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Full-length article

A comprehensive review for wind, solar, and electrical load forecasting methods

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Abstract: Wind power, solar power, and electrical load forecasting are essential works to ensure the safe and stable operation of the electric power system. With the increasing permeability of new energy and the rising demand response load, the uncertainty on the production and load sides are both increased, bringing new challenges to the forecasting work and putting forward higher requirements to the forecasting accuracy. Most review/survey papers focus on one specific forecasting object (wind, solar, or load), a few involve the above two or three objects, but the forecasting objects are surveyed separately. Some papers predict at least two kinds of objects simultaneously to cope with the increasing uncertainty at both production and load sides. However, there is no corresponding review at present. Hence, our study provides a comprehensive review of wind, solar, and electrical load forecasting methods. Furthermore, the survey of Numerical Weather Prediction wind speed/irradiance correction methods is also included in this manuscript. Challenges and future research directions are discussed at last.

Keywords: Wind power, Solar power, Electrical load, Forecasting, Numerical Weather Prediction, Correlation.

0 Introduction

To deal with climate change, environmental pollution, and fossil energy shortage, the energy systems of major countries are in a period of clean, low-carbon, and intelligent transformation; the structure of the generation side and load side of the power systems are changing significantly.

On the generation side, a high proportion of renewable energy is becoming the critical characteristic of the future power system. Wind and solar energy, which with strong volatility, will become the main power supply [1]. Europe

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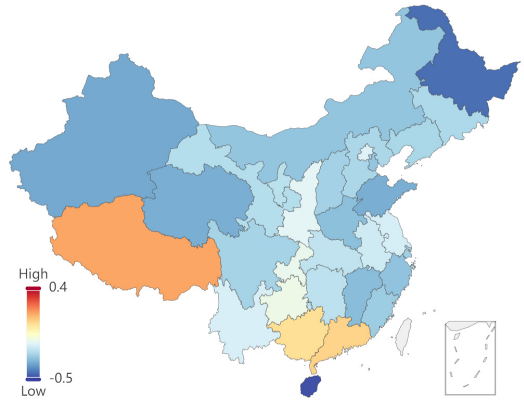
[2] and the United States [3] put forward the blueprint of realizing 100% and 80% renewable energy power systems in 2050, respectively. On the load side, intelligent power consumption is an essential component of the smart grid. At present, the United States, Britain, France, Japan, Finland, et al. have already implemented the demand response projects, including load response and price response [4], [5].

The increase of wind power and solar power penetration rate on the generation side and the gradual implementation of the demand response on the load side lead to the power system having strong uncertainty at both sides, which brings greater challenges to the safe and economic operation of the system.

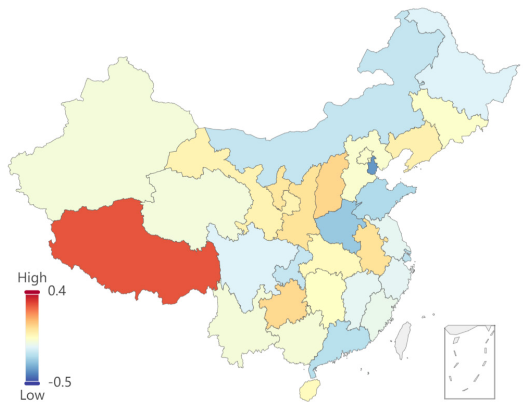
Renewable energy and load forecasting is an important work to deal with the dual uncertainty of the power system [6], [7]. Wind and solar power forecasting are the significant basis to ensure the safe and stable operation of the power system with a high proportion of new energy [8], [9]. From the perspective of the power station, accurate forecasting results can improve its operation and maintenance level, reduce the energy curtailment rate, and improve its market competitiveness. From the perspective of the power system, reliable forecasting results can effectively reduce the adverse effects of wind and solar power uncertainty, help the dispatching department formulate and adjust the dispatching plan in time, and reduce the operation cost. Load forecasting is the prerequisite to balancing the power supply and demand, which plays a key role in the planning and operation of the power system. Accurate and reliable forecasting results are of great significance to the dispatch, maintenance, emergency management, and power flow analysis of the power system [10], [11].

There are a lot of research works published regarding wind power, solar power, and load forecasting, and several review/survey articles have been presented. Most review/survey articles focus on a specific forecasting object (wind, solar, or load) [9], [12], [13]. A few involve the above two or three forecasting objects, but they are reviewed separately [14], [15].

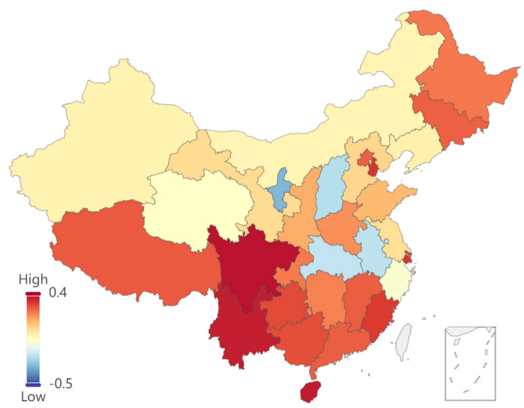
Actually, wind power, solar power, and electrical load are closely related to meteorological factors such as wind speed, temperature, irradiance, and relative humidity. They all have a certain interactive coupling relationship under different operation scenarios of the power system. The per-unit wind power and solar power data in 2016, and typical year's per-unit electric load data in all provinces of China (excluding Hong Kong, Macao, Taiwan, and South China Sea Islands) are used to further illustrate the correlation between wind power, solar power, and electrical load. Pearson correlation coefficient (ρ_p) is used to quantify the correlation between variables, as shown in Fig. 1.



(a) wind power and solar power



(b) wind power and electrical load



(c) solar power and electrical load

Fig. 1 Correlation of wind power, solar power, and electrical load

As can be seen, 1) wind power and solar power basically have a negative correlation in different provinces, and the correlation in Northern China is generally higher than that in Southern China. This is mainly due to the flatter terrain and the higher meteorological similarity in adjacent locations in Northern China. 2) Wind power and electrical load negatively correlate in most provinces, but the correlation is weaker than the correlation between new energy and load. This is because the correlation between wind speed and irradiance, irradiance and load are higher than that between wind speed and load. 3) Solar power and electrical load basically show a positive correlation in different provinces, and the correlation in Southern China is generally higher than that in Northern China. This is mainly due to the lower temperature and the broad utilization of coal (or natural gas) for heating in Northern China.

The forecasting accuracy can be effectively improved if this relationship is considered. Some articles predict at least two kinds of objects simultaneously to cope with the increasing uncertainty at both production and load sides. However, there is no corresponding review at present. Aiming at this problem, our study provides a comprehensive review of wind power, solar power, and electrical load forecasting methods.

The main contributions of this paper are as follows.

1) A bird's eye view of wind, solar, and electrical load forecasting articles is provided.

2) A survey of Numerical Weather Prediction (NWP) wind speed/irradiance correction is provided. NWP is the most critical factor affecting wind and solar power forecasting accuracy, especially under the short-term time scale. It is necessary to correct the NWP wind speed/radiation before wind power and solar power forecasting.

3) An exhaustive review of wind power, solar power, and electrical load forecasting is provided. Different from the review papers, which only focus on a specific type of forecasting methods, such as deep learning methods [15], support vector machine models [14], ensemble methods [6], et al., all forecasting methods are considered in this manuscript. The existing forecasting methods are divided in terms of different classification criteria. Furthermore, the applicable scenarios, advantages, and disadvantages of different forecasting methods are also described.

4) A survey of wind power-solar power-electrical load forecasting methods is provided. There is no corresponding paper at present.

