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Short-Term Forecasting Method of Wind Energy and Photovoltaic Power Generation Based on Big Data Analysis

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Abstract: With the continuous depletion of fossil energy and the continuous destruction of the ecological environment, wind energy(WE) and photovoltaic PG(PPG) are more and more emerging power generation(PG) technologies, and WE and PPG systems will become the mainstream of PG in my country's power grid in the future industry. PPG will be affected by the weather, resulting in great uncertainty in the PG output of the photovoltaic system(PS). If it is integrated into the large power grid, it will also bring immeasurable impact to the power grid. Therefore, in order to ensure the safe and stable operation of the power system and the coordinated development of power supply and distribution, it is crucial to use big data technology to establish a PG prediction model(PM). For wind PG, this paper establishes a short-term(ST) PG PM based on BP-NN, and proposes several correction models; for PPG, this paper establishes LS-SVM combined with Markov's PM, which can predict both sunny and rainy days. Predict the PPG in different weather. Through the research on wind PG forecasting methods and PPG forecasting methods, the accurate forecast of ST PG can be achieved, which provides certain theoretical and technical support for the PG industry of the power grid to better supply power to users in the future.

1. Introduction

In order to meet the supply and demand balance between the PG output and the power demand of the grid, accurately predicting the power generated by wind PG and PSs can facilitate the overall management of power consumption and PG by the dispatching department. Prediction and regulation not only help to improve the power quality of the power grid, but also better maintain electrical equipment, ensuring efficient and high-quality electricity consumption by users.

At present, many scholars have established ST power PMs for WE and PPG, and have achieved good prediction results. For example, a scholar uses a binary sigmoid function as the nonlinear activation function of neurons in a neural network(NN). This function is basically trained in a fully saturated manner. After preprocessing the input data of the NN, the wind PG power can be predicted. [1]. By analyzing a large number of photovoltaic influencing factors such as solar irradiance, cloud shielding degree and ambient temperature, some scholars further analyze the correlation between each influencing factor and photovoltaic output. The regression coefficient equation is used to analyze the correlation between the impact factor and the PS, so as to establish power PMs of different architectures, such as support vector machines, NNs and time series models [2]. A scholar analyzes the correlation between PG and environmental meteorological information by calculation, and then uses the self-organizing feature mapping algorithm to perform cluster identification analysis, and takes the temperature and humidity data information in environmental factors as the input variable of the BP NN PM. The distance analysis calculates the correlation between the output power(OP) and the meteorological information, and takes the temperature and humidity conditions as the input target variation, so that the power generated by the PS can be well predicted [3]. Although there are many kinds of PMs, to achieve a better prediction effect, need to optimize the performance of the model.

This paper firstly introduces the WE and PPG forecasting methods under the big data technology, and then proposes a ST PG PM for wind PG and PPG respectively, and then a PPG power prediction simulation system is established, and finally the PM of this paper is simulated, and the prediction accuracy of the PM is obtained.

2. Introduction to Forecasting Methods

2.1. PG Prediction Method Based on Big Data Analysis

Historical data from wind farms and photovoltaic power plants provide researchers with a valuable source of data to improve the performance of wind and PSs through research and analysis of these data. The big data-driven approach to ST PG forecasting does not directly simulate the physical process of wind and PPG, and applies statistical or other learning algorithms to analyze large amounts of historical data such as meteorology, solar radiation, and PPG operations, and establishes wind and photovoltaic power output and solar PG. Radiation predictions or relationships with other input variables. According to the different mining and analysis methods of big data, the ST forecasting methods of WE and PPG include NN method, support wavelet decomposition method and other methods [4-5].

2.2. Wind PG Power Prediction Method

Wind PG is a complex nonlinear and non-stationary signal, and it is difficult to obtain satisfactory prediction accuracy using general linear prediction methods [6]. The nonlinear fitting ability of NN can solve this problem. Predicting the ST PG of wind PG is to construct a nonlinear mapping relationship between input and output. The BP NN is a multi-layer feedback NN composed of nonlinear transmission units, and its output is a continuous value between 0 and 1, which can map any input value to an output value. Therefore, BP NN is used in this paper to construct the PM of wind PG [7]. In the actual situation, the wind power plant records the corresponding data information even when the equipment is maintained or shut down due to unexpected reasons. These data are abnormal data, which will reduce the prediction accuracy. These data need to be preprocessed to propose abnormal data. Since the NN pays special attention to the validity of the input data, the training process of the NN will be more efficient if certain preprocessing steps are performed on the input information and target values. In many cases, raw data is not the best input data for training a NN. Therefore, the original data should be normalized to solve this problem. Therefore, preprocessing is required to remove abnormal or redundant data and adapt it to model training of NNs [8-9].

