

Coastal Wind Power Forecasting Research Scheme Design

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Abstract: As global resource and environmental problems become increasingly acute and climate change becomes more and more obvious, the large-scale development and utilization of new energy sources are highly valued by all countries in the world. Wind energy is highly valued because of its many advantages. Wind power, especially offshore wind power, has become one of the key development directions of renewable energy. To address the problem that coastal wind farms are in urgent need of accurate wind power forecasting, the authors of this paper investigate and summarize the relevant research work in this field. At the same time, the coastal meteorological micro-scale differences are obvious, and a research program for coastal wind farm power forecasting is designed to lay the foundation for subsequent specific research for the characteristics of this region.

Keywords: Wind Power Forecasting; Renewable Energy.

1. Introduction

Energy is an important cornerstone of human survival and civilization development, and the lifeblood of social and economic development. Wind energy has become the most promising renewable energy source with no pollution, wide distribution and large storage capacity. As the main development method of wind energy, wind power generation has received extensive attention worldwide, and wind power generation technology is becoming more and more mature, and the scale and commercialization are gradually increasing.

China's offshore wind energy resources are abundant, and the southeast coast has great potential for development, and the central and southern Zhejiang Province can use offshore wind energy resources to reach a rich level. In China's "carbon peak, carbon neutral" overall goal, the Zhejiang Provincial Development and Reform Commission for Zhejiang Province "14 five" wind power set up a development goal: to the "14 five" at the end, strive to wind power installed Reach 6.4 million kilowatts or more, new installations in more than 4.5 million kilowatts, while actively promoting coastal offshore wind power, explore the deep-sea wind power test demonstration.

With the rapid growth of installed coastal wind power capacity and its increasing proportion in the power grid, the problem of peak regulation and wind power consumption in the power grid is becoming more and more prominent. Wind is generated through atmospheric motion and is affected by various factors such as temperature, pressure, topography, altitude, latitude, etc., and has a strong randomness and volatility, resulting in large fluctuations in the output power of coastal wind farms [1] as shown in Figure 1. This poses a greater challenge to the operation and management of coastal wind farms as well as to the planning and scheduling of regional power systems. To solve this problem, it is inevitable to rely on accurate wind power output power forecasting.

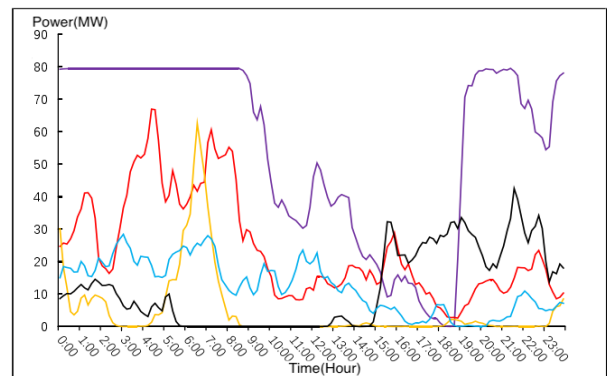


Figure 1. Power curve of a wind farm for several consecutive days

Improving the accuracy of output power forecasting of coastal wind farms can significantly improve the adverse impact of wind power grid connection on the power system, and can play a positive role in developing more scientific power generation plans for the power system, reasonably reducing operating costs and improving the competitiveness of wind power enterprises, which has a very important application value. [2] The application value is very important. Firstly, wind power forecasting provides a basis for coastal wind farms to make operation plans and grid dispatching departments to adjust dispatching plans, thus alleviating the impact of wind power access on the grid and ensuring the efficient and stable operation of the power system. [3] Secondly, it is helpful for coastal wind farms to develop reasonable operation plans. Secondly, it helps coastal wind farms to make reasonable power trading plans and improve profitability; finally, coastal wind farms can make equipment maintenance and overhaul plans based on wind power forecasting results, so that the impact of maintenance and overhaul on production can be minimized. [4] Finally, coastal wind farms can develop equipment maintenance and overhaul plans based on wind power forecasting results to minimize the impact of maintenance and overhaul on production.

2. Review of current research work

In this paper, we conduct an extensive research and analysis of wind power forecasting research work, firstly, we classify

and summarize the progress of wind power forecasting research, and then we describe the application situation at home and abroad.