The rest of the manuscript is organized as follows. Section 1 provides a bird's eye view of SCI articles about wind, solar, and load forecasting, and highlights our contributions. Section 2, Section 3, and Section 4 offer a complete summary of NWP wind speed/irradiation correction, wind power/solar power forecasting, and electrical load forecasting from different perspectives. Section 5 describes the existing forecasting methods of wind power-solar power-electrical load. The current challenges and future research directions are discussed in Section 6. Section 7 concludes the review.

1 A Bird's eye view

A bird's eye view of wind, solar, and electrical load forecasting articles is shown in this section. The view mainly focuses on the papers indexed by SCI during 2011-2020.

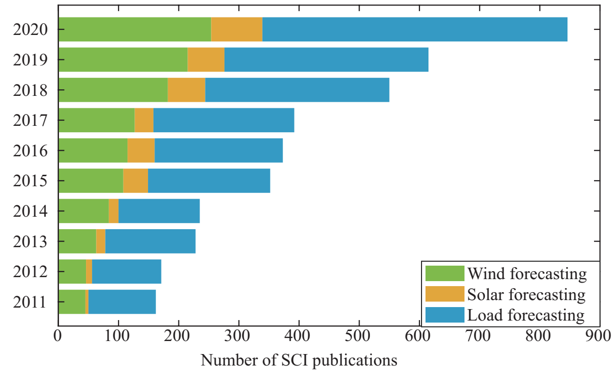
First, we performed a keyword-based search of research studied using Web of Science; the keywords are listed in Table 1.

Table 1 Keywords for wind, solar, and electrical load forecasting

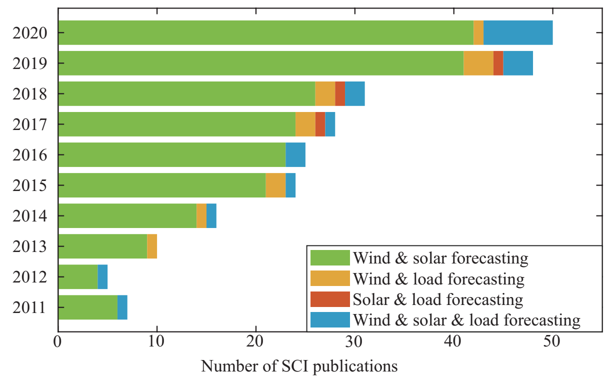
<table>
<tr><th>Forecasting objects</th><th colspan="2">Keywords</th></tr>
<tr><td>wind</td><td>wind power/wind speed</td><td rowspan="7">+forecasting /prediction</td></tr>
<tr><td>solar</td><td>solar power/irradiance</td></tr>
<tr><td>load</td><td>electrical load/electricity demand</td></tr>
<tr><td>wind & solar</td><td>renewable energy/wind solar/wind irradiance</td></tr>
<tr><td>wind & load</td><td>wind power/wind speed + electrical load/electricity demand</td></tr>
<tr><td>solar & load</td><td>solar power/irradiance + electrical load/electricity demand</td></tr>
<tr><td>wind & solar & load</td><td>wind power/wind speed + solar power/irradiance + electrical load/electricity demand;
renewable energy + electrical load/electricity demand</td></tr>
</table>

Then, we performed a preliminary screening of the retrieved research papers found through the previous step. The screening criteria for papers are related to wind, solar, or electrical load forecasting, and indexed by SCI. The number of SCI publications about wind, solar, and load forecasting during 2011-2020 is depicted in Fig.2. As shown in these two figures, while the number of prediction articles is increasing annually, more and more scholars are paying attention to predict least two objects simultaneously.

The countries and research institutions that published papers in SCI-Q1 journals during 2011-2020 are paid more attention, as shown in Fig. 3 and Table 2. As can be seen, China has published the largest number of papers in new energy and load forecasting (accounting for 43.7%), followed by USA (accounting for 14.3%). In terms of the published number, the following institutions deserve more attention: Central South University, Dongbei University of Finance & Economics, Huazhong University of Science & Technology, Lanzhou University, North China Electric Power University, Tsinghua University, et al. in China; Southern Methodist University, United States Department of Energy, et al. in USA; Yildiz Technical University in Turkey; Nanyang Technological University, National University of Singapore in Singapore; INESC in Portugal; Technical University of Denmark in Denmark.



(a) for one forecasting object



(b) for at least two forecasting objects

Fig. 2 Number of SCI publications about wind, solar, and load forecasting in 2011-2020

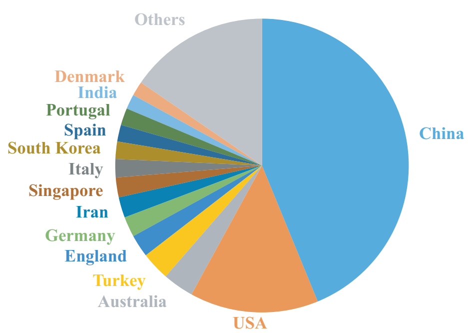


Fig. 3 A classification of SCI-Q1 publications about wind, solar, and load forecasting in 2011-2020 (from perspective of country)

Finally, the review/survey articles with higher citation rates are further focused. A comparative analysis of our work and existing review/survey studies is listed in Table 3. As can be seen, there is no survey/review of wind, solar, and load forecasting articles that consider the coupling relationship among prediction objects.

Table 2 A classification of SCI-Q1 publications about wind, solar, and load forecasting in 2011-2020

Country	Institution	Num.	Pro.
China	Central South University	26	4.4%
	Chinese Academy of Sciences	6	1.0%
	Chongqing University	5	0.9%
	City University of Hong Kong	7	1.2%
	Dongbei University of Finance & Economics	21	3.6%
	Guangdong University of Technology	6	1.0%
	Hefei University of Technology	5	0.9%
	Huazhong University of Science & Technology	16	2.7%
	Hunan University	5	0.9%
	Lanzhou University	12	2.0%
	North China Electric Power University	20	3.4%
	Tianjin University	8	1.4%
	Tsinghua University	12	2.0%
	University of Electronic Science & Technology of China	6	1.0%
	Xi'an Jiaotong University	5	0.9%
	Others	97	16.5%
	Total	257	43.7%
USA	Southern Methodist University	9	1.5%
	United States Department of Energy	11	1.9%
	University of California System	7	1.2%
	University of North Carolina	6	1.0%
	University of Texas System	7	1.2%
	Others	44	7.5%
	Total	84	14.3%
Turkey	Yildiz Technical University	5	0.9%
	Others	13	2.2%
	Total	18	3.1%
Singapore	Nanyang Technological University	6	1.0%
	National University of Singapore	5	0.9%
	Others	2	0.3%
	Total	13	2.2%
Portugal	INESC	6	1.0%
	Others	5	0.9%
	Total	11	1.9%
Denmark	Technical University of Denmark	7	1.2%
	Others	2	0.3%
	Total	9	1.5%
Others		196	33.3%

2 NWP wind speed/irradiation correction

NWP model is composed of a set of basic differential equations that can describe the physical laws of the atmosphere. NWP predicts future atmospheric states based on the current weather conditions, including initial values and boundary conditions. The maximum prediction time scale is 15 d [29]. NWP can be divided into global NWP and mesoscale NWP according to the prediction range. The global NWP model operates at about 15 meteorological service stations, e.g., Global Forecast System (GFS) and European Centre for Medium-Range Weather Forecasts (ECMWF). The temporal and spatial resolution is generally 3-6 h and 16-50 km, respectively. The mesoscale NWP model takes the outputs of the global NWP model as inputs and predicts the future atmospheric state by considering the characteristics of different regions, e.g., Fifth-Generation Mesoscale Model (MM5) and The Weather Research and Forecasting Model (WRF). The mesoscale NWP has a higher temporal and spatial resolution, the temporal resolution is usually 10 min-1 h, and the spatial resolution is usually 3-20 km, even up to 1 km [21].

