction is also large. Cluster#1 shows that in short-term load prediction, the most common methods are artificial neural network and short-term memory in deep learning. In machine learning, feature selection and sensitivity analysis are important auxiliary work. The weather variable is a very important factor in short-term load forecasting. Cluster#2 explains that machine learning is commonly used for load forecasting, solar energy forecasting and short-term building energy forecasting. As can be seen from the Key Words, the data used for forecasting sometimes needs to be resamred. Cluster#3 indicates that wind power forecasting usually uses extreme learning machine to analyze multidimensional data, and the use of some data augmentation. Cluster#4 points out that deep learning includes multiple time series, sensitivity analysis, Adaptive Wind Driven Optimization (awdo) algorithm, neural networks, game theory and other methods. Cluster#5 indicates that artificial neural networks are mostly used in wind speed prediction and power grid load prediction, and trim aggregation is a commonly used auxiliary measure. Cluster#6 shows that the load model usually includes machine learning, statistical dynamic downscaling, signal decomposition and other methods, while the prediction model is mostly used for the prediction of renewable energy, and cyclic neural network and convolutional neural network are mostly used. Cluster#7 shows some additional learning machines, such as adaboost algorithm, some hybrid prediction models for power consumption prediction and wind speed prediction. Cluster#8 shows the value of renewable energy in today's electricity market, and also contains explanations of power market distribution system, operation strategy, power engineering calculation, etc. Cluster#9 shows that wind energy is a very important part of renewable energy, and it mainly adopts time series to analyze its sustainability and fuzzy reasoning to improve the accuracy of wind speed prediction. From keyword co-occurrence and cluster analysis, we can clearly and intuitively see the concentrated areas of distributed energy prediction, and show various important methods of prediction.

4. Machine learning in smart grids

The application of power load forecasting and renewable energy forecasting in the smart grid plays a crucial role in the sustainable development of the smart grid and the sustainable use of energy.

Researchers have developed a variety of machine learning methods for power load forecasting and renewable energy forecasting, which all follow similar steps. First, the data is preprocessed, the data is normalized and the training set is divided into the test set. Secondly, the model is trained and the mixed model is built. Finally, the constructed model is used to make predictions and the results are analyzed. This section will introduce the machine learning methods and conclusions of short-term power load, wind energy and solar energy prediction in turn, and analyze and summarize the literature, and explain the common features among different literatures.

4.1 Power load forecasting

Short-term power load forecasting for commercial areas, residential users and industrial areas plays an important role in today's smart grid [22]. With the continuous development of machine learning, short-term power load is more and more frequently combined with machine learning methods to improve the accuracy of prediction. Table 3 illustrates the various data sets used in short-term power load forecasting as well as the machine learning methods used and conclusions.

Table 3 Provides a summary of data sets and forecasting methods used in power load forecasting

Reference	Method	Dataset	Recording Step	Factor(s)	Outcome
[23]	CNN-BiGRU-NN hybrid model	The load data in question A of the 9th National Electrical Mathematical Modeling Competition held in 2016	15min	Maximum temperature, minimum temperature, average temperature, average relative humidity, rainfall	The hybrid model presented in this paper shows higher accuracy. The working day MAPE was 2.51% and the RMSE was 309.2MW.
[24]	CNN-LSTM hybrid model	Bangladesh power system (BPS) load data from January 2014 to December 2019	30min	Time frame (24h, one week, one month)	The newly created algorithm has a higher accuracy. MAE, RMSE and MAPE are 324.7693%, 434.4985% and 4.3275% less than LSTM networks, respectively.
[25]	CNN-GRU hybrid model	the AEP dataset and the IHEPC dataset	10min	AEP data set: outdoor temperature, air pressure, outdoor humidity, wind speed, visibility, etc. IHEPC data set: voltage, global active power, etc	The newly proposed hybrid model shows better results in terms of accuracy. For the IHEPC dataset, the MSE is 0.22; For AEP data sets, MSE is 0.09, both of which are the lowest.
[28]	LGBM-XGB-MLP hybrid model	Data set and New England Control Area and its Eight Wholesale Load (ISO-NE) records obtained by an electricity supply industry in Johor,	60min	Temperature	The experimental results show that the prediction accuracy of the hybrid model is high. It has the lowest RMSE at 1509.74 MW

		Malaysia			
[29]	LSTM-NN hybrid model	Electricity price and load data for the last 4 weeks of each season of the 2006 PJM market year; Electricity market price data for Spain		Season	The proposed model shows the predictive accuracy of power load and price. For the 2018 PJM electricity market dataset, the average MAPE is 4.3765.

