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An Overview: the Development of Prediction Technology of Wind and Photovoltaic Power Generation

Zheng Z. W.[a], Chen Y. Y.[b], Huo M. M.[a*], Zhao B.[c]

[a] *Department of Computer, Zhejiang University City College, Hangzhou 310015, China*
[b] *College of Computer Science and Technology, Zhejiang University, Hangzhou 310027 China*
[c] *Institute of Zhejiang Electric Power Test & Research, Hangzhou 310014, China*

Abstract

The energy management information system has became a research hotspot with the rapid development of smart grid, which using for the integration of micro-grid and traditional electric power grid. However, renewable energy sources (such as wind energy, tidal energy, etc.) with unstable, intermittent and controllability characteristics bring a number of challenges to the integration of micro-grid and traditional electric power grid. Solving these problems depend on accurately forecast micro-grid power generation output in a certain time. This article outlines and tracks the main prediction technologies of wind and photovoltaic power generation over the past 10 years, and highlights these prediction models based on statistics (such as Kalman filtering, data mining and wavelet transform, etc.) and artificial intelligence (such as neural networks, fuzzy inference and biological intelligence algorithm, etc.). Finally, this paper also pointed out the shortcomings and improved directions of various forecasting techniques to help researchers in related fields propose better prediction model of power generation forecast. □

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1. Introduction

Develop renewable resources is the main approach to solve energy crisis, while renewable energy generation is the most efficient and clean way to use renewable resources, only for wind power generation, it will meet 12% of global electricity demand by 2020[1].

Micro-grid provides a new operating model for renewable energy generation. However, the characteristics of renewable energy sources (such as unstable, intermittent and controllability, etc.) bring

* Corresponding author. Tel.: 057188018813.
E-mail address: huomeimei@zucc.edu.cn.

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many challenges for the integration of micro-grid and the traditional power grid: I. the energy storage capacity of micro-grid is generally 2-3 times than the rated load, and frequent charging and discharging will shorten the life of energy storage devices; II. the scheduling strategy after combination cannot be pre-arranged; III. weakened the competitive advantages of the renewable energy compared to traditional energy generation. The key to solve the above problems is predicting accurately for renewable energy generation. Meanwhile, power generation forecast also has the following functions [2]: I. to determine the current flow direction between traditional grid and micro-grid; II. to make the dispatching scheme of power system; III. to develop the energy reserve plan; IV. to manage renewable energy power plants; to enhance the competitive advantages of renewable energy generation.

In recent years, with continuous increasing of the computer calculation speed, researchers propose a number of power prediction models based on complex statistics and artificial intelligence techniques. These scenarios tend to spend a lot of time on building prediction model, but can get a better prediction compared to the traditional forecasting techniques. This article focuses on the ideas and improvement directions of these techniques, which is very useful for the new researchers in the field, and it can also help managers of wind and photovoltaic power plants choose the appropriate prediction model to obtain greater economic benefits.

The remaining sections of this paper are organized as follows: the second part describes the various prediction scenarios of wind power generation; the third part describes various prediction scenarios of photovoltaic power generation; Finally, the last part gives a summary to the full text.

2. The Present Status of Wind Power Prediction

The analysis of low-dimensional nonlinear dynamic model showed that [3]: the time series data of wind power generation output have chaotic characteristics, so they can be predicted. Wind power generation prediction generally includes wind speed forecast, power curve calculation and model output statistics[1], and the key is wind speed forecast. Due to temperature and pressure difference, air density and topography and other factors, make wind speed become one of the most difficult meteorological parameters to predict. According to the range of forecast time, wind power generation prediction can be divided into long-term forecast(3-10 days), medium-term forecast(6-72h), short-term prediction(0-6h), and the most useful prediction is short-term prediction [4].

All the wind power generation prediction models include two stages: I. data collection; II. data processing. The role of data collection is to provide input information for the prediction model. As for wind power prediction, the most important information are meteorological parameters and historical wind power output data. The meteorological parameters come from measuring device (such as weather sensors, etc.) deployed around wind farms and weather forecast information of meteorological department.