NWP can provide the meteorological data required for wind power and solar power forecasting, such as wind speed, irradiance, temperature. However, the low temporal and spatial resolution of NWP leads to its low prediction accuracy. The cubic relationship between wind speed and wind power, and the approximately linear relationship between irradiance and solar power make tiny NWP prediction errors can cause huge power forecasting errors [30], [31], [32]. Therefore, it is necessary to correct the NWP wind speed/radiation. The studies can be divided into NWP correction at a single location and NWP correction considering the spatial coupling characteristics according to the inputs of the correction model, i.e., the spatial range of NWP data.

2.1 Correction at a single location

This category corrects the NWP wind speed/irradiance by establishing the mapping relationship between the NWP and measured data at a specific location. The spatial location of the NWP data is single [33], [34].

Liu et al. established the frequency distribution model of NWP wind speed error based on non-parametric kernel density estimation, and corrected the wind speed through historical prediction error [35]. Zheng et al. used the Kalman filtering method to correct NWP wind speed in the next 16 steps. The Mean Absolute Error (MAE) of wind speed at step 16 is reduced by 0.47 m/s, compared with the original NWP [36]. Hu et al. proposed a hybrid NWP wind speed correction model based on Principal Component Analysis (PCA) and improved Deep Belief Network (DBN). The improved DBN can automatically adjust the learning step to improve the convergence speed of the algorithm. The NWP wind speed correction accuracy is increased by 16% and 30% by using the improved DBN model and the hybrid model, respectively, compared with the traditional DBN [37]. Wang et al. proposed a Sequence Transfer Correction Algorithm (STCA) for NWP wind speed; the sequence transfer relationship is introduced to improve the certainty between inputs and outputs of the correction model. Then, 5 NWP corrected models based on STCA are established, respectively, by using Linear Regression (LR), Support Vector Machine (SVM), Back-Propagation Neural Network (BPNN), Random Forest (RF), and Radial Basis Function Neural Network (RBFNN). The NWP accuracy is improved by 0.20-2.25 m/s in two wind farms [38].

Lopes et al. established two models to correct NWP irradiance based on the NWP data and ground observation results of two years, including a linear regression model between NWP and measured irradiance; a multiple regression model among NWP irradiance, other NWP variables (temperature, relative humidity, wind speed, total precipitation) and measured irradiance [39]. Reikard et al. proposed an Autoregressive Integrated Moving Average model (ARIMA) with the time-varying coefficient based on the physical characteristics reflected in the weather model to correct the NWP irradiance. The proposed model can adapt to the changing atmospheric conditions. The results show that the corrected NWP irradiance has a great advantage under the time scale of 1-4 h, compared with the original NWP irradiance and the forecasted irradiance using the time series method [40].

Some scholars aimed at the characteristic that the mapping relationships between NWP and measured data are different under different weather conditions [41], [42]. The weather conditions are classified according to weather factors such as wind speed, wind direction [43], irradiance, clear sky index [44], atmospheric stability [45], seasons [46], [47]; or by using the clustering, reduced-scenario methods [48]. Then, the NWP correction model in each weather condition is established to improve the correction accuracy.

Some scholars corrected the NWP data from the perspective of frequency domains. First, the measured and NWP wind speed/irradiance series is decomposed into different frequency domains. Then, the mapping relationship between measured and NWP data is established in each frequency domain. Finally, the results in different frequency domains are combined to obtain the correction results of NWP data [49]. The commonly used decomposition

Table 3 A comparative analysis of our work and existing review/survey studies

Reference	WF	SF	LF	Whether related	Published year	Journal	Country	Institution
Yan et al. [12]	√	×	×	/	2015	Renewable and Sustainable Energy Reviews	China	North China Electric Power University
Zhang et al. [16]	√	×	×	/	2014	Renewable and Sustainable Energy Reviews	China	Xi'an Jiaotong University
Wang et al. [17]	√	×	×	/	2016	Renewable and Sustainable Energy Reviews	China	Dongbei University of Finance and Economics
Gallego-Castillo et al. [18]	√	×	×	/	2015	Renewable and Sustainable Energy Reviews	Spain	Universidad Politécnica de Madrid
Jung et al. [19]	√	×	×	/	2014	Renewable and Sustainable Energy Reviews	USA	Virginia Polytechnic Institute and State University
Tascikaraoglu et al. [20]	√	×	×	/	2014	Renewable and Sustainable Energy Reviews	Turkey	Yildiz Technical University
Inman et al. [9]	×	√	×	/	2013	Progress in Energy and Combustion Science	USA	University of California
Diagne et al. [21]	×	√	×	/	2013	Renewable and Sustainable Energy Reviews	Reunion	Reuniwatt Company
Wang et al. [22]	×	√	×	/	2020	Energy Conversion and Management	China	Shenzhen University
Ahmed et al. [23]	×	√	×	/	2020	Renewable and Sustainable Energy Reviews	Australia	The University of Western Australia
Khan et al. [10]	×	×	√	/	2016	Renewable and Sustainable Energy Reviews	Pakistan	COMSATS Institute of Information Technology
Raza et al. [5]	×	×	√	/	2015	Renewable and Sustainable Energy Reviews	Australia	University of Queensland
Yildiz et al. [7]	×	×	√	/	2017	Renewable and Sustainable Energy Reviews	Australia	University of New South Wales
Kuster et al. [13]	×	×	√	/	2017	Sustainable Cities and Society	United Kingdom	Cardiff University
Zhang et al. [24]	×	×	√	/	2021	Applied Energy	USA	National Renewable Energy Laboratory
Wang et al. [25]	√	√	×	×	2019	Energy Conversion and Management	China	Shenzhen University
Widen et al. [26]	√	√	×	×	2015	Renewable and Sustainable Energy Reviews	Sweden	Uppsala University
Zendehboudi et al. [14]	√	√	×	×	2018	Journal of Cleaner Production	China	Tsinghua University
Ren et al. [6]	√	√	×	×	2015	Renewable and Sustainable Energy Reviews	Singapore	Nanyang Technological University
Aslam et al. [15]	√	√	√	×	2021	Renewable and Sustainable Energy Reviews	Cyprus	Cyprus University of Technology
Lee et al. [27]	√	√	√	×	2016	International Conference on Smart Grids for Smart Cities	Canada	University of Toronto
Aburiyana et al. [28]	√	√	√	×	2017	2017 IEEE Electrical Power and Energy Conference (EPEC)	Canada	Dalhousie University
Our work	√	√	√	√	-	-	China	Tsinghua University

methods include Empirical Mode Decomposition (EMD), Variational Mode Decomposition (VMD) [50], Wavelet Decomposition (WD) [51], etc.

2.2 Correction considering spatial coupling characteristics

This category considers the coupling relationship among wind speed/irradiance at different spatial locations, i.e., when correcting the NWP at one location, in addition to the NWP and measured data at that location, the information in the adjacent area is also taken into account. The NWP wind speed/irradiance is corrected by establishing the mapping relationship among NWP data at multiple points and measured data at a single point, or the mapping relationship among NWP and measured data at multiple points [39], [52].

Cai et al. established the corresponding relationship among the NWP and measured wind speed at different points by SVM to obtain the reference NWP wind speed series. Then they corrected the NWP through the multi-task Gaussian process [53]. Chu et al. first calculated the correlation coefficient between the measured wind speed series at the location of the wind turbine and the NWP wind speed series at each spatial point, respectively. Then, the NWP series with higher correlation are selected as inputs to correct the NWP by the proposed variable weight combined method [54]. Yan et al. established an NWP correction model with multiple inputs and multiple outputs based on the stacked denoising autoencoder, which can consider the spatial coupling characteristics of wind speed. The proposed model can improve the correction accuracy by 15% and 18%, respectively, compared with the neural network and SVM with single input and output [55].