Gated Recurrent Unit (GRU) is a variation form based on Long Short-Term Memory (LSTM), which can solve problems such as gradient explosion of basic Recurrent Neural Network (RNN), GRU can solve the problem of slow convergence of LSTM. Therefore, some scholars preferentially choose GRU as a part of neural network when using different data sets. The technique mentioned in literature [23] uses BiGRU (Bidirectional gated cyclic unit) to propose a short-term load forecasting method. The author introduced factors such as holidays and seasons, and compared the forecast results with multiple models respectively. The results show that the hybrid model has better prediction accuracy. Another work [25] was also based on the GRU, A hybrid model, which takes into account two datasets: Appliance Energy Prediction [26] (AEP) and Individual Household Electric Power Consumption[27] (IHEPC). The difference is that the paper also considers the influence of voltage, global active power and other factors on the power load prediction, and the results show that this method can be effectively used in the power load prediction of residential buildings.

Gholamreza Memarzadeh et al. [29] use Wavelet transform (WT) and Feature selection (FS) techniques to first eliminate the fluctuations of power load and other complex inputs, and take LSTM as a part of the model. To verify multiple data sets, this model has a good ability in predicting electric load and electricity price. In addition, literature [24] also proposes a hybrid model using LSTM for short-term load prediction, but it uses Convolutional Neural Networks (CNN) to illustrate the potential connections between power load data and to compare them in multiple time dimensions. The results prove the validity of the hybrid model.

In literature [28], the stacking generalization method is used to combine XGB, LGBM and multi-layer perceptron (MLP). Different from other literatures, the author uses hyperparameter optimization method to find the best parameters. Subsequently, the data sets of Malaysia and New England were verified, and although the prediction accuracy would decrease after 24h, the prediction results proved the rationality of the model and the use of hyperparameter method.

Most of the short-term load forecasting has been combined with machine learning, and the results show that the prediction accuracy of the hybrid model will be better than that of the independent or traditional model. Short-term load forecasting is also related to many factors, such as temperature, humidity, seasons, holidays, etc. For enterprises or individuals, the load will also vary according to the degree of use of various types of appliances by each enterprise. The hyperparameter optimization method or the improved hyperparameter optimization method has also been applied to the hybrid model, which can effectively improve the accuracy of prediction and provide some ideas for the subsequent research of power load prediction.

4.2 Wind power generation forecast

In recent years, as the country attaches more and more importance to the environment, more and more attention has been paid to wind power generation because it is a kind of renewable energy and does not produce pollutants threatening the environment in the process of power generation [30]. Jacobson, M. Z., pointed out that wind power is expected to account for half or more of the electricity market by 2030 [31]. Wind power generation forecasting plays a key role in the operation and planning of power systems [32], and wind power generation forecasting continues to evolve and improve with advances in machine learning. Table 4 illustrates the various data sets used in wind power generation forecasting as well as the machine learning methods and conclusions used.

Table 4 Data sets and summary of prediction methods used for wind energy prediction

Reference	Method	Dataset	Recording Step	Factor(s)	Outcome
[33]	IDA-SVM hybrid model	Operational data of the first wind turbines at La Haute Borne Wind Farm in 2017	60min	Wind speed and direction	The newly proposed algorithm shows greater accuracy. R^2 was 0.9544 and MAPE was 8.64%.
[34]	VMD-WT-PCA-BP-RBF hybrid model	Data from Sotavento Wind Farm in Spain and Changma Wind Farm in China		Wind speed, wind direction, temperature, pressure, etc	The hybrid model adopted in this paper has remarkable results in wind power prediction. For Sotavento Wind Farm, the RMSE is 0.1674 and for Changma Wind Farm in China, the RMSE is 0.2387. The RMse is 0.1674 and for Changma wind farm in China, the RMSE is 0.2387
[36]	LTDBO-VMD-LTDBO-LSTM hybrid model	Wind power cluster data of 30 2MW single wind turbines in Australia from February 1 to March 12, 2016	15min	Wind direction, wind speed, temperature, humidity, air pressure	The proposed model has high accuracy in wind power prediction. RMSE, MAE and MAPE were 0.422, 0.363 and 2.757%, respectively.
[37]	VMD-PE-MulitiBiLSTM hybrid model	The actual power generation of a wind farm in Guizhou	15min		The developed model is feasible in wind power prediction. Compared with VMD-LSTM model, MAE decreases by 1.36
[38]	LSTM-NN hybrid model	Data set for La Haute Borne Wind Farm (Open Data Wind Farm)	10min	Surface atmospheric pressure, outdoor temperature, specific humidity, absolute wind direction	The method proposed in the literature has a high accuracy. The RMSE for 12h was 0.168 and the comparison model was 0.256

