Survey of Wind Power Output Power Forecasting Technology

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Abstract. Because of the randomness of wind energy and the non-linearity of power system, there are many dubious variables that should be noticed when forecasting the output power of the wind power. Physical method is often used in the medium-term forecasting, as its model does not require the historical data of the wind farm. The statistical method is simple and requires a small amount of data. It can be applied in those situations where data acquisition is difficult. The artificial intelligence model is suitable in the random or non — linear system as it does not rely on the accurate mode of the objective. The combined forecasting model maximizes favorable factors and minimizes unfavorable ones as contained in above-mentioned methods. This article gives out a brief summary and proposes some improvement measures against the main existing problems in prediction field.

Keywords: Wind power, non-linearity, power system, artificial intelligence model

1. Introduction

As the fast progress of the social economy, the relevant energy requirement has also magnified significantly, and conventional fossil energy is being confronted the challenge of energy depletion. Meanwhile, the problems of global warming and severe environmental contamination attributed to the massive usage of conventional fossil energy are getting increasingly prominent, posing a grim menace to the ecosystem, social economy and human health. To cope with the shortage of conventional fossil energy and the environmental contamination, clean energy has become the development direction of various governments. The exploitation and utilization of renewable energy has opened up a new way to solve the problems above, and possesses important strategic significance for improving the energy structure and ensuring the sustainable development of the national economy. At present, wind power has become the green energy with the most large-scale commercial development value. However, as a mass of wind power has begun to come into use, and its quantity has increased year by year, there are many following troubles to the power system and serious threat to the normal operation and long-term planning, thus limiting the further progress of wind power. This is because climatic factors including wind speed, wind direction, etc. can impact the work of the wind turbines, which leads to the volatility of power generation, and it will make the grid dispatching seriously difficult. At present, one of the important methods is to build a wind power forecasting system with higher prediction accuracy and more complete functions, which helps to predict the change trend, thereby reducing the influence on the power system. It is not only beneficial for dispatchers to adjust dispatching plans timely, but also further improves the operation safety and economy, and enhances the competitiveness in the power market, which possesses necessary research and practical value. Nowadays, there are several prediction methods being researched and come into use like physical methods, statistical methods, artificial methods and etc. In this article, all prediction methods mentioned above are introduced and contrasted in order to come to a conclusion on how to deal with main existing problems and further promote the forecasting precision and efficiency.

2. Classification of WPF

2.1. Classification according to time horizons

On the basis of various time horizons, wind power forecasting could be split into many categories. Various time horizon possesses all kinds of range and application purpose. Table 1 is the specific classification [1].

Table 1. Specific classification of WPP according to time horizons

Time Horizon	Purpose
Immediate short term (in minutes)	① Wind Turbine Control ② Real-time Dispatch Planning
Short term (in hours)	① Further Dispatch Planning ② Decision of Load Regulation
Medium term (in days)	① Electricity Market Operational Safety ② Arrangements for Wind Farm Maintenance
Long term (in years)	① Feasibility Research and Location Selection of Wind Farm Design ② Annual Maintenance Scheduling

2.2. Classification according to prediction physical quantity

On basis of the various prediction physical quantity, it can be split into speed (indirect method) and power (direct method). The former method is mainly split into two steps: first, predict the elements that affect the wind power; then the actual power of the generator is infer with the help of power curve of wind power generation equipment. The latter method in the first step takes the advantages of the meteorological information of Numerical Weather Prediction (NWP) and has a wide coverage. However, meteorological information changes rapidly, and its small changes can lead to large deviations in wind power forecasting. What's more, there is the cost of building meteorological information wind measuring towers. The direct forecasting method uses historical wind power data to straightforwardly forecast the output power. This method can decrease the consumption of forecasting and promote the quality of forecasting, and thus have better forecasting accuracy; its disadvantage is that it demands a mass of historical data.

2.3. Classification according to forecasting models

According to the classification of forecasting models, it could be roughly split into physical methods, statistical methods and combined methods.