3 Wind power/solar power forecasting

Wind and solar power forecasting methods can be divided in terms of different classification criteria. The forecasting can be divided into physical and statistical forecasting according to the modeling principle; ultra-short-term, short-term, and mid-long-term forecasting according to the temporal scale; station and regional forecasting according to the spatial scale; deterministic and uncertain forecasting according to the displaying ways of results.

3.1 Physical method and statistical method

The wind power physical forecasting method first establishes the computational fluid dynamics model to calculate the wind condition at the hub height of each wind turbine with the initial NWP, which considers the impact of terrain, altitude, and surface roughness changes. Then, the wind speed is converted into wind power through the speed-power curve, and the wind farm output is calculated by adding each wind turbine output [56]. The physical method can be subdivided into the analytical diagnosis method [57] and the numerical simulation method [58], [59].

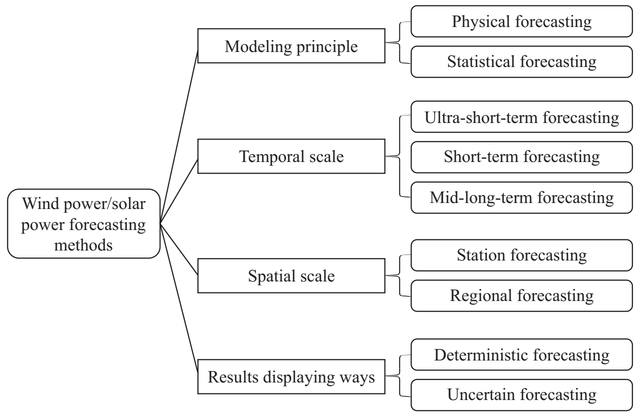


Fig. 4 Classification of wind power/solar power forecasting methods

The solar power physical forecasting method first establishes the solar radiation transfer equation, the photovoltaic module operation equation, etc., to calculate the output of each photovoltaic array with the initial NWP, which considers the geographic information of the solar power station and module parameters. Then, the solar power station output is calculated by adding each photovoltaic array output [60], [61], [62].

The statistical forecasting method establishes the mapping relationship among the operation data series or the mapping relationship between the operation data and NWP data of the wind/solar power station, and the power is forecasted based on the mapping model. It can predict the wind/solar power directly; or predict the wind speed/irradiance and other meteorological information first, then convert them to power [63]. The commonly used methods include ARIMA, Kalman filter, SVM, Relevance Vector Machine (RVM), Least Square method (LS), RF, Artificial Neural Network (ANN), Deep Learning (DP), and combined method, etc. [26], [64], [65], [66].

The physical method does not need much historical data and is suitable for new wind/solar power stations. However, the complexity of the model increases exponentially with the area and the forecasting accuracy, which requires a lot of time and computing resources. The application scope of the physical method usually concentrates inside the power station. The statistical method can be applied to power forecasting in single and regional power stations, but it needs a large number of historical data to dig the mapping laws of series. It is more suitable for wind/solar power stations that have been built for some time.

3.2 Ultra-short-term, short-term, and mid-long-term forecasting

Ultra-short-term wind/solar power forecasting provides the results of power stations in the next few hours, generally within 4 h [67]. The forecasting results can be used for online economic dispatching, rotating reserve capacity optimization, power tracking, etc. The ultra-short-term wind power forecasting is usually based on the statistical laws among historical data series [68], [69]. The meteorological factors, spatial correlations, etc., can also be considered to improve the forecasting accuracy [70]. For the solar plant, in addition to the above methods, the ultra-short-term forecasting results can be obtained through the cloud image [71], [72]. This method forecasts the shielding of the cloud to the sunlight by calculating the cloud movement path. The commonly used cloud images include ground-based and meteorological satellite images.

Short-term wind/solar power forecasting is usually based on wind speed, irradiance, and other meteorological data provided by NWP [73]. The forecasting is performed by establishing the mapping relationship between NWP data and actual power data, and the prediction time scale is generally 6 h-3 d [74], [75]. The forecasting results can provide effective support for the formulation and adjustment of maintenance plans for stations, and the formulation of day-ahead dispatching plans for the electric power system. The forecasting results are directly affected by NWP accuracy. Therefore, how to improve the NWP accuracy is crucial for reducing the power forecasting error in short-term new energy forecasting.

Mid-long-term wind/solar forecasting is generally aimed at power generation or wind speed/irradiance, and the prediction time scale is usually months, quarters, and years [19]. The forecasting results are usually applied to arrange major maintenance, power system planning, site selection of wind and solar power stations, etc.

3.3 Station and regional forecasting

The station and regional forecasting refer to the output forecasting of a single wind/solar power station and multiple power stations in an area. The regional forecasting can forecast the total power directly; or forecast the predictable stations in the region first, and then use the direct superposition method or the statistical upscaling method to obtain the prediction results of the total power [76], [77].

The direct superposition method adds the forecasting results of each station to obtain the regional power forecasting results. The calculation method is straightforward, but the regional power forecasting accuracy is greatly affected by the forecasting results of each station, and all stations in the area are required to be predictable objects. The regional power forecasting results are unavailable if the forecasting results of any station are missing.

The statistical upscaling method establishes the mapping relationship among the predictable stations and the regional power data. The regional power forecasting results are calculated with the forecasting results of several stations through the established model. The participated power stations are usually screened according to the data quality of the power station, the correlation between the station and regional power data, and the forecasting accuracy of the station. This method can effectively reduce the influence of stations with high prediction error and does not require all stations in the area to be predictable objects. It can be dynamically adjusted according to the actual condition and has strong robustness.

The power forecasting accuracy of regional stations is usually higher than that of a single station. On the one hand, the volatility of regional power is generally weaker than that of the power in a single station. On the other hand, the forecasting errors of wind farms or solar plants in an area can offset each other to some extent when the regional power forecasting results are obtained through the single stations.

3.4 Deterministic and uncertain forecasting

Deterministic forecasting refers to the single-point prediction result, i.e., the expectation of future wind/solar power from the mathematical view [78], [79]. Uncertainty forecasting refers to the interval prediction results of wind/solar power, which can reduce the decision risk of the power system [80], [81]. Uncertainty forecasting can be divided into probabilistic forecasting, risk index forecasting, and scenario forecasting according to the expression of uncertainty [82], [83].

Probabilistic forecasting focuses on the value and the occurrence time of the prediction error. It can be divided into the parametric method [84] and non-parametric method [85], [86], [87] according to whether the distribution of single-point prediction error is assumed in advance. The parameter method assumes that the prediction error follows pre-defined distribution, such as generalized lognormal distribution, Beta distribution, Gaussian distribution, etc., and then extends the single-point prediction results to the interval prediction results. However, the wind/solar power forecasting error does not conform to any distribution form; the application premise of the parameter method is limited. The non-parametric method does not need to presume the distribution of prediction errors, but it requires more computational resources. The commonly used methods include resampling, kernel density estimation, quantile regression, etc.

Risk index forecasting can provide intuitive uncertainty information [88]. The commonly used risk indexes include atmospheric stability risk index, prediction risk index, standardized prediction risk index, etc.

Scenario forecasting provides a series of power scenarios to describe the prediction uncertainty [72]. The commonly used methods include Monte Carlo algorithm, multivariate Gaussian random variable method, multivariate autoregressive moving average (ARMA) model, etc.