Literature [33] proposed an SVM model based on Dragonfly algorithm optimization. The author introduced adaptive learning factors and differential evolution strategies to improve the Dragonfly algorithm, then searched for the optimal parameters through the improved optimization algorithm, and verified the data set. Experimental results proved the effectiveness of the method. In addition, Wang Di et al. [36] also used a similar method and introduced Logistic mapping to improve the dung beetle algorithm, and then applied it to Variational Mode Decomposition (VMD) and LSTM to find the best parameters. The experimental results show that the model is highly accurate. These literatures show that it is feasible to introduce some methods to improve the optimization algorithm, and then search for the best parameters of the target model.

In literature [34], the author first proposed VMD and Wavelet transform (WT) methods, which transform the unstable wind speed series into some relatively stable quantities, then adopted PCA-BP technology to reduce the prediction complexity, and finally proposed the VMD-Wt-PCA-BP-RBF model. In the experiments of Sotavento Wind Farm [35] and Changma Wind Farm in China, it is proved that the model has high prediction accuracy. In addition, literature [37] proposed that the VMD technology was also used to decompose the wind power series and then construct a model to verify the data set, which proved the effectiveness of this work. These literatures indicate that it is possible to preprocess the data by VMD, WT and other technologies to solve the problems of mode aliasing and end effect, so as to improve the prediction performance. The difference between the two is that literature [34] also uses BP algorithm to screen the output data of PCA, which further improves the prediction accuracy.

The document [38] used Exploratory Data Analysis (EDA) to compare the characteristic relationship between various data, and concluded that the application of LSTM method to short-term forecast of up to 24 hours may be recommended as a reliable statistical technology. Different from other literatures, the author considers the application of data-driven analysis in wind power prediction and the importance of supplementing missing data in this paper, which provides a new way of thinking for future research on wind power.

It can be seen from the above literature that Deep Neural Network will be used more frequently in wind power generation prediction, and Deep Neural Network (DNN) will have better prediction results compared with other prediction models. DNN will also be combined with a large number of optimization algorithms to find the best parameters or use variational mode decomposition technology to transform unstable data series into relatively stable quantities. These methods aim to make up for some defects of DNN and improve the prediction accuracy. Most of the references show that for the selected data set, the prediction accuracy of wind power generation by constructing a hybrid model is higher than that by constructing a single traditional model. The prediction of wind power generation may encounter problems such as data limitation or lack of meteorological observation equipment in wind farms, and the proposal of these hybrid models will provide solutions to these problems.

4.3 Prediction of solar power generation

The traditional way of power generation will produce a lot of greenhouse gases, which will cause large environmental pollution. As a result, the world has shifted its focus to renewable energy sources, such as solar panels. But solar power is extremely volatile, which is why solar power forecasts are so important. Table 5 illustrates the various data sets used in solar power prediction as well as the machine learning methods and conclusions used.

Table 5 Data sets and summary of prediction methods used for wind energy prediction

Reference	Method	Dataset	Recording Step	Factor(s)	Outcome
[39]	CNN-LSTM hybrid model	1B Data of DKASC and Alice Springs photovoltaic system from 2014 to 2017	5min	Temperature, global horizontal radiation, diffuse horizontal radiation, etc	The newly created model has a higher accuracy. When the time series data length is 2.5Y, 3Y, 3.5Y, etc., the RMSE value of the mixed model is increased by 54.92%, 13.82% and 13.83%, respectively, compared with the LSTM
[40]	IWOA-BiLSTM-Attention hybrid model	Data of photovoltaic power station at the Australian Desert Knowledge Solar	5min	Temperature, relative humidity, global horizontal radiation, wind direction, diffuse horizontal	The established hybrid model has higher accuracy. Compared with the benchmark model, RMSE on sunny, cloudy and rainy days of the hybrid forecasting model decreased by 86.54%, 71.01% and 72.71% on average, respectively.

		Center		radiation	
[41]	PC-LSTM hybrid model	Two data sets of photovoltaic power stations in different regions of Australia	60min	Solar radiation intensity, temperature, humidity, wind speed	The established model shows the effectiveness of the work. Compared with traditional machine learning methods, the prediction accuracy of the two photovoltaic power stations improved by about 12.9% and 8.0%, respectively.
[42]	SSA-BO-BiLSTM hybrid model	A rooftop photovoltaic plant in eastern China	7.5 min		The proposed model has high accuracy in photovoltaic power generation prediction. MAE and RMSE were 6.18 and 9.25, respectively
[43]	Multiple machine learning models	Alice Springs, Aug. 2020 Desert Knowledge Australia Centre		Temperature, relative humidity, global horizontal radiation, diffuse horizontal radiation, and daily precipitation	The paper uses multiple machine learning models to predict short - and long-term PV generation, and the results show that the random forest algorithm has better prediction results.