2.1. Different classifications of wind power forecasting studies

Wind power output forecasting is essentially the measurement of wind power output values at a certain point in the future according to a certain fitting curve based on known multi-factor information, and wind power forecasting can be divided into the following categories according to different distinguishing conditions. [5] Wind power forecasting can be divided into the following categories.

2.1.1. Classification according to the time scale

According to the length of the forecast time scale, there are usually ultra-short-term forecasts, short-term forecasts, medium-term forecasts and long-term forecasts. The ultra-short-term forecast is mainly used to avoid the short-term fluctuation of wind power to the stability of the power supply system, and its time forecast unit is very small, usually in "seconds" or "minutes"; short-term forecast is in "hours" Short-term forecasts are made in "hours", usually 24 to 48 hours in advance, to forecast the power output in the next few hours, mainly to facilitate grid scheduling so as to adjust the scheduling plan in time to ensure the quality of power supply; medium-term forecasts are made in "days", which are broadcasted a week in advance to guide the scheduling of wind turbine maintenance or power supply stability. This is mainly used for wind farms to plan the optimal downtime of wind turbines and reduce the economic losses caused by downtime by optimizing the downtime plan; long-term forecasts are made in "months" or "years", and need to be carried out several years in advance. Long-term forecasts are made in "months" or "years" and need to be prepared several years in advance for forecasting studies to design and plan the annual power production and generation plan of the wind farm in question, with the forecasted annual power production as the basic goal.

Demolli et al. [6] A statistical review of the literature on different time scales found that about 87% of the wind power forecasting studies were ultra-short or short-term. Domestic studies are also ultra-short-term or short-term in the majority, and Zhu Youcheng et al. [7] analyzed that, on the one hand, due to the low application scenarios of medium- and long-term wind power forecasting, and on the other hand, the data on power generation and meteorology of wind farms in China are usually only available back to the previous 5-7 years, resulting in the lack of sufficient samples for medium- and long-term forecasting.

2.1.2. Classification According to the modeling method

According to the different modeling methods, they can be mainly divided into physical modeling method, statistical modeling method, intelligent learning method, and combined modeling method.

(1) Physical model method

The physical model method mainly uses NWP (Numerical Weather Prediction) to determine the meteorological information in the future time period, and after analyzing the topography, wake and spatial correlation in the area around the wind turbine, the micro-scale meteorological information such as wind speed and wind direction at the hub height of the wind turbine is obtained, and finally the original power is

solved by following the equations of mass, momentum and energy conservation. The output power of the wind turbine is solved by the mapping of the original power curve. This method does not require training with historical data, and with the support of high-precision meteorological forecast data, the prediction results are relatively accurate and suitable for ultra-short-term forecasting. However, this method relies on a large amount of topographic and meteorological data, requires the cooperation of experts in multiple fields, constructs a model with many empirical parameters, and the model is very complex leading to poor portability, which makes the method inapplicable in many cases [8].

(2) Statistical modeling method

The statistical modeling method analyzes mathematical distribution patterns from historical data, i.e., it summarizes spatial and temporal information in the data to make forecasts. [9] The statistical modeling method is usually based on wind power time series and wind speed time series. Conventional statistical modeling method usually takes wind power time series and wind speed time series as the basis, and establishes the mapping relationship between historical data and predicted power values according to the process of model identification, parameter estimation and model validation. [10] The statistical model method requires only historical data. The statistical modeling method only requires historical data to establish the mapping between the input characteristics and the output power series to be predicted, and then obtains the predicted values by substituting the measured data through this mapping relationship. This method fits a large amount of historical meteorological data and power data by statistical regression, and the commonly used methods are regression analysis and time series method. For example, Wang et al.[11] proposed an adaptive robust multicore regression model to solve the problem of inconsistency between the generic Gaussian assumption of the prediction model error term and the real wind power forecasting error distribution; Zhong et al.[12] proposed a genetic algorithm nonlinear time series prediction method based on singular spectrum analysis for predicting wind resources at sites in the South China Sea, and the results were better than the persistence model.

Statistical methods are usually easier to implement than other methods, models are economical and save computational power. However, wind energy has typical nonlinear and non-stationary characteristics, and only by establishing a functional form can we achieve some effect on wind power forecasting. If the wind power forecasting accuracy is to be further improved, the wind power model needs to be further optimized and the statistical methods become very unstable over a longer time range [9].