Training data can be normalized using two basic methods, even if the input data lies between 0 and 1 and -1 to 1, which are called max/min normalization, respectively. This paper uses maximum warping to preprocess the input parameters. All data were normalized to the 0.0 to 1.0 range according to formula (1) [10].

$$x^{'}(n)=\frac{x(n)-x_{\min}(n)}{x_{\max}(n)-x_{\min}(n)} \tag{1}$$

$x^{'}(n)$ and x(n) respectively represent the data after normalization and before normalization (including historical power data, wind speed and wind direction); $x_{\max}(n)$ and $x_{\min}(n)$ represent the maximum and minimum values of x(n), respectively.

In order to make the prediction accuracy more accurate, BP-NN is revised in this paper. The revised models include wavelet NN (WNN), combination of genetic algorithm and NN (GA-NN), and empirical mode decomposition combined with GA-NN (EMD-GA-NN).

Non-linear and non-stationary signals are decomposed using EMD into eigenmode function components with different oscillation periods and a residual component, and their mutual influences are isolated. Therefore, using EMD wind PG power information can weaken the influence of nonlinear and non-stationary features on WE prediction, thereby improving the prediction accuracy [11].

2.3. LS-SVM Combined with Markov's ST Forecast Analysis of Photovoltaic Output

In recent years, with the improvement of prediction accuracy, many improved LS-SVMs have come to the fore, such as grey-LS-SVM theory, robust-LS-SVM theory, ACPSO-based LS-SVM theory and incorporating least squares support. The optimal combination prediction method of vector machines, etc. Many examples show that LS-SVM or the improved LS-SVM is more suitable for the prediction of nonlinear samples than SVM, and its prediction accuracy is higher than that of other types of prediction theories, and it has a relatively broad development prospect in the field of PPG prediction [12-13].

PPG is a non-stationary stochastic process, and the output shows strong randomness and volatility. It is difficult to ensure the accuracy of prediction by using a single LS-SVM PM. Therefore, combining the Markov correction model on the basis of the original model can improve the prediction accuracy [14].

The combined PM of LS-SVM and Markov based on similar days, its realization principle is to use the similar days algorithm for data screening. The prediction flow chart of the PM is as follows:

(1) Collect the historical output and meteorological data of the PS, and sample the OP value and the corresponding meteorological information during the daily photovoltaic output period (7:00~18:00) in steps of 1h.

(2) Preprocessing the sampled data

(3) Select similar daily samples in each prediction period and filter out training samples.

(4) Establish a ST PM of photovoltaic output LS-SVM, and use the cross-validation method to find parameters to predict the photovoltaic output every 1h in the future.

(5) Divide the prediction error into the specified interval, calculate the state transition probability for it, determine the state of the variable, and calculate its maximum probability value, and calculate the error value of the photovoltaic prediction by calculating the next turning probability of the variable. make corrections [15].

3. Photovoltaic Power Station Power Prediction Simulation Application System

The system effectively combines forecasting theory, network communication, and database knowledge. The host computer monitoring and forecasting interface is established through Visual Basic to realize the functions of system analysis, management forecasting and so on. The system can predict and display the power output by the power station on a certain day. In addition, it can also display various parameters of the power station to realize monitoring and control of the power station. The parameters can be stored in the database, which is convenient for dispatchers to query, which brings great convenience to the grid connection of photovoltaic power plants [16].