Currently, all the wind power prediction models can be divided into two categories: A, indirect prediction; B, direct prediction.

2.1. The Indirect Prediction Method of Wind Power Output

Because wind power generation output is mainly determined by wind speed, most of wind power prediction models firstly predict wind speed and then use the power curve to convert wind speed into power output. As for wind speed forecast, there are four basic prediction models: I. physical prediction model; II. prediction model based on statistics; III. prediction model based on artificial intelligence; IV. combination prediction model.

1) Physical prediction

The physical model [5-7] based on numerical weather prediction is a traditional forecasts technology

of wind speed, similar to general weather forecast, its main idea is putting some meteorological observation data in a certain time as initial value and solve equations of atmospheric dynamics and thermo dynamics to get wind speed forecast value.

Physical prediction model can get good results for long-term wind speed forecasts (3-10 days), but for short-term wind speed forecasts (0-6h) is less effective. Moreover, the physical model easily lead to system errors when forecasting some meteorological parameters (such as wind speed, wind direction, especially near the ground); the shortcomings of physical state parameters make the prediction model can not get a good result for subnet phenomena, for example, the wind band caused by terrain is often systematically underestimated. The method to eliminate systematic errors in physical model is using statistical techniques to post-process the predicted results.

2) Prediction method based on statistics method

The idea of statistical prediction is based on wind speed time series data, using curve fitting and parameter estimation to build wind speed prediction model, and using the error between forecast value and actual wind speed to adjust the model parameters. Statistical model is more easily building compared to other prediction models and very effective for short-term prediction, but due to wind speed time series with autocorrelation and standard deviation make the prediction error increasing with the prediction time increasing and so it cannot be satisfactory for long-term prediction[8][9].

S.Dutta et al[10]proposed a prediction model based on the space correlation of wind speed among adjacent locations, and the paper also pointed out the building prediction model is better than persistent prediction. D. Lei et al[11] used artificial neural networks based on chaotic time series to forecast short-term wind power generation. Wavelet transform decompose time series into different resolution, which separate approximate part and detail parts. Then, different ANNs are built according to phase space reconstruction. The prediction model based on this method has better prediction properties than its similar back-propagation networks for prediction of wind power generation. N. A. Karim et al[12] used linrealized time series to forecast short-term wind speed. Wind speed data through regression analysis to build normal distribution and linear predictive coefficients are calculated using finite impulse response filter (FIR) and infinite impulse response filter (IRR). A. Kusiak et al[13] proposed the idea that custom prediction model to improve forecast accuracy, a set of the most relevant parameters(predictors) was selected using the underlying physic and k-means clustering algorithm, and then according to different standards to cluster analysis for testing and training data sets, and last select the most appropriate forecasting algorithm for each cluster dataset. P. Louka and G. Galanis et al[14]used Kalman filter to preprocess wind speed time series data to eliminate system error, and then used numerical weather prediction model to forecasts wind speed. K. Philippopoulois et al[15]used a random statistical autocorrelation moving average ARMA (p, q) model to simulate wind speed sequenced data, ARMA (p, q) model considers the statistical characteristics of average hourly wind speed data, such as autocorrelation, non-normal distribution and daily non-stationary and so on. L.Kamal and Y. Z. Jafri[16] used ARMA model with multiple parameters to fit hourly average wind speed and convert raw data to make their distribution close to normal distribution, and the raw data were standardized to eliminate daily non-stationary. J. Juban et al[17] proposed a kernel density estimation techniques based on discrete model to produce a complete forecast probability density function. L. Lin et al[18] proposed two measures to improve the forecasting accuracy: optimization of smoothing parameter, or in different regions use different input data with different smoothing parameter; Smoothing parameter gradually evolve with time. S. Bivona et al[19] proposed a new keneral density forecasting methods for short-term wind speed prediction, and used methods based on normal distribution, kernel density estimation and bayesian estimation to predict the uncertainty of wind speed.