(3) Intelligent learning method

With the in-depth development of computer hardware and software technology, the continuous improvement of machine computing power, and the popular application of artificial intelligence theory, machine intelligence learning methods have been extended in statistical methods. The essence of the intelligent learning method is not to describe the relationship between wind power and related influencing factors in the form of mathematical analytic formula, but to establish a nonlinear model by extracting the relationship between input and output variables with artificial intelligence, train the model using labeled data and predict with the converged model. And with the deep development of deep learning theory and its successful application in various fields,

researchers have started to try to use deep learning methods in the field of wind power forecasting. Xue-Wen Lei[13] investigated the application of fully connected neural networks in wind power forecasting and joint scheduling of power systems. Xin Zhang [14] investigated CNN (Convolutional Neural Networks) combined with dynamic modeling for short-term wind power forecasting. Yu et al. [15] proposed an improved LSTM (Long Short-Term Memory) model for wind power forecasting, based on correlation, filtering wind unit feature data at a certain distance, and further optimizing the wind power forecasting effect by clustering. Shahi et al. [16] proposed a new genetic long-term short-term memory (GLSTM) framework consisting of LSTM and genetic algorithm to predict short-term wind power generation, using LSTM to automatically learn features from sequence data while using global optimization strategy of genetic algorithm to optimize the window size and number of neurons in LSTM layers, providing reliable predictions for seven wind farms in Europe.

(4) Combined model method

The combination method is to combine one or more of the above mentioned models to fully utilize the advantages of each model to improve the wind power output prediction accuracy. Zhang et al. [17] used a combination of time series and neural network forecasting methods, using wind speed time series as input data and wind speed data time series features as input attributes of neural network, and using neural network to construct models and train them, after the combination, the advantages of each method are fully utilized and the forecasting accuracy is improved. Alessandrini et al. [18] Combination of different physical methods using NWP prediction model gives better prediction results than single NWP model. Chen et al. [19] combined physical methods with intelligent computing methods to construct a combined NWP and GPR model, and the prediction accuracy was significantly improved compared with the traditional neural network; Lingling Li et al. [20] exploited the respective advantages of statistical models and intelligent learning models to constitute a combined model that outperforms time series models and RBF models in terms of prediction effectiveness.

2.2. Applications of wind power forecasting research

(1) Foreign applications

Countries and regions with abundant ocean wind resources, such as Denmark, the United States, Germany, Spain, Ireland, Japan and Australia, have started to study wind power forecasting in the 1980s, and also have more in-depth research and more mature results, and their wind power forecasting systems have been commercially applied [8]. These early wind power research and production countries use NWP as the basic input set and have built a relatively complete wind power forecasting system with an average forecast accuracy of over 85%, with the main errors caused by meteorological forecast errors. [21] The main errors are caused by meteorological forecast errors.

The WPPT (Wind Power forecasting Tool) based on a statistical model was developed by the Danish University of Science and Technology in 1994, which can predict wind power within a time frame of half a day to three days and has been used in practical applications in the power systems of many countries such as Denmark and Ireland. [22] It has been

used in many countries such as Denmark and Ireland. AWS Truewind developed the e-Wind wind power forecasting system in 1998 based on a combination of NWP numerical meteorological and statistical models. [23] The system uses Bayesian neural networks to eliminate systematic errors, uses dynamic numerical weather forecast data, and also takes into account the effects of small regional meteorological conditions on wind power output, enabling a relatively accurate prediction of wind power over the next 48 hours. In addition, the University of Oldenburg, Germany, and Energy & Meteo Systems, Inc. collaborated to develop the Previento wind power forecasting system in 2002; in the same year, two wind power forecasting systems, Local Pred and Regio Pred, were developed by relevant Spanish institutions, all three of which are based on the NWP physical method for prediction.