The uncertain forecasting results of wind power and solar power are shown in Fig.5 and Fig.6, respectively.

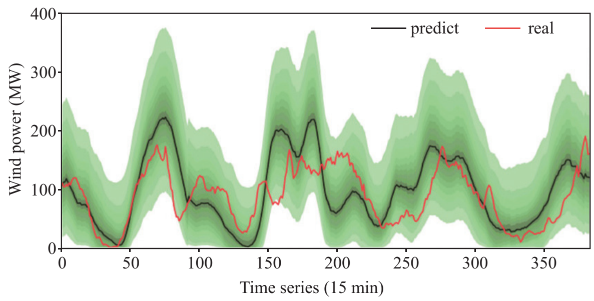


Fig. 5 Uncertain forecasting results of wind power

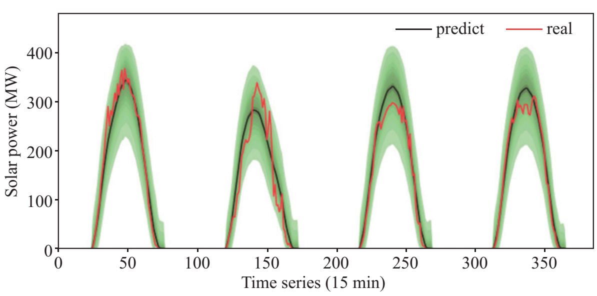


Fig. 6 Uncertain forecasting results of solar power

4 Electrical load forecasting

Electrical load forecasting is an essential component of the smart grid. It can only base on the historical load data; or also take the meteorological factors (such as temperature, humidity, irradiance), time labels (time point within the day, weekday/weekend/holiday), and economic factors into account to improve the forecasting accuracy.

The forecasting methods of electrical load can be divided in terms of different classification criteria. The forecasting methods can be divided into ultra-short-term, short-term, and mid-long-term forecasting according to the temporal scale; mathematical equation and artificial intelligence forecasting according to whether the prediction model is a black-box model; single-point and probabilistic forecasting according to the information contained in results.

4.1 Ultra-short-term, short-term, medium-term, and long-term forecasting

Ultra-short-term load forecasting results can serve real-time dispatching and demand response of the power system. The forecasting time scale is usually 1 min to 1 h; the spatial scale is small, generally a building. The forecasting time step is minutes [89].

Short-term load forecasting results can serve the day-ahead dispatching of the power system, unit commitment, and electricity market transactions, etc. The forecasting time scale is usually 1 hour to 1 week; the spatial scale is generally a building or an area [90], [91]. The forecasting step can be minutes, hours, and days [92].

Medium-term load forecasting results can provide the basis for the formulation of power system planning schemes. The forecasting time scale is usually weeks, months, and quarters; the spatial scale is generally a building or an area. The forecasting step can be hours, weeks, months, and quarters. In addition to forecasting, some scholars use Markov chain, Monte Carlo, etc., to generate the medium-term load simulation results [13].

Long-term load forecasting results can serve the power system planning and the formulation of strategic energy policies. The forecasting time scale is usually one year to several years; the spatial scale can vary from buildings, areas to cities, countries. The forecasting time step can span from hours to years [93].

4.2 Mathematical equation method and artificial intelligence method

The method selection is the core issue of electrical load forecasting. The forecasting methods should be selected based on scenarios to ensure forecasting accuracy. The existing load forecasting methods can be divided into the following two categories according to whether the prediction model is a black-box model: mathematical equation method and artificial intelligence method [7], [10].

The load forecasting based on mathematical equation method is a non-black-box model [94]. The commonly used methods include regression analysis, exponential smoothing, iterative weighted least square, load derivation, etc. The corresponding relationship between the load forecasting result and its driving factors is clear, but it is necessary to understand the load characteristics and specify the model type before forecasting.

Table 4 Summary of different wind power/solar power forecasting methods

Classification criteria	Forecasting methods	Applicable scenarios	Advantages	Disadvantages
Modeling principle	Physical forecasting	New power station Inside the station	Not need much historical data	Model's complexity increases exponentially with the area and forecasting accuracy Require a lot of time and computing resources
	Statistical forecasting	Power station that has been built for some time Single or regional stations	Wider applicable scenarios	Need a large number of historical data to dig the mapping laws of series

Classification criteria	Forecasting methods	Applicable scenarios	Roles of forecasting results
Temporal scale	Ultra-short-term forecasting	4 hours ahead	Online economic dispatching Rotating reserve capacity optimization Power tracking
	Short-term forecasting	6 hours to 3 days ahead	Formulation and adjustment of maintenance plans for stations Formulation day-ahead dispatching plans for electric power system
	Mid-long-term forecasting	Months, quarters, and years ahead	Arrange major maintenance Power system planning Site selection of wind and solar power stations

Classification criteria	Forecasting methods	Applicable scenarios	Accesses to forecasting results
Spatial scale	Station forecasting	Single station	Obtained by normal modeling
	Regional forecasting	Multiple stations	Forecast the regional power directly Forecast the predictable stations in the region first, and then use the direct superposition method or the statistical upscaling method to obtain regional power forecasting results

Classification criteria	Forecasting methods	Applicable scenarios	Accesses to forecasting results
Results displaying ways	Deterministic forecasting	Scenarios need single-point forecasting results	Obtained by normal modeling
	Uncertain forecasting	Scenarios need interval forecasting results	Probabilistic forecasting: parametric method, non-parametric method Risk index forecasting: atmospheric stability risk index, prediction risk index, standardized prediction risk index Scenario forecasting: Monte Carlo algorithm, multivariate Gaussian random variable method, multivariate autoregressive moving average model, et al.

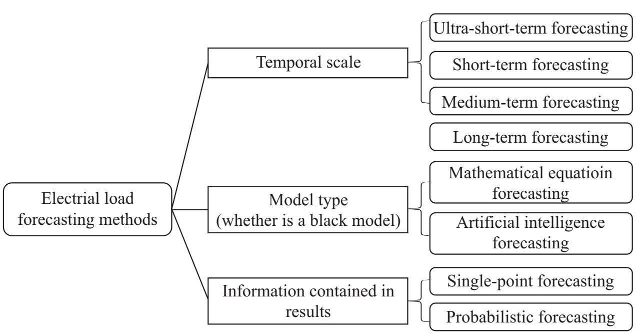


Fig. 7 Classification of electrical load forecasting methods

The load forecasting based on artificial intelligence method is a black-box model [93]. The commonly used methods include ANN, SVM, RVM, expert system method, fuzzy forecasting method, gradient boosting method, etc. The mapping relationship among input variables and load does not need to specify in advance in this method, and the model can be adjusted based on forecasting results. However, compared with the forecasting method based on mathematical equation, this method requires a large amount of historical data, and the interpretability is poor.

The load forecasting category can be selected first according to the amount of data: the mathematical equation method is more suitable for the forecasting scenario of small data; the artificial intelligence method is more suitable for the forecasting scenario of extensive data. Then, the specific forecasting method can be selected according to the time scale: the regression analysis is usually used for mid-long-term load forecasting with periodicity; the other methods are generally used for ultra-short-term and short-term load forecasting with greater volatility.

4.3 Single-point and probabilistic forecasting

The forecasting accuracy of load is relatively higher than that of wind/solar power, but the probability of single-point forecasting error is still 100% [95]. The fierce market competition, aging infrastructure, and the increasing proportion of renewable energy integration make the importance of probabilistic load forecasting is growing with each passing day.