Prediction model based on statistics is not suitable for long-term prediction and without the ability to learn, the state and measurement equations of kalman filter is difficult to derive, so it is very difficult for

prediction model based on statistics to further improve prediction accuracy. In recent years, the rapid development of artificial intelligence technology provides a good solution to further improve the prediction accuracy of wind speed.

3) Prediction method based on Artificial Intelligence

The essential of AI(Artificial Intelligence)is to simulate the process of human thought, the prediction model based on artificial intelligence have learning ability and so prediction accuracy can be improved with the increase of historical data. Relative to statistical prediction models, artificial intelligence prediction models does not need determine mathematical expressions between the input data and output data, instead get forecast value through the training of prediction model.

P. Flores et al[20]used an artificial neural network based on back-propagation algorithm to build wind speed prediction model. W. Potter et al[21]used artificial neural networks to build a prediction model, in which the parameters of artificial neural network(such as weights and bias)are obtained by back-propagation algorithm, and meanwhile using differential mode to preprocess the input data. C. Wang et al[22]used improved PSO algorithm to train BP neural network for accelerating the convergence speed of neural networks; neural network gradually approximate the nonlinear relationship between input and output by the training, and the established prediction model also takes the temperature and other weather factors into account. K. Y. Huang et al[23]used adaptive learning to train BP neural network as the traditional neural network may enter local convergence and the wind speed forecast model achieve better prediction effect. G. Damousis et al[24]exploited spatial correlation existing among wind speed time series to build a fuzzy expert system to forecasts wind speed, and a real-coded and a binary-coded genetic algorithm are used to train the fuzzy expert system. W. Potter et al[21]used an adaptive neural fuzzy inference system (ANFIS) to forecast wind vectors(wind speed and wind direction), and the learning algorithms of prediction model include least squares and the gradient descent method. Y. Gao and R. Billinton[25]used a genetic algorithms method to adjust the ARMA models to simulate hourly wind speeds based on the degree of wind speed correlation between the wind sites and introduced a method to generate random numbers with specified correlation coefficients.

The main advantage of prediction model based on artificial intelligence technology is using different datasets, so we can build prediction model apply to long-term and short-term wind speed prediction, and the prediction model have ability to learn.

4) Combination Prediction

Combination prediction models are special statistical models that produce an optimal forecast by compositing forecasts from a lot of different forecast techniques. Combination prediction is based on research that has demonstrated that a composite of forecasts from an appropriate ensemble of forecast generating techniques is often superior to those produced by any one member of the ensemble. The fundamental concept is that if the errors in the forecasts produced by the different methods are unbiased and have a low degree of correlation with one another, the random errors from the individual forecasts will tend to offset each other, with the result that a composite of the forecasts will have a lower error than any individual forecast. If all of the input forecasts are highly correlated the impact of ensembling will be minimal. This means that the underlying forecast methods must be quite different in how they construct the relationships between the raw observational data and their forecasts or the type or amount of input data going into the methods must be significantly different.

Y. A. Katsigiannis et al[26]used a combined neuro-fuzzy and artificial neural network model to forecast, the output of fuzzy system are used to construct the network structure of artificial neural networks, and used the memory of fuzzy data model to get more accurate wind speed forecast. S. Kariniotakis et al[27]used statistical and physical technology to build an accurate short-term forecasting model in ANEMOS project and the forecast time of the model is 48 hours. R. Jursa et al[28]built the prediction model based on nearest neighbor search for the input data through particle swarm optimization

algorithm selection, and by combine use nearest neighbor search and particle swarm optimization to reduce prediction error.

2.2. The Direct Prediction Method of Wind Power Output

The idea of direct prediction is putting historical information of wind power output as the prediction model's input and the output of the prediction model is the predicted value of wind power generation.