2.3.1 Physical method

The physical method refers to Numerical Weather Prediction (NWP) data in order to obtain weather data and then reaches the optimal estimated value of relevant data according to the physical information around the wind turbine, and finally gives model on basis of the existing calculation model [2]. This model is also a relatively mature and well-recognized method at present. Especially in medium-term forecasting, NWP is the first step to improve forecast accuracy. The physical model does not require the historical data of the wind farm, but has a strong dependence on meteorological, topographical and other data, and the data collection and processing are also cumbersome. Various conditions of the geographical location of the wind farm need to be analyzed and studied. Due to the low frequency of daily update of weather forecasts, physical forecasting methods are usually suitable for the medium-term prediction. At the same time, the computational complexity and time complexity of high-precision prediction are very high, as the time increases, the forecasting precision decreases, resulting in unreliable forecasting consequence of a single physical model. Therefore, adding high-precision NWP data as model input can further promote the forecasting precision of the model.

2.3.2 Statistical methods

The statistical methods establish predictive models by existing historical data and wind power data. Statistical models can be split into persistence method, time series models and learning methods

(1) Persistence method

As the most classic traditional statistical method, the persistence method uses the wind power value at present as the forecast value [1] or takes the wind speed or power forecast value as the sliding average of several recent wind speed historical values. Although this means is simple, the forecasting error is large and the forecasting results are unstable, so it is only used for ultra-short-term prediction. This method often plays a role as a baseline model rather than a separate prediction model.

(2) Time series model

This model works by analyzing a mass of historical data information and then determining an appropriate model. Existing models include Autoregressive (AR), Moving Average (MA), Auto Regression Moving Average (ARMA), and Autoregressive Integrated Moving Average (Autoregressive Integrated Moving Average, ARIMA), etc. The AR model is a model that deals with the internal association of data. It considers that the value at a certain or a specific period of time after the observation point is described by the observation values at several times before the point. For the MA model, the observations at the current moment are represented by a linear combination of white noise sequences called random disturbances. The ARMA model is composed of two parts, AR and MA. It combines the advantages of AR and MA, and is more commonly used than the AR model. The value in the ARMA model depends on the composition of the past observation points and the past random interference terms. The research consequence of Croonenbroeck, C. and Dahl, C. M. [3] implies that the corrected ARMA model significantly promotes the precision of short-term and medium-term prediction. This method uses a mass of historical data for modeling, and confirms a statistical model that can describe the time series, and then derives a prediction model from this model. AR and ARMA models are suitable for stationary data, so the use of non-stationary data will cause larger errors. However, the time series of relevant data has the characteristics of non-stationary random sequence. Therefore, when establishing an ARMA model for prediction, it is important to first perform the increasing trend of data time series and periodic non-stationary processing. The ARIMA model combines the difference operation on the basis of the ARMA model to convert non-stationary data into stationary data. Therefore, the application of ARIMA model is more extensive. However, the time series model only analyzes the potential relationship of time series data variables, and it is hard to mine the nonlinear relationship between data. Therefore, this type of model is only suitable for static data analysis, which is an obvious flaw of this type of model. At the same time, with the increasing complexity of the data, the effect of a single time series analysis model for feature extraction between data is not enough to meet the needs of prediction accuracy.

(3) Kalman filter method

The Kalman filter method only needs observation data in a limited time, and the recursive algorithm is simple, but it can only be used for linear signal processes, and the noise signal must obey a Gaussian distribution. This method assumes that the statistical properties of noise, which it is not easy to estimate in practice, are known, and this is absolutely a flaw that should not be overlooked [4].

2.3.3 Artificial intelligence model

Using the classical mathematical statistics method to predict wind power has the characteristics of fast speed and simple prediction model. However, due to the fact that the work process of the gird are complex nonlinear dynamic processes, the actual change of wind farm power cannot be accurately described by mathematical statistics methods, and the artificial intelligence model does not require the precise mathematical model of the research object, which can effectively compensate for the above-mentioned defects. At present, the artificial intelligence technologies go as follows [5].

(1) Artificial Neural Network

This method is a large-scale parallel distributed processing system developed on the basis of modern neurobiological research results that imitates the information disposing process of the human brain, which has the advantages of fast, more practical and economical features for modeling and prediction of nonlinear complex systems. In addition, it is good at information synthesis, and can regulate various input information relationships, and is appropriate for describing the complicated nonlinear characteristics of wind power prediction models. Huang, J.H. and Peng, H. used artificial neural networks and their improved methods to forecast wind power from different angles, and comparative analysis indicates that the neural network forecasting means possesses higher prediction precision than traditional statistical methods [6]. The neural network method is used for actual prediction to complete the following steps: establishing the expression, selecting the model, determining the input parameters, selecting the training mode, and network testing. For this reason, artificial neural network training takes a long time, requires a mass of original data, demands high similarity of training samples.