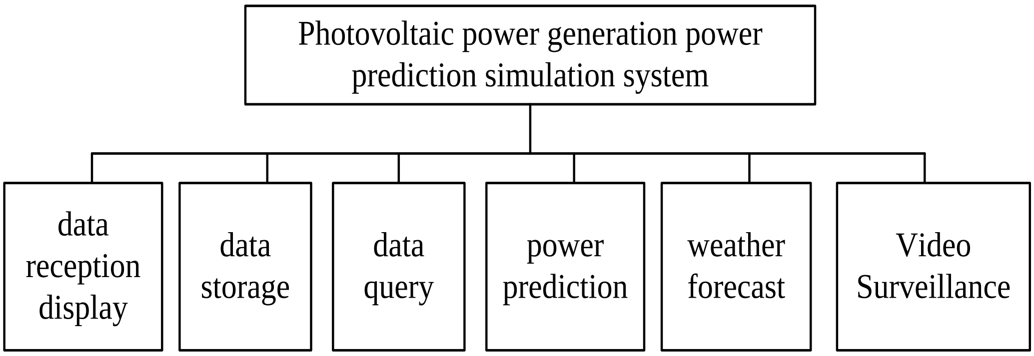

Figure 1. System functional structure

The system is mainly designed with two functions, one is to predict the output energy of photovoltaic plants in the short term in the future, and the other is to manage the operating parameters of photovoltaic power plants in a unified manner, and to collect data for the power prediction of the system in the early stage [17]. The functional structure of the system is shown in Figure 1.

Power prediction: Input the historical data in the database into the Matlab program for data prediction, and display the prediction results on the VB interface.

Weather forecast: The weather information is updated every half an hour, and parameters such as current temperature and relative humidity can be displayed.

Data reception and display: establish a wireless communication connection through the Winsock control in Visual Basic, and use the Text control to display the received electrical parameter data in real time.

Data storage: The PG parameters are stored in the Access database, and the Adode control combined with the Timer control can be used to import the received data into the database in real time, providing effective and accurate historical data for the prediction function of the system [18].

Data query: Using DTPicker combined with Adodc control, it is possible to query and modify the operating parameter information of photovoltaic power plants on any day, and at the same time, the predicted parameters can also be queried and modified. Assist dispatchers to manage the power grid [19].

Video surveillance: real-time monitoring of the work of dispatchers, which is beneficial to the management of photovoltaic enterprises.

4. Prediction Result Analysis

4.1. ST Forecast Results of Wind PG Based on NN Forecast Model

Predictive model evaluation criteria include mean percentage error (MAPE) and root mean square error (RMSE).

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|W(t_i)-W_p(t_i)\right|}{W(t_i)} \tag{2}$$

$$RMSE = \frac{1}{\sqrt{N}}\sqrt{\sum_{i=1}^{N}\left(W(t_i)-W_p(t_i)\right)^2} \tag{3}$$

Among them, N represents the time, $W_p(t_i)$ represents the predicted value of wind power at the t_i time, and $W(t_i)$ represents the actual value at the t_i time.

Table 1. Errors in wind power prediction results

	MAPE(%)	RMSE
BP-NN	21.42	102.3kW
WNN	18.37	91.8kW
GA-NN	13.54	76.5kW
EMD-GA-WNN	7.68	53.9kW

Table 1 shows the errors of the prediction results of various prediction methods. It can be seen that with the improvement of the prediction method, the predicted MAPE of wind PG gradually decreases from 21.42% to 7.68%, and the prediction effect gradually improves. The final predicted MAPE of the EMD-GA-wavelet NN is 7.68%. The RMSE of wind power prediction is also gradually decreasing, and the RMSE of the forecast data is gradually reduced from 102.3kW to 53.9kW, which improves the prediction accuracy. The above data analysis results show the effectiveness and rationality of the EMD-GA-wavelet NN prediction algorithm.

4.2. ST Prediction Results of PPG Based on LS-SVM and Markov Combined Model

In order to ensure the scientific validity of the PM, this paper selects the data from 7:00 am to 16:00 am in May of a certain year, a total of 500 groups, each group including 10 data on the hour. Using the measured data of the photovoltaic station, the power is predicted by the trained LS-SVM and Markov combined PM, and the PG between 7:00 and 16:00 every day in August of that year is predicted. In the 31 consecutive days to be predicted in August, one day was selected for each of the two weather types, sunny and rainy, for qualitative and quantitative research and analysis. The prediction results of the PM and the comparison results of the measured power are shown in Table 2 and Figure 2, respectively.