(2) Domestic applications

Domestic scholars have followed the international research frontiers in wind power forecasting theory and methods, and at the same time, significant progress has been made in the development of related prediction systems. The CWPPS (CEPRI Wind Power forecasting System) developed by the Chinese Academy of Electric Power Research (CAS) was put into commercial operation in 2008, which can provide reasonable guidance for power generation planning and scheduling. In the same year, the WPFS Wind Power forecasting System, jointly developed by the New Energy Research Institute of Chinese Academy of Electric Power and foreign countries, was also put into operation in a number of wind farms across China. [24] In 2010, Tsinghua University used a combined forecasting approach to construct a wind power forecasting model, and the system used the National Weather Bureau NWP numerical weather forecast as input data. In 2011, North China Electric Power University developed the SWPPS system to achieve short-term and ultra-short-term forecasts within 4-72 hours. In 2018, Shandong University and Shandong Electric Power Research Institute developed a system based on kernel density estimation and sparse Bayesian approach, developed a new energy data platform forecasting system for Shandong Province [25].

2.3. Summary of similar research work

Firstly, the research object has limitations. Most of the domestic research takes inland wind farms as the research object, and directly uses large regional weather forecasts for each turbine power forecasting modeling, with little consideration of the differences in wind energy resources borne by each turbine. This has little impact on the vast terrain of inland wind farms, but for coastal wind farms is a problem that cannot be ignored. Because the inland and marine meteorological characteristics are different, as the junction of the two coastal areas, meteorological complexity and change. In addition, the coastal Zhejiang hilly, island landscape, even if the same wind farm of different wind turbines, but also because of the altitude of the wrong, local micro-meteorological fluctuations, resulting in the actual measured wind speed of each turbine and the large regional forecast wind speed there are obvious differences.

Secondly, there are differences in research methods. Most of the foreign wind power forecasting systems use physical models or combined models, because the higher accuracy and resolution of NWP in these countries provide better data support for wind power forecasting. In contrast, China's NWP meteorological forecasting research started relatively late,

and the publicly available meteorological forecasts are difficult to directly meet the refined modeling at the turbine level. Therefore, using statistical modeling method or intelligent learning method to further improve the accuracy of wind power forecasting is the current mainstream research task.

In summary, the research on coastal wind power forecasting, combined with the latest advances in the field of artificial intelligence, expands the application of wind power forecasting technology in the coastal environment and also explores the research innovation of the type of intelligent learning method under the condition of limited NWP accuracy.

3. Coastal Wind Power Forecasting Research Scheme

Wind power is the process of converting the kinetic energy of the wind into electrical energy, so the output power of a wind turbine is closely related to the wind, wind direction and other meteorological data. At the same time, according to the working principle of wind turbine, its output power is also related to the state and historical output of the wind turbine. Therefore, coastal wind power forecasting is essentially finding the relationship between the output power of coastal wind farms and the meteorological data, turbine status data, and historical output power of the region. In this paper, based on the measured historical data of coastal wind farms, we carry out the research of wind power forecasting by combining the characteristics of obvious differences in coastal meteorological microscale. The main contents are as follows.

3.1. Wind power history data pre-processing

The historical data required for wind power prediction model training include four main types: regional meteorological forecast data, actual meteorological data of wind turbines, wind turbine status data, and wind turbine power data, which are characterized as shown in Table 1.

Table 1. Data required for wind power prediction model training

Data Name	Sampling Interval	Data Quality	Data Source
Regional weather forecast data	1 hour	More complete, no distortion	Downloaded from weather forecast website and saved to local database
Wind turbine measured meteorological data	Second or minute level	Missing or distorted	Wind turbine SCADA system
Fan status data			
Fan power data			

From this, it can be found that the three types of data from the wind turbine SCADA (Supervisory Control And Data Acquisition) system are of relatively low quality. The harsh natural environment at sea may cause electronic equipment failures, which can lead to individual data missing or distorted.

In addition, unplanned shutdowns or systemic failures of the turbines can cause concentrated distortion of values over long periods of time.

On the other hand, the sampling interval of these four data is not uniform. The regional weather forecast data originates from the weather forecast website and has a sampling interval of 1 hour. For the other three types of data, the sampling interval is set differently for different wind turbine SCADA systems at different wind farms, resulting in different data accuracy, both at the second level and at the minute level.

In summary, wind power plants generate a wide variety of data, a large amount of data, data formats and time intervals are not uniform, there are also missing data and distorted data, etc. These data are all interrelated and contain the main factors required for the normal operation of the turbine, and need to be pre-processed such as cleaning.