(2) Support Vector Machine Method

This method is based on statistical theory which is unlike the conventional method, since it has strict mathematical theory and the minimized structural risk. At the same time, the minimum empirical risk and the minimum confidence range are considered, so that the model has a fantastic generalizability and can deal with the nonlinear regression estimation problem; What's more, this method can deal with the nonlinear problem as the linear one thus ingeniously solving the complex calculation. At the same time, it effectively overcomes the curse of dimensionality and the local minima problem. As a result, SVM is widely used in the prediction field. According to the characteristics of wind power data, subsequent researchers have improved the SVM model and proposed models such as PSVM and LSSVM. These models further promote the robustness of the SVM model and the precision of the output power forecasting [7].

2.3.4 Combined forecasting model

On account of the high randomness and uncertain of wind power, even if each forecasting model has its own superiority, the forecasting effect of a single model still cannot meet the actual needs. The principle of combinatorial prediction is to combine two or more methods to synthesize various useful information to make the process faster and more efficient. In recent years, combined model research combining the advantages of multiple single models has become a popular direction in wind power forecasting research. At present, combined prediction models can be roughly split into four kinds, combined forecasting methods based on multi-model weighting, combined forecasting methods based on data decomposition, combined forecasting methods based on optimization techniques, and combined forecasting methods based on error correction [8].

(1) Combined forecasting method according to multi-model weighting

The combined forecasting method based on multi-model weighting uses multiple sub-models to forecast separately, and weights the results for output. Such as the weighted combination prediction method of LSSVM and RBFNN; the weighted combination prediction method of SVM and LSTM, ARIMA and other models, etc. These methods combine multiple single base models to improve the model's predictions. To prove that the weighted combinatorial model predicts better than a single model, Chang, G.W., Lu, H.J., Wang, P.K., et al. compared ARMA, radial base model, and SVM with the combined model to verify the excellence and accuracy of the combined model [9]. In addition, the optimization of the internal structure of the model and the multi-feature prediction method can also further improve the overall effect. Multi-feature forecasting improves the forecasting effect and robustness of the wind power forecasting model by predicting some feature data in the original data and inputting the forecast value as supplementary data into the wind power forecasting model.

(2) Combined forecasting method according to data decomposition

The combined forecasting method based on data decomposition is a combined forecasting method that uses data preprocessing technology to decompose the original data into multiple stationary subsequences, and uses the model to forecast the subsequences separately. These methods combine the idea of signal decomposition, use data decomposition techniques to decompose the original data, and use a prediction model to predict the decomposed data separately. The LSTM-SARIMA ultra-short-term wind power forecasting model is proposed by Zhou, B., Liu, C., et al. [10], in the decomposition process, meteorological and seasonal factors are considered, and the forecasting precision of the model is greatly improved. Contrasted with other combined prediction methods, the combined prediction method according to data preprocessing has a simpler structure and higher computational efficiency, and is easy to migrate to scenarios such as point forecasting, multi-step forecasting, day-ahead forecasting, etc. However, the entirety forecasting precision is limited, and the theoretical analysis of forecasting errors is lacking.

(3) Combined forecasting method according to optimization technology

The combined prediction method according optimization technology optimizes the model parameters by using optimization technology, so as to promote the prediction effect. The LSSVM-GSA model based on Gravitational Search Algorithm (GSA) are combined with optimization algorithms to select optimal parameters to promote model forecasting precision [11]. Due to the influence of its own limitations and other factors, traditional optimization algorithms cannot meet the needs of high-level parameter optimization. Optimization techniques improved based on traditional optimization algorithms also play a role. For example, Li, L., Cen, Z.-Y., et al. put forward a mixture promoted cuckoo search algorithm to optimize hyperparameters of support vector machines, used for short-term wind power prediction [12]. Compared with the limited application of traditional optimization techniques, intelligent optimization techniques such as GA also have strong adaptability to data uncertainty, and some can achieve faster convergence rates and better generalization errors. However, compared with traditional optimization techniques, such theoretical analysis is not perfect, and there is a problem that the solution cannot guarantee the optimal solution.