Literature [39] and literature [41] both use LSTM as part of the mixed model. The difference is that the author compared the prediction accuracy of different input time series length comparison models in literature [39]. In the literature [41], physical constraints were selected from the knowledge field of volatility of photovoltaics (PV) to add to the construction of the hybrid model, and a hybrid method was used to screen the feature variables with high correlation. Experimental results show that the hybrid models proposed in these two literatures both prove the effectiveness of the authors' work. Researchers can add input time series length or related field knowledge to the reference in the subsequent study to achieve higher prediction accuracy.

Reference [40] optimizes the Whale optimization algorithm (WOA) to reduce the complexity of prediction, and explores the optimal hyperparameters of bi-directional long short-term memory (BiLSTM) by improving WOA through Gaussian mapping and other methods. In addition, a similar method was used in literature [42] to find the optimal parameters of BiLSTM model by using Bayesian optimization algorithm. Both of them use BiLSTM model, because the bidirectional propagation of this model can consider the correlation between past data and future data, and solve the problem that LSTM cannot fully utilize data. Singular Spectrum Analysis (SSA) was adopted in the reference [40] to reduce the complexity of the data based on improved VMD and to classify the data into sunny, cloudy and rainy days for research based on weather conditions. The reference [41] adopted the method of Singular Spectrum Analysis (SSA) to denoise the data. Thus reducing the complexity of the forecast. The experimental results all show that the hybrid model proposed in the literature can effectively improve the prediction accuracy.

Different from other literatures, the author [43] used decision tree regression, support vector regression, random forest and other single machine learning algorithms for comparative analysis, instead of building a mixed model. The author also analyzed the influence of data standardization on the prediction results.

Solar photovoltaic power generation can be affected by a number of factors, such as temperature, irradiance, wind direction and so on. The use of each model in the prediction of solar power generation has its advantages and disadvantages, for different data sets, there are corresponding best methods, no forecasting model is relatively the best, only the most suitable forecasting model. However, from the above analysis of the literature, most studies show that the hybrid model of LSTM has better prediction results, because LSTM can deal with the problem of gradient disappearance and gradient explosion in RNN. In addition, the research shows that the prediction accuracy of the hybrid model for solar power generation is higher than that of the single prediction model.

5. Current challenges and future prospects

Combining machine learning methods with forecasting is an efficient way to improve the efficiency of smart grids, which can greatly improve the accuracy of power load forecasting and renewable energy forecasting [44]. However, there are some challenges in the forecasting process.

The first is data quality and integrity. Power load data often contains noise and missing values, which will affect the training and forecasting performance of machine learning models. The second is that existing machine models tend to perform well on specific data sets, but have limited ability to recognize and adapt to new samples in different regions or over different time periods. There are a variety of uncertainties in renewable energy, such as weather changes, user behavior, etc., and these uncertainties all bring great challenges to forecasting. In order to solve these problems, researchers can develop more efficient machine learning algorithms, reduce model training time and error, and improve prediction accuracy. Since the accuracy of a single model prediction is not high, researchers can combine a variety of optimization algorithms to optimize the model, form a hybrid model, and find the most suitable hyperparameters for the model. Secondly, more advanced data preprocessing technology can be studied to improve data quality and reduce the impact of noise and missing values. In addition, researchers can develop more comprehensive forecasting models by combining knowledge from other disciplines, such as meteorology and mathematics.

6. Conclusions

In looking at machine learning in short-term power loads and renewable energy forecasting, we came to some important conclusions. Firstly, through the bibliometric analysis of the literature in recent years, it can be found that machine learning occupies an increasing proportion in the power load and renewable energy forecast, and machine learning technology has shown high accuracy and forecasting ability in the power load forecast. By using historical data and other relevant factors, machine learning models are able to accurately predict future power demand.

Secondly, in terms of renewable energy forecasting, machine learning technology also plays an important role. Due to the instability and unpredictability of renewable energy, accurately predicting its output is essential for the stable operation of the energy system. By analyzing other relevant factors such as meteorological data, machine learning models are able to better predict the output of renewable energy.

Despite some challenges, there is great potential for the application of machine learning in the field of short-term power loads and renewable energy forecasting. With the advancement of data collection technology and the continuous development of machine learning algorithms, with further research and improvement, machine learning can bring more value to the power industry and the renewable energy field, and promote the sustainable development of the energy system.

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