Probabilistic forecasting can provide more comprehensive and accurate information than single-point forecasting. The applications of probabilistic forecasting results in the electric power system mainly include power flow calculation, unit commitment, and reliability analysis [96], [97], [98]. The power flow calculation is a numerical analysis for the steady-state of the power system, and the load forecasting error is the critical influence factor that causes its analysis uncertainty. The unit commitment refers to arranging the generation plan with the minimum cost while meeting the power demand and achieving the balance with a given load, i.e., design when and at what level to operate which unit. The load forecasting error affects the optimized results of unit commitment significantly. Reliability is an essential performance in the planning and operation of the power generation and transmission system. Loss of Load Probability (LOLP) is the most widely used index to evaluate the power grid's reliability by calculating the probability that the generation cannot meet the demand. LOLP is directly affected by the load forecasting error. Probabilistic forecasting can provide information on load forecasting error, which is beneficial to the power flow calculation, unit commitment, and reliability analysis of the power system.

The probabilistic forecasting results of electrical load are shown in Fig. 8.

Table 5 Summary of different electrical load forecasting methods

Classification criteria	Forecasting methods	Applicable scenarios	Roles of forecasting results	
Temporal scale	Ultra-short-term forecasting	Temporal scale: 1 minute to 1 hour ahead Spatial scale: generally a building	Real-time dispatching Demand response of power system	
	Short-term forecasting	Temporal scale: 1 hour to 1 week ahead Spatial scale: generally a building or an area	Day-ahead dispatching of power system Unit commitment Electricity derivative	
	Medium-term forecasting	Temporal scale: weeks, months, quarters ahead Spatial scale: generally a building or an area	Power system planning	
	Long-term forecasting	Temporal scale: 1 year to several years ahead Spatial scale: vary from buildings, areas to cities, countries	Power system planning Formulation of strategic energy policies	
Classification criteria	**Forecasting methods**	**Applicable scenarios**	**Advantages**	**Disadvantages**
Model type (whether is a black model)	Mathematical equation forecasting	Small samples	Not0 need much historical data The corresponding relationship between load forecasting result and its driving factors is clear	Need to understand the load characteristics and specify the model type before forecasting
	Artificial intelligence forecasting	Big data	The mapping relationship among input variables and load does not need to specify in advance The model can be adjusted according to forecasting results	Require a large amount of historical data Model's interpretability is poor

continue

Classification criteria	Forecasting methods	Applicable scenarios	Roles of forecasting results
Information contained in results	Single-point forecasting	Scenarios need single-point forecasting results	Prerequisite to balance the power supply and demand
	Probabilistic forecasting	Scenarios need interval forecasting results	Prerequisite to balance the power supply and demand Power flow calculation Unit commitment Reliability analysis

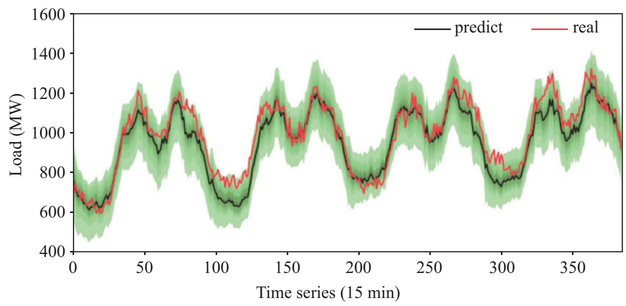


Fig. 8 Probabilistic forecasting results of electrical load

5 Wind power-solar power-electrical load forecasting

To predict the wind power and solar power on the source side, and the electrical load on the load side simultaneously can effectively improve the safety and reliability of the power system. At present, the study of wind power-solar power-electrical load forecasting can be divided into two categories according to whether the correlation between variables is considered.

5.1 Independent forecasting without considering the correlation

At present, most of the studies are independent forecasting without considering the correlation between variables, i.e., wind power, solar power, electrical load is modeled and forecasted respectively in the article.

1) The same method is used to forecast different objects separately. This kind of literature accounts for a large amount and can be further divided according to the forecasting objects.

a. Wind power and solar power forecasting at the source side [99]. Carlos et al. first proposed an online adjustable clustering algorithm based on typical and eccentric data analysis, and then used the multivariate evolution fuzzy time series model to predict wind and solar power, respectively, under each classification [100]. Cui et al. established wind and solar power forecasting models based on BPNN [101]. Gupta et al. used ANN to predict wind speed and irradiance, respectively [102]. Wang et al. proposed an approximate prediction model based on ensemble EMD to solve two problems. The decomposed sub-sequences are sensitive to original time series; the other is that the correlation with key environmental factors is lost when using EMD to forecast the wind speed/irradiance time series. The superiority of the proposed model is proved compared with the existing prediction methods based on EMD and non-decomposition [103]. Heydari et al. established the interval prediction models of wind speed and irradiance, respectively, based on the neural network grouping method and the improved multi-objective fruit fly optimization algorithm [104].

b. Wind power or solar power forecasting at the source side and electrical load forecasting [105]. Quan et al. took the narrowest prediction interval width as the loss function, and used the particle swarm algorithm with mutation to optimize the connection weights of the neural network. Then, the upper and lower limits of wind power/load prediction interval can be directly obtained [106]. Ke et al. used the probabilistic neural network to predict daily load/solar power [107]. Xiong et al. established the short-term prediction model of solar power/load based on Long Short-Term Memory (LSTM) and DBN, and then used the linear regression equation to dynamically weight the outputs of two networks to obtain the final prediction results [108].

Zhu et al. took the factors such as meteorological and social information into account and established the distributed solar power/load forecasting models based on RF [109]. Yang et al. took the haze into account and selected the similar days of solar power/load first through principal component analysis, grey correlation analysis, and weighted similarity equation. Then, they established the wavelet neural network model with additional adaptive dynamic programming correction to predict the solar power and load, respectively [110].

c. Wind power and solar power forecasting at the source side and electrical load forecasting. Alipour et al. first used the unsupervised autoencoder to extract the features of wind power, solar power, and load. Then, they adopted a supervised cascaded neural network to model and predict these three objects, respectively, according to the extracted features above [111]. Saez et al. proposed a fuzzy prediction interval model based on the data covariance to predict the wind power, solar power, and load in 15 minutes, 1 hour, and 1 day [112]. Gangwar et al. first used the maximal overlap discrete wavelet transform to decompose the wind speed/irradiance/load time series, and then predicted the series in each frequency domain separately through ARIMA. The Root Mean Square Error (RMSE) of the predicted and actual values are used as the evaluation index to adaptively select the optimal input length of each prediction model [113].

The above studies use the same method to predict different objects without considering the different characteristics of wind power, solar power, and load. Some scholars have carried out the following research to improve forecasting accuracy.

2) Different methods are used to forecast various objects separately according to their characteristics. Reikard et al. used the random coefficient regression model for wind power forecasting aiming at its strong volatility; used the ARIMA model for solar power forecasting aiming at its nonlinear changes affected by cloud cover, atmospheric turbidity, precipitation, etc. [114]. Faraji et al. adopted the adaptive neural fuzzy inference system, multilayer perceptron artificial neural network, and RBFNN to predict wind speed, irradiance, and load. RMSE is used to select the most suitable prediction model for each object [115]. Huang et al. applied the load adaptive forecasting technology and ARIMA model to predict the load and wind power, respectively [116]. Zhang et al. proposed a short-term load forecasting method based on frequency domain decomposition; the Elman Neural Network (ENN) and RF are used to predict the series in each frequency domain, respectively. In addition, they established a solar power forecasting model based on the iForest algorithm and LSTM [117].

5.2 Forecasting considering the correlation

Wind power, solar power, and load are closely related to meteorological factors such as wind speed, irradiance, and temperature. They have certain interactive coupling relationships in different operation scenarios of the power system. Therefore, some scholars consider the correlation among wind power, solar power, and load to improve forecasting accuracy. The studies can be roughly divided into the following three categories according to consideration ways.