C. Mabel et al[29]proposed a power prediction model with three input variables (wind speed, relative air humidity and power generation time)based on artificial neural network. M. Negnevitsky et al[30]used adaptive fuzzy inference system to predict wind power generation, the model use wind speed, wind direction, wind vector and other different parameters to predict, and pointed out advantages and disadvantages of these parameters. T. Kitajima et al[31]expressed the wind information (wind speed and direction) by complex numbers on the complex coordinates, and use them as input information of the complex-valued neural network, prediction model was trained by using complex back propagation algorithm so the prediction error decreases. Furthermore, the CVNN can process complex numbers directly and naturally, so the proposed output prediction system are more accuracy than using the real-valued neural network (RVNN). G. N. Kariniotakis et al[32]developed an advanced model based on recurrent high order neural networks, and proposed a new algorithm replaced trial-and-error method to maximize the generalization capability of forecasting model.

3. The Present Status of PV Power Prediction

Photovoltaic power generation is a power generation technology that uses photovoltaic effect of semiconductor interface to convert solar energy directly to electrical energy. By 2030, renewable energy in total energy structure will account for 30%, while photovoltaic power generation will meet more than 10% of the total energy demand in the world. Relative to the mature wind power forecasting techniques, now the research of photovoltaic power generation prediction is still in the initial stage and the proposed scenarios in the literature are relatively few.

G. Capizzi and F. Bonanno[33]used a biorthogonal wavelet decomposition to design neural networks and put solar radiation as a signal of wavelet space, and compressed signal coefficients set are used to properly modify the adaptive amplitude structure of the recurrent learning algorithm for a predictive neural network, and the proposed regressive nonlinear autoregressive BPTT neural network improves the forecasting performances. K. Mitsuru et al[34]proposed direct and indirect methods to forecast next day power generation in a PV system. In the indirect forecast method, solar radiation is predicted using past weather samples and the estimated solar radiation is then converted into generated power; In the direct method, the generated power is predicted directly using weather/power data samples acquired during system operation. And it showed the direct method was better. A. Chaouachi et al[35]proposed four neural networks, namely: multi-layered perceptron, radial basis function, recurrent and a neural network ensemble consisting in ensemble of bagged networks to ensemble a artificial neural networks for 24 hour ahead solar power generation forecasting of a 20 kW photovoltaic system, and each network of the ensemble over-fits to some extent and lead to a diversity which enhances the noise tolerance and forecasting generalization performance comparing to the conventional networks. Y.-Z. Li et al[36]proposed a grey-Markov model based on the Grey forecast GM (l, l) model and the stochastic processes Markov model to forecast and reflect the trend of the solar photovoltaic generations when the forecast results was expressed as forecast range instead of a value. And the authors pointed out the Grey-Markov chain model can improve the accuracy of forecast in the random fluctuating data sequence. Y.-Z. Li et al[37]built a Markov Chain model of the power generation forecast based on the Markov decision

theory, and it showed the forecast results depend on the accuracy of raw data, which all forecast method cannot surpass. Y.-Z. Li et al[38]proposed an advanced Grey-Markov chain model to forecast short-term Grid-Connected photovoltaic system generation daily power generation, it is shown daily power generation are changed in exponent rule and fluctuant in a certain time so advanced Grey-Markov chain model is more accurate.

4. Conclusion

This article summarizes wind power and photovoltaic generation forecasting techniques since last 10 years, and highlights these prediction models based on statistics and artificial intelligence technologies, meanwhile we also illustrates advantages and disadvantages of these prediction models and their improved directions. Finally, we also give the following recommendations for future wind power and photovoltaic generation forecast: I. In wind power prediction, an important reason leads to forecast error of indirect forecast is using power curve provided by wind turbine manufacturer to convert wind speed into power output directly. But the power curve provided by wind turbine manufacturer is obtained under certain conditions, and it cannot accurately describe the relationship between wind speed and power output in any case. In order to further improve precision, we should according to the actual situation use techniques such as statistical methods to determine the precise relationship between wind speed and power output; II. The prediction accuracy of all prediction models rely on the accuracy of raw input data (such as photovoltaic power generation forecast needs accurate weather information, etc.), we can deploy remote weather sensors (such as Doppler radars, Lidars, Wind Profiles, etc.) to collect the weather information in real time.

This article aims to help new researchers in the field understand and track the latest research progress of wind power and photovoltaic generation forecast techniques and then build more accurate forecast models.

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