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OPINION
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# Wind Speed and Power Prediction Approaches: Classifications, Methodologies, and Comments

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## INTRODUCTION

With the swift development of economy, traditional energy resources have been exposed to problems such as decreasing reserves, environmental pollution, and health hazards of human beings (Yang et al., 2020a; Yang et al., 2021a). Nowadays, renewable energy resources (RESs) have been given great importance by the public and achieved significant development under the support of government policies (Sun and Yang, 2020; Mahidin et al., 2021). Among a variety of RESs, wind energy resources are abundant, cheap to develop, have high conversion efficiency, and are environmentally friendly (Guchhait and Banerjee, 2020; Li et al., 2020). As a result, wind farms have sprung up all over the country. However, with the gradually increasing proportion of wind turbine commitment in the grid, the severe effects of randomness and intermittency of wind farms on the grid cannot be ignored (Xi et al., 2016).

In order to settle the above issues, wind forecasting technology is proposed (Sachdeva and Verma, 2008), whose contribution is mainly reflected in the following three aspects: 1) optimize the scheduling of grid and provide conditions for wind power bidding on-grid; 2) easy maintenance and overhaul of wind turbines; and 3) reduce reserve capacity and operating cost. In general, the classification of wind speed and power prediction is mainly carried out from two views, as shown in **Table 1**. Wind speed and power forecasting technologies are classified as long-term forecasting, medium-term forecasting, short-term forecasting, and ultra-short-term forecasting on the basis of the time scale. Based on the prediction model, these research techniques are classified as physical approaches, statistical approaches, and learning approaches.

## DATA PRE-PROCESSING

It is particularly crucial for accurate wind speed and power prediction to pre-process data, which is mainly reflected in avoiding the adverse impact of redundant invalid data, data denoising, and making up missing data. In literature (Cui et al., 2012), the atomic decomposition technique is used to eliminate wavelet coefficients of noises for every subseries based on wavelet function and dissolution levels. In addition, the atomic decomposition technique is easy to execute and takes less consumption time (Yang et al., 2021b). Singular spectrum analysis (SSA) is introduced to identify noise, and trend, periodic oscillation of original signals with the merits of fewer parameters. But phase shift phenomenon takes place during the denoising process by SSA (Jung and Broadwater, 2014). In general, decomposition-based denoising methods containing the former two approaches remove the noises of the divisional subseries (Qian et al., 2019). Moreover, decomposition-based denoising methods have the advantage of clear configuration but may weaken prediction accuracy (Yang et al., 2021b).

**TABLE 1 |** Prediction approaches on time/model horizon.

| Basis of classification | Forecasting ways | Description | Features/applications |
|---|---|---|---|
| Time scale | Long-term forecasting | Prediction of 1 year based on annual data | The judgment basis for the site selection of wind farm and to predict the potential economic benefits |
| | Medium-term forecasting | Prediction of 1 day to 1 month | To arrange the maintenance and debugging of equipment; mainly use the numerical weather forecast model |
| | Short-term forecasting | Prediction of hours | Applicable to the scientific control of power system; relatively higher accuracy; the research focus |
| | Ultra-short-term forecasting | Prediction of minutes | To meet the demands of wind turbine control and effectively ensure the scientific operation of equipment |
| Modeling method | Physical prediction method | Use the external parameters of the fan, including meteorological information, to get wind speed and direction around the blade, and then compares the wind turbine power curve to get the output | High requirements for physical parameter information of wind generator |
| | Statistical prediction method | In order to obtain the function relation between the historical data series and the wind generator output | Easy to implement, mature and complete theoretical basis |
| | Learning prediction method | Establish the nonlinear model between input and output by using the artificial intelligence method | Represented by support vector, machine wavelet analysis, and neural network |

In terms of data completion, there are some relatively simple methods, including the continuous method, adjacent fan method, and linear regression method. Literature (Barbara and Richard, 1984) states that the values of adjacent points on a continuous curve are the same, so when the sampling interval is small, the nearest data point can be used to supplement the missing data, which is called the persistence model. The adjacent fan method finds the power generation relation between the two wind generators with high spatial correlation so as to complete data completion (Ji et al., 2014). Based on the spatial-temporal characteristics of wind generator distribution, the literature (Ma et al., 2013) uses the linear regression method to complete the missing data in three dimensions, but this method is not applicable to nonlinear cases. Adaptive network-based fuzzy inference system (ANFIS) is proposed in reference (Yang et al., 2014), which integrates the merits and application range of various methods and can take different data completion measures according to specific situations. It has been proved that the effect of ANFIS is more satisfactory than that of the linear regression method.