1) To predict the total value of wind power, solar power, and load [118]. Alipour et al. used the unsupervised autoencoder and supervised cascaded neural network to predict the net load (total load minus wind and solar power) in short-term and medium-term time scales [111]. Van et al. first adopted the cross-validation method to obtain the suitable covariance function, then made a probability forecasting for the net load (total load minus solar power) based on the dynamic Gaussian process [119]. Wood proposed a transparent open-box method to predict the total power of wind and solar time series. The transparency and anti-overfitting ability of the proposed method provide advantages for its processing of scattered and non-uniformly distributed renewable energy data [120].

2) Besides the target object to be predicted, other objects are also used as inputs of the model [121]. Ding et al. proposed a load forecasting model considering the impact of large-scale solar access. They first used the mutual information theory to analyze the correlation between solar power and bus jurisdiction load, then established a hybrid learning model based on the XGBoost and extreme learning machine algorithms. The historical load and distributed solar power are used in the load forecasting model [122]. He et al. proposed a probabilistic load forecasting method based on the minimum absolute shrinkage and selection operator-quantile regression, and the critical characteristics extracted from historical load and wind power sequences are used as inputs. The results show that the proposed method can obtain more accurate probability load forecasting results when the impacts of wind power on load are considered [123].

3) Model of multiple inputs and outputs is established to predict at least two objects of wind power, solar power, and load simultaneously [124]. Zhang et al. first assumed the residual sequence and sample sequence have similar distributions, and the distribution is more similar with the sample closer. Then, they proposed a novel interval prediction method based on LSTM to synchronously predict wind speed and irradiance [125]. Li et al. proposed an improved SVM model based on the leapfrog algorithm to realize the wind power and solar power forecasting at the same time, which took the wind speed, global irradiance, scattered irradiance, and related power data of the past 48 hours as inputs [126]. Laouafi et al. established a BPNN model in each season to predict wind power, solar power, and load in 1 hour based on historical data [127].

Based on the above research, we focus on the high citation papers to further comb the current research status in the field of wind power, solar power, and electrical load forecasting, from the perspectives of forecasting object(s), method(s), temporal and spatial scales, error and the highlights of the paper. Table 6 shows some articles published in the journal of SCI-Q1 after 2015 and have been

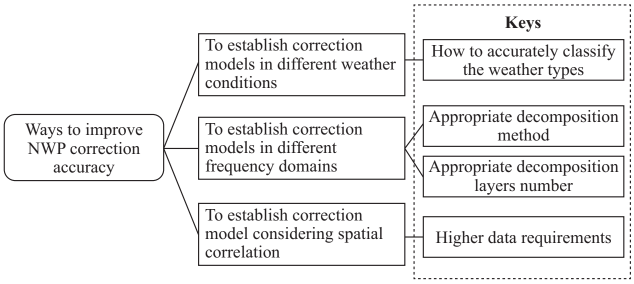


Fig. 9 Ways to improve NWP correction accuracy

cited more than 100 times, which can provide the reference for future research directions and the forecasting errors of different objects under different temporal scales. Besides, the indexes used to evaluate the prediction accuracy should be further standardized.

6 Discussion, challenges, and future research directions

1) NWP correction

The NWP wind speed/irradiance correction methods can be divided into the correction at a single location and the correction considering spatial coupling characteristics. The ways to improve correction accuracy include the following three categories.

a. To establish correction models in different weather conditions. The weather conditions are complex and diverse, how to accurately classify the weather types is the key of this method, which is also the main research direction in the future.

b. To establish correction models in different frequency domains, the appropriate decomposition method and the number of decomposition layers are crucial factors. If the decomposed layers are nimiety, data sequences in similar domains are decomposed and modeled separately, which leads to the meaningless increase of the model complexity. If the decomposed layers are not enough, the data in different frequency domains is not wholly separated, even decreasing the correction accuracy.

c. To establish the correction model considering the correlation among wind speed/irradiance time series at different spatial locations. This method can generally improve forecasting accuracy, but it has higher data requirements, which needs the NWP results in various points.

2) Wind power, solar power, and load forecasting

The classification, applicable scenarios, advantages, and disadvantages of different forecasting methods for wind power, solar power, and electrical load have been described in detail in Section 4 and Section 5. Therefore, we focus on the forecasting methods that simultaneously contain at least two objects in the following text.

At present, most studies have not considered the correlation among wind, solar, and load, different objects are modeled and predicted independently. The existing ways to consider the correlation among wind, solar, and load mainly include the following three categories.

a. The correlation among wind, solar, and load is hidden in the time series, i.e., wind power and solar power are usually regarded as “negative-load”, and the net load is predicted directly. This category cannot obtain the forecasting results of different objects, and the application scenarios are mainly concentrated in the microgrid or distribution network.

b. The data of other prediction objects are also used as inputs of the model. This category method is usually applied in load forecasting. In addition to historical load and meteorological factors, the information of historical wind power or solar power is also used as the inputs of the load forecasting model. However, the variation of wind and solar power time series is large, leading to the historical data has less representative of the future.

c. Wind power, solar power, and load are predicted through the multi-input and multi-output models. This category has a wide range of applications. When the prediction objects are at the source side, i.e., wind power and solar power, the prediction can be based on NWP or historical data. When the prediction objects are both at the source and end sides, the prediction is based on historical data. However, for short-term wind and solar power forecasting, the forecasting accuracy is relatively low, which cannot meet the assessment requirements of the power system.

New methods for integrated forecasting of wind, solar, and electrical load need to research in the future. It may be a good way to predict the wind/solar power or wind speed/irradiance at first, and then take the predicted wind/solar data as partial inputs to predict the load.

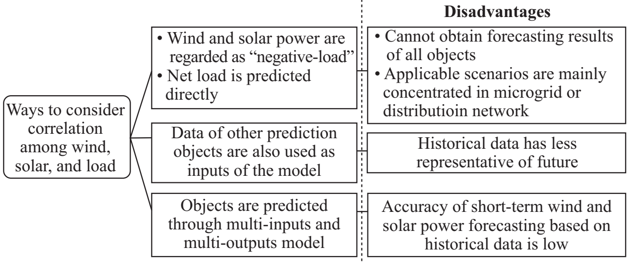


Fig. 10 Ways to consider correlation among wind, solar, and load

7 Conclusion

A comprehensive review of wind, solar, and electrical

Table 6 Summary of wind, solar, and electrical load forecasting (with higher citation)