3.2. Refinement of spatial and temporal scales of meteorological forecasting

According to the experience of industry experts, the power of a wind turbine is highly correlated with the meteorological data at the hub of the turbine. For a single wind turbine, the accuracy of meteorological forecast data at the hub has a large impact on its power prediction accuracy. However, the accuracy of public or paid meteorological forecast data at home and abroad does not yet meet the demand for coastal wind power prediction, as shown by the following.

(1) Inadequate spatial scale

The complexity of the coastal topography causes differences in micro-meteorological conditions within a small area. This is evidenced by the measured meteorological data of the wind turbines, where the wind speed and direction vary for different turbines at the same wind farm at the same moment. Currently, the domestic public weather forecasting service has a spatial scale roughly at the county level; foreign paid weather forecasting services, typically such as windy.com, can predict weather data at any latitude and longitude, but according to actual tests, there is no difference in weather forecasting data within 5*5 km², a spatial scale similar to the area of coastal wind farms. Therefore, the current spatial scale of domestic and international meteorological forecast data is not yet sufficient to support high-precision power prediction at the turbine level.

(2) Insufficient time scale

According to the requirements of local power companies, wind farms need to report their output power forecasts for the next 24 hours to the county transfer (county dispatch center) with a time scale of 15 minutes. As far as the research team knows, the minimum time scale of public or paid weather forecasting services at home and abroad is 1 hour, which is not enough to meet the reporting requirements of wind farms.

In summary, it is necessary to mine the relationship between weather forecasts on a larger regional scale and weather data at the hub of each wind turbine based on historical regional weather forecast data, and actual meteorological data of the turbine, as shown in Figure 2. In this way, when executing the forecast, the future meteorological forecast data is input to obtain an estimate of the meteorological data at the hub of each turbine, and then the time scale of this estimate is refined to 15 minutes by interpolation, thus providing suitable input data for the subsequent power prediction model.

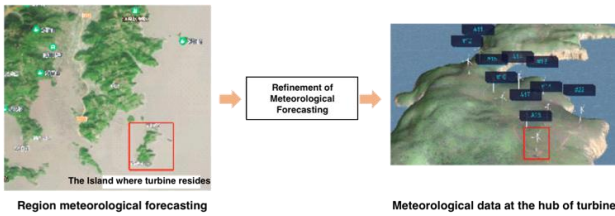


Figure2. Meteorological forecasting refinement

3.3. Wind power prediction modeling

The wind power output power has a certain periodicity, the wind power input data obtained after the previous link is time series data, and the predicted output power data is also series data with time-periodic characteristics, and the deep learning model of RNN (Recurrent Neural Networks) series can usually be used to deal with the end-to-end time series data. The disadvantage of the original RNN is that when the input time series or the time series to be predicted is long, the historical series information will be replaced by more recent information, resulting in the disappearance or explosion of the distal information obtained from training. LSTM (Long Short Term Memory) is an improvement of RNN, which adds input gates, output gates, forgetting gates and The four structures of memory units are added to achieve a reasonable retention and forgetting of the wind power sequence history state, which makes the wind power long sequence training state propagate better in the network and eliminates the gradient disappearance or explosion problem.

However, LSTM still has the following shortcomings in wind power prediction: (i) hidden features in the data are more important than usual during extreme weather or large power fluctuations, but LSTM cannot identify the differences of these high-dimensional features; (ii) in the face of multi-dimensional long series of wind power data, there are problems such as easy to ignore the sequence structure information and difficult to solve the long-time dependence. Therefore, the authors of this paper propose to conduct an innovative research based on LSTM networks to solve the above problems.

3.4. Wind Power Forecasting Application System Development

In order to make the researched wind power prediction innovation applied to coastal wind farms and produce practical value, this paper will develop a wind power prediction application system based on the aforementioned research content. The system functions roughly include: weather forecast crawler, daily scheduled execution of forecast, wind farm management, and analysis of forecast results.

4. Conclusion

Coastal wind power has become one of the key development directions of renewable energy. To address the problem that coastal wind farms are in urgent need of accurate wind power prediction, we summarized the relevant research work in this field and then proposed a research scheme for coastal wind farm power prediction. The aim of this scheme is to tack the micro-scale meteorological differences problem and lay the foundation for subsequent specific research for the characteristics of this region.

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