(4) Combined forecasting method according to error correction

The combined forecasting method based on error correction is a combined forecasting algorithm that mainly uses the combined method of data post-processing technology to weaken the adverse effects of the error in the forecasting method. This type of method usually uses statistical methods to estimate the error to improve the entirety prediction results. For example, Markov is used in the article to correct the prediction results of the Fuzzy Neural Networks (FNN) model [13]. In addition, machine learning methods are also commonly used in error estimation. The document uses an RBF-based LSSVM for error correction [14]. Compared with the forecasting model without error correction, the forecasting precision of the revised one is significantly improved. The method according to error correction quantifies the uncertainty of model error size and data noise, has high forecasting precision, and can give statistical analysis of forecasting errors. However, compared with other combined algorithms, the overall computational efficiency is low.

3. The Development of Wind Power Forecasting around the World

Wind Power Forecasting technology has history of about 20 years in foreign country, and its forecasting errors can be controlled between 15% to 20%. China began to study this field much later, the forecasting precision and WPP systems are both not enough to meet dispatching demands compared to the actual rate of the development. Table 2 is a contrast of representative WPP system [15].

Table 2. Contrast of representative WPP system

Nations	Developers	Name of models	categories	Commissioning time
Germany	ISET	WPMS AWPT	Artificial Neural Network	2001
	Oldenburg University	Previento	Combined forecasting model	2002
Denmark	Riso	Predictor	Physical method	1994
	IMM&DTU	WPPT	Statistical method	1994
	Technical University of Denmark	Zephyr	Combined forecasting model	2003
Spain	M. Perez at CENER, formerly CIEMET	LocalPredRegioPre	Combined forecasting model	2001
	University Carlos III & Red Eléctrica de Españ a	Siperólico	Statistical method	2002
USA	AWS Truewind	eWind5	Combined forecasting model	1998
UK	Garradd Hassan	GH Forecaster	Statistical method	--
	Natural Power	Foresite	Combined forecasting model	--
France	France	AWPPS (MoreCare)	Statistical method	1998
Ireland	Ireland	Honeymoon	Physical method	--
·China	EPRI of China; East Environment Energy	WPFSVerl.O	Physical and statistical method	2008
	Tsinghua University	WPP system	Physical and statistical method	2010
	Beijing FuRui Electric	FR3000F	Combined forecasting model	--
	Beijing SPRIXIN545	SPWF-3000	Physical method	--

4. Future Scope

Although certain achievements have been made in predicting wind power at present, there are still many aspects that need to be studied in depth: (1) In the actual prediction, we cannot only use historical wind speed data, but also consider the actual effect of atmospheric temperature, humidity, air density, and terrain and ground conditions on wind speed, increase the amount of input information, and reduce the prediction error. (2) When using wind power prediction methods, various methods should be comprehensively utilized, and the combined model composed of multiple single models solves the shortcomings of the single model itself to a certain extent, so that the overall wind power prediction accuracy exceeds or is equal to the optimal single model prediction accuracy, but different types of combined models have different advantages and disadvantages, and should be based on practical problems in order to not only improve and maintain the stability of prediction accuracy but also avoid local minimization. (3) Strengthening the construction of numerical weather forecasting systems. Due to the error in the NWP data, there is a certain degree of error in the later period prediction of wind power. For the existing meteorological information forecasting model, multiple models can be combined to forecast, effectively overcoming large deviations in bad weather for the sake of promoting the resolution of numerical weather forecasting systems and minimizing the error of meteorological information data. (4) Formulating a clear wind power prediction performance evaluation system which fully considers the problem of deviation and fluctuation of the prediction results, and comprehensively evaluates the advantages and disadvantages of a certain forecasting method in combination with the practical value of the prediction model, such as accuracy, efficiency, and cost.(5) In the context of smart grid, using the various information collected by the wide-area measurement system to ensure that the predicted wind power meets the actual requirements of the site, so that large-scale wind power generation can gradually achieve predictable, controllable and dispatchable, and realize information interaction and coordinated control with the power grid, so as to promote the improvement of the safety and stability.

5. Conclusion

In all, based on the existing wind power forecasting data, the forecasting method is summarized and sorted out according to different time horizons, different prediction objects, and different prediction models, and as a result, combined prediction models synthesized the advantages of multiple single models are one of the most excellent answers to promote the forecasting precision and efficiency. Then, the research status of wind power prediction in various countries is introduced. It is obvious that foreign countries began to study in this field much earlier and relevant technology are much more mature. China started much later so there are many aspects still need to struggle for Chinese. Finally, in view of the above situation, some suggestions for the future development are proposed such as improving the accuracy and comprehensiveness of the prediction reference data, using combined prediction models or promoting the evaluation system and etc.

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