Reference	Object(s)	Method(s)	Temporal scale	Spatial scale	Errors	Focus	Summarized highlights
Wang et al. [81]	Wind power forecasting	Deep learning based ensemble approach	5 min	Wind farm	✓15 min ahead: CRPS/NP=1.98% ✓30 min ahead: CRPS/NP=3.39% ✓1 h ahead: CRPS/NP=4.08% ✓2 h ahead: CRPS/NP=4.90%	Convolutional neural network Ensemble approach Deep learning Wavelet transform	Convolutional neural network is designed for probabilistic wind power forecasting. Ensemble technique is used to cancel out the diverse errors of point forecasters. The model misspecification and data noise in wind power are separately evaluated. The competitive performance and robustness of the proposed method were proved.
Chitsaz et al. [66]	Wind power forecasting	Using wavelet neural network trained by improved Clonal selection algorithm	1 h	Wind power participate in Alberta's electricity market	✓6 h ahead: nRMSE=13.24% nMAE=9.70%	Wavelet neural network Clonal optimization	The proposed engine has the structure of Wavelet Neural Network (WNN) with the activation functions of the hidden neurons constructed based on multi-dimensional Morlet wavelets. This forecast engine is trained by a new improved Clonal selection algorithm. Maximum Correntropy Criterion (MCC) has been utilized instead of Mean Squared Error as the error measure in training phase of the forecasting model.
Wang et al. [67]	Wind speed forecasting	Hybrid of wavelet transform, deep belief network and spine quantile regression	1 h	Wind farm	✓1 h ahead (PINC=95%): MAE=0.43~0.49 m/s RMSE=0.55~0.64 m/s MAPE=6.39%~7.04% ACE=0.21%~0.96% IS=-0.35~-0.19 m/s	Deep belief network Deep learning Quantile regression Wavelet transform	For the first time, deep belief network is designed for wind speed forecast (WSF). The nonlinear features in wind speed are used to improve forecast accuracy. The uncertainties of wind speed are evaluated using quantile regression. The competitive performance and high-stability of the proposed method were proved.
Liu et al. [63]	Wind speed forecasting	Hybrid approach based on the Secondary Decomposition Algorithm and Elman neural networks	30 min	Wind farm	✓30 min ahead: MAE=0.05~0.29 m/s MAPE=0.28%~2.21% RMSE=0.07~0.41 m/s ✓1 h ahead: MAE=0.11~0.60 m/s MAPE=0.61%~4.95% RMSE=0.15~0.82 m/s	Secondary decomposition algorithm Wavelet packet decomposition Fast ensemble empirical mode decomposition Elman neural network	A new WPD-FEEMD-Elman method is proposed for the wind speed predictions. A new secondary algorithm is presented for the wind speed decomposition. The FEEMD algorithm is adopted in the hybrid decomposition. The Elman neural network is employed in the hybrid forecasting.
Alessandrini et al. [75]	Solar power forecasting	An analog ensemble method	1 h	Solar plant	✓3 days ahead: CRPS/MP=15%~21% MAE/MP=18%~25%	Uncertainty quantification Ensemble verification	A novel method for solar power probabilistic forecasting is proposed. The forecast accuracy does not depend on the nominal power. The impact of climatology on forecast accuracy is evaluated.

continue

Reference	Object(s)	Method(s)	Temporal scale	Spatial scale	Errors	Focus	Summarized highlights
Sheng et al. [70]	Solar power forecasting	Employing the weighted Gaussian process regression approach	5 min	Solar plant	✓5 min ahead: nMSE=0.02% nRMSE=6.61%	Gaussian process regression Outlier detection Weighted Euclidean distance	Data samples with higher outlier potential have a low weight. A novel concept of the degree of nonlinear correlation is incorporated to compute the contribution of every individual data attribute. Effectiveness of the proposed method is demonstrated by performing an experimental analysis and making comparisons with other typical data-based approaches.
Jang et al. [79]	Irradiance forecasting	Based on various satellite images and support vector machine	15 min	-	✓1 h ahead: RMSE=44.14 W/m^2 MRE=7.73% R2=0.94 ✓4 h ahead: RMSE=76.23 W/m^2 MRE=16.26% R2=0.79	Satellite images Support vector machine Machine learning	The motion vectors of clouds are forecasted by utilizing satellite images of atmospheric motion vectors (AMVs). Analyzed 4 years' historical satellite images and utilized them to configure a large number of input and output data sets for the SVM learning. Effectiveness of the proposed method is proved with that of the conventional time-series and ANN models.
Chen et al. [90]	Electrical load forecasting	SVR forecasting model with the ambient temperature of two hours before DR event as input variables.	1 h	Office building	✓1 day ahead (eight hours on working days): MAE=1.57%	Demand response SVR model Short-term baseline	A new SVR model to forecast the demand response baseline for office buildings. Take temperature two hours before DR event can improve the forecasting accuracy. The forecasting accuracy is better than other seven existing methods in DR programs. The model is very generic and can be applied to a wide variety of office buildings.
Li et al. [95]	Electrical load forecasting	A ensemble method based on wavelet transform, ELM and partial least squares regression	1 h	ISO New England	✓1 h ahead: MAPE (winter)=0.27% MAPE (summer)=0.52% ✓1 day ahead: MAPE (winter)=1.43% MAPE (summer)=2.82%	Ensemble method Extreme learning machine Partial least squares regression Wavelet transform	An ensemble STLF method based on ELM is proposed. A wavelet-based ensemble scheme is introduced to STLF. A parallel model of 24 ELMs is established for 24-h load prediction. Both 1-h and 24-h ahead load forecasting are evaluated. The proposed method outperforms other techniques on the public datasets.
Cai et al. [91]	Electrical load forecasting	Deep learning driven models	1 h	Building	✓1 h ahead: MAPE (non-cool)=2.23% MAPE (cool)=2.38% ✓1 day ahead: nRMSE (non-cool)=2.78% nRMSE (cool)=2.66%	Deep learning Gating mechanism Seasonal ARIMAX	Reduced forecasting errors compared to conventional time-series model. Capable of handling high level uncertainty in the building load. Multi-step formulated convolutional neural network provides the highest accuracy. High computational efficiency is also offered by convolutional neural network.
Saez et al. [112]	Wind power forecasting; Solar power forecasting; Electric load forecasting	Fuzzy prediction interval models	15 min	One wind turbine; Two photovoltaic systems; Load in village of Huatacondo	✓1 day ahead (PINC=90%): WF nRMSE=13.31% WF nMAE=8.85% SF nRMSE=5.80% SF nMAE=3.67% LF nRMSE=6.73% LF nMAE=4.53% LF NAW=19.08%	Energy management system Fuzzy modeling Microgrid	The proposed modeling generates fuzzy prediction interval models that incorporate an uncertainty representation of future predictions. The model is demonstrated to obtain the expected values together with fuzzy prediction intervals to represent future measurement bounds with a certain coverage probability. The proposed prediction interval models would help to enable the development of robust microgrid EMS.

load forecasting methods is provided in this paper. Our work includes the survey of NWP wind speed/irradiance correction methods, wind power and solar power forecasting methods at the production side, and load forecasting methods at the demand side. Papers containing at least two of these forecasting objects are also surveyed in this manuscript, which has no relevant review at present. Furthermore, challenges and future research directions of wind power, solar power, and electrical load forecasting are discussed last.

Nomenclature

NWP	Numerical Weather Prediction
WF	Wind Forecasting
SF	Solar Forecasting
LF	Load Forecasting
GFS	Global Forecast System
ECMWF	European Centre for Medium-Range Weather Forecasts
MM5	Fifth-Generation Mesoscale Model
WRF	Weather Research and Forecasting Model
MAE	Mean Absolute Error
PCA	Principal Component Analysis
DBN	Deep Belief Network
STCA	Sequence Transfer Correction Algorithm
LR	Linear Regression
SVM	Support Vector Machine
BPNN	Back-Propagation Neural Network
RF	Random Forest
RBFNN	Radial Basis Function Neural Network
ARMA	Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
EMD	Empirical Mode Decomposition
VMD	Variational Mode Decomposition
WD	Wavelet Decomposition
RVM	Relevance Vector Machine
LS	Least Square
ANN	Artificial Neural Network
DP	Deep Learning
LOLP	Loss of Load Probability
LSTM	Long Short-Term Memory
ENN	Elman Neural Network
RMSE	Root Mean Square Error
CRPS	Continuous Ranking Probability Score
MAPE	Mean Absolute Percentage Error
ACE	Average Coverage Error
IS	Interval Sharpness
MP	Measured Power
SVR	Support Vector Regression
DR	Demand Response
MSE	Mean Square Error
MRE	Mean Relative Error
R^2	Coefficient of Determination
NAW	Normalized Average Width
ELM	Extreme Learning Machine
CV	Coefficient of Variance

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Declaration of Competing Interest

We declare that we have no conflict of interest.

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