## PHYSICAL PREDICTION APPROACHES

The essence of the physical forecasting method is to make the best of all pivotal physical parameters of wind generators, among which meteorological information is the most important parameter (Zhao et al., 2011). First, the meteorological information, including temperature, barometric pressure, and wind speed and direction, are collected from the meteorological platform; meanwhile, the surrounding parameters of the wind turbine are recorded. Then the actual values of wind speed and direction around the wind generator hub are calculated by combining these two sets of data. Then the wind power output of corresponding parameters is obtained by comparing the wind turbine power curve provided by the manufacturer. The physical method relies on the accuracy of the prediction model, so the physical parameter information around the wind generator is very critical, which could bring bias to wind speed values (Tascikaraoglu and Uzunoglu, 2014). In addition, the update speed of meteorological forecasts is low; hence, the data collected from meteorological departments often fail to meet the requirements of forecasting models. Back in the 1990s, Landberg predicted the wind output power through a wind turbine power curve with the wind speed information based on numerical weather prediction (NWP). The process of wind speed and power forecasting based on the physical model is demonstrated in **Figure 1**.

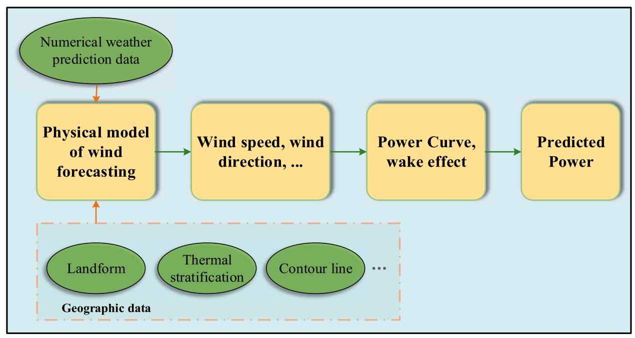


**FIGURE 1 |** Process of the wind speed and power prediction based on physical model.

## STATISTICAL PREDICTION APPROACHES

The purpose of the statistical method is to establish the mapping functions, mainly linear, between various factors affecting power output or historical power output data series and output data (wind speed or power). Statistical method owns early formed theory and the mature application experience, which includes the time sequence approach, exponential smoothing method, Kalman filter, grey prediction method, and regression analysis technique.

Time sequence method, a classical, mature, and earlier developed load or power prediction method, takes historical wind generator output data series collected according to fixed time as time sequences. In addition, this method establishes an accurate time sequence statistical model based on the historical power data and the power prediction expression. According to the established time sequence statistical model and power prediction expression, wind speed and power prediction are carried out. According to the types of linear filters, the time sequence method is further classified as follows: generalized autoregressive conditional heteroskedasticity (GARCH) (Zhou et al., 2011), GARCH in mean (GARCH-M) (Chen et al., 2013), component GARCH-M (CGARCH-M) (Chen et al., 2015), autoregressive moving average (ARMA) (Torres et al., 2005), autoregressive integrated moving average (ARIMA) (Yatiyana et al., 2017), and fractional ARIMA (Kavasseri and Seetharaman, 2009). Component GARCH-M model is presented in reference (Chen et al., 2015) to execute power forecasting by decomposing the volatility configuration to the everlasting and transient component. ARIMA method is applied to develop a statistical model for forecasting both wind speed and direction and attains good precision with an error of less than 5% for wind speed (Yatiyana et al., 2017).