Table 2. PPG on sunny days

	Measured value	Predictive value
7:00	0.6573	0.5769
8:00	3.7428	2.1572
9:00	11.3654	11.3935
10:00	15.9603	15.8526
11:00	19.3692	19.7471
12:00	21.5746	20.3819
13:00	20.4207	20.5367
14:00	18.6852	19.0511
15:00	16.2781	15.4755
16:00	10.6532	11.5426

Table 2 shows the predicted and measured values of PPG in sunny days. During the time periods from 9:00 to 11:00 and from 13:00 to 14:00, the predicted value almost coincides with the measured value, but the prediction deviation of the first and last time periods is relatively large. The light energy received by the PG system is extremely weak, the amount of electricity generated by the conversion is extremely small, and the output value of the power fluctuates greatly, resulting in inaccurate statistics of the data by the staff, which eventually leads to a large deviation in the prediction results.

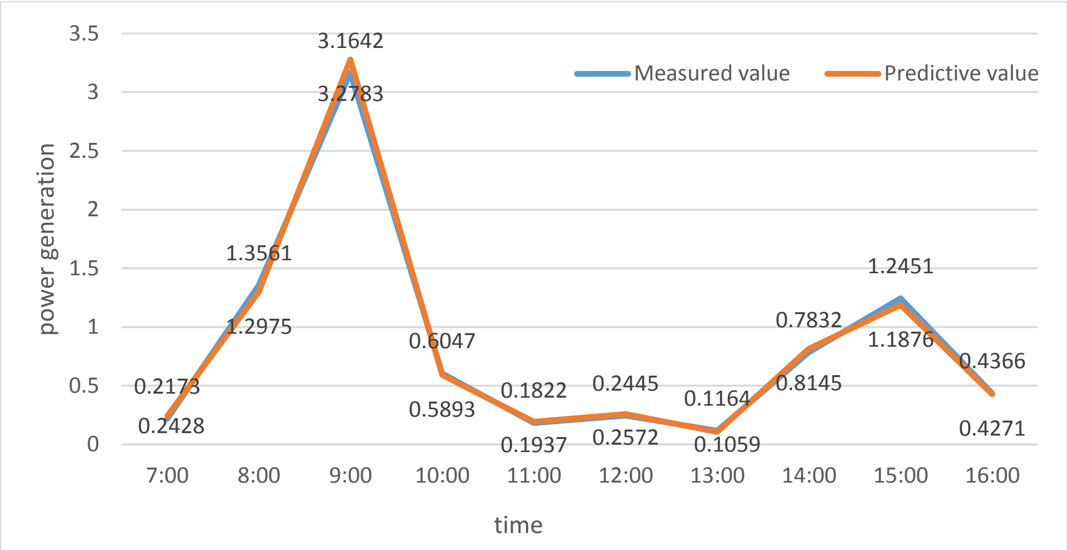

Figure 2. PPG in rainy days

Figure 2 shows the predicted and measured curves of PPG in rainy days. The trend of the model prediction results fluctuates more obviously, especially after 10 o'clock. It may be because the uncertainty of the rainy day itself is larger, which brings more trouble to the prediction process and makes the prediction results deviate from the actual measurement. More results.

Table 3. Comparison of forecast errors for different weather types

	RMSE	TIC
Sunny	16.75%	0.021
Rain	25.34%	0.076

TIC is the Hill inequality coefficient, the value is between 0 and 1, and the smaller the better. From the comparative analysis results in Table 3, the power PM has higher prediction accuracy and better prediction effect in sunny days, with RMSE of 14.91% and TIC of 0.021. It may be due to the relatively stable changes in environmental conditions in sunny days, which usually do not affect PG. The output of the system produces a certain disturbance. In rainy days, due to the change of weather, the surrounding environment is volatile, and there are certain difficulties in prediction. The RMSE is 25.34% and the TIC is 0.076.

5. Conclusion

Wind power forecasting can effectively utilize WE resources and reduce the use of fossil energy, and the improvement of ST PPG forecasting accuracy plays a key role in integrating PPG systems into existing power grids and the utilization and development of solar energy. Therefore, this paper studies the ST forecast of WE and PPG, and establishes a suitable forecast model for different PG modes. By comparing the prediction accuracy of wind PG power forecasting Mixing, it is obtained that the error of the EMD-GA-NN PM is the smallest, while the prediction accuracy of the PPG power PM combined with LS-SVM and Markov in rainy days is lower than that in sunny days.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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