Kalman filter prediction is another statistical method commonly used to predict wind speed and direction. Although the wind prediction model established by the time series method owns the superiority of time sequence and autocorrelation, without the need to analyze the background and conditions of signal series, it still has the demerits of poor forecasting precision for low-order model. The Kalman filter prediction method makes up for the above shortcomings due to its ability to dynamically modify the prediction weight. The Kalman filter prediction method can obtain high precision by predicting recursive equations. In literature (Babazadeh et al., 2012), a Gauss–Markov based Kalman filter is applied in forecasting the wind speed of a single wind farm an hour ahead. An unscented Kalman filter is proposed in the literature (Chen and Yu, 2014) to predict the wind speed of a single wind turbine which has stable dependability and robustness. In addition, the Kalman filter prediction method has difficulty in establishing the Kalman equation of state and measurement equation. To overcome this drawback, Tian et al. (2014) developed the adaptive Kalman filter which is simple to acquire Kalman state and measurement equations. In addition, the case studies on single wind power stations verify that the adaptive Kalman filter decreases the error and time delay of predicted wind speed.

Regression analysis, a statistical mathematical method, starting with the transformation law reflected by historical data, explores the relationship between input variables and output variables which is implied in the transformation law. When applied to wind power prediction, the regression analysis method can predict the wind power value in the future according to the historical wind power data, whose basic expression is as follows:

$$f(t) = k_0 + k_1 x_1(t) + \cdots + k_n x_n(t) + \omega(t) \tag{1}$$

where $f(t)$ is the wind power value at time $t$; $x_1(t), x_2(t)\cdots, x_n(t)$ represent the related factors; $\omega(t)$ means the noises; and $k_0, k_2\cdots, k_n$ are regression coefficients.

## LEARNING PREDICTION APPROACHES

Nowadays, wind speed and power prediction based on the learning method is a research hotspot thanks to its pre-eminent nonlinear processing capability. Learning methods, characterized by artificial intelligence methods, derive the mapping between input and output through training of a large number of samples. Different from the statistical methods, learning methods establish nonlinear models, which cannot be simply expressed by a mathematical formula. At present, the main learning methods include wavelet analysis, support vector machine (SVM), and neural network.

Higher-order SVM based on Gaussian can enhance the prediction precision of wind speed (Mohandes et al., 2004; Yang et al., 2020b). Moreover, the combined model of the least square method and SVM can achieve high accuracy and generalization ability with faster computing speed and fewer factors (Maria et al., 2014; Chen et al., 2021). In recent years, variants of SVM are also developed, such as convolutional SVM (Mi et al., 2019; Yang et al., 2020c), SVM-enhanced Markov model (Yang et al., 2015), and SVM based on multi-variable regression (Park and Hur, 2017). In literature (Li and Shi, 2010), three artificial neural networks, feed-forward BP, radial basis function, and ADALINE neural network, are applied to wind speed prediction and compared with each other. The case studies reveal that the prediction precision relies on the quality of inputs data, and the combined performance of those three neural networks is similar. However, the original neural network sometimes makes failed feature identification under complex conditions. Hence, some wind prediction models based on deep learning algorithms are developed, such as transfer learning (Lin et al., 2017), convolutional neural network (Hu et al., 2016), recurrent neural network (Cheng et al., 2018), structural learning (Mi and Zhao, 2020), and long short-term memory (Liu et al., 2018).

## DISCUSSION AND CONCLUSIONS

Wind forecasting technique can effectively alleviate the impact of large-scale wind generator grid-connected and requires further studies (Desai and Makwana, 2021; Xu et al., 2021). Several perspectives for future researches are proposed as follows:

1) Offshore wind resources are more abundant, so more research on offshore wind speed and power prediction should be carried out;
2) The combination of a data-driven neural network and physical model is a promising method for wind forecasting;
3) The structure of neural networks has a significant influence on the accuracy of a prediction model. Therefore, a more stable

and efficient heuristic algorithm should be used to improve the structure of neural networks.

## AUTHOR CONTRIBUTIONS

HY: writing the original draft and editing. BY: conceptualization. YH: formal analysis. QL: visualization. JD: writing–reviewing and editing. ST: investigation and validation.

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