Research on Artificial Neural Network Wind Power Prediction

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Abstract

Wind power prediction is very important to the steadiness and economy of the power system. The current ex-ist predicting method including various artificial neural network (ANN) predicting methods are almost static ones. Relatively good results can be obtained by these methods when wind speed and direction are relatively steady while the predicting result will deteriorate when large changes occur. To solve this problem, a new kind of dynamic neural network wind power predicting model is proposed. This model is composed of a series of differentiators to represent the dynamic character and a multilayer feedforward ANN to represent the nonlin-ear relation. The trend of the variables will appear in the model through the differentiation of the variables and the nonlinear relation will be well established through the reasonable structure of the ANN. It is verified by the experiment that this kind of dynamic ANN predicting system will obtain better result compared with the traditional static ANN predicting system.

Keywords

Wind Power Prediction; Artificial Neural Network (ANN); Static Model; Dynamic Model.

1. General instructions

Wind power has the characters of intermittent and randomness, which will affect the steadiness and economy of the power system if they are directly connected to the main grid without wind power prediction and control [1]. The accurate prediction of the wind power is very important to improve the power capacity and ensure the steadiness and economy of the power market [2, 3]. Wind power predicting system usually predicts the next few hours of the power output of a wind farm and the predicting results are usually used as a fundamental reference of peak load regulation. The predicting accuracy therefore has a significant impact on the operation of power grid security [4, 5].

Wind power predicting methods are mainly including the followings: artificial neural network (ANN) method [6,7], support vector machine (SVM) method [8], Kalman filter method [9] and so on. Researches indicate that ANN predicting methods are better than other methods in predicting accuracy and generalization ability in case the historical data are sufficient [5, 10], hence it draws much more researches and applications.

However, the ANNs used in the current predicting methods are usually static ones and they cannot reflect the dynamic characteristics of the wind power system. The predicting accuracy will deteriorate when the large changes of the wind speed or wind direction occur, which will bring trouble to the power regulation and probably lead to the wind power abandon.

To solve this problem, we present a kind of dynamic ANN predicting model. This model is composed of a static ANN to represent the nonlinear characteristics and a series of differentiators to represent the dynamic behavior, thus the complete characteristics of the system can be described and realized.

2. Principle of artificial neural network wind power prediction

Currently, most of the ANN wind power predicting systems use the following static model:

$$Y = f(\boldsymbol{X}) \tag{1}$$

where Y represents the predicted power of the wind farm, $\boldsymbol{X}$ represents the auxiliary input variables of the predicting model including wind speed, wind direction, etc, and f represents the nonlinear relations between the inputs and output which is usually realized by a multilayer feedforward ANN.

From equation (1), we can see that most of the ANN predicting models only adopt the current information of the auxiliary variables and exclude the dynamic information of the system, which makes them static models and unable to reflect the dynamic characteristics of the system. Such models may get good predicting result when the wind speed and wind direction are relatively steady while the predicting accuracy will deteriorate when large changes of wind speed or wind direction occur.

To solve this problem, some researchers introduce dynamic ANNs to construct the predicting models [11]. These kinds of dynamic ANNs usually utilize delay units and feedbacks to represent the dynamic characteristics, which will make the physical meaning and dynamic performance not clear and even lead to the non-convergence of the ANN. Therefore, other kind of dynamic predicting system should be adopted.

In this paper, we present a kind of dynamic predicting model as follows:

$$Y = f_{ANN}(\boldsymbol{X}, \dot{\boldsymbol{X}}, \ddot{\boldsymbol{X}}) \tag{2}$$

where $\dot{\boldsymbol{X}}, \ddot{\boldsymbol{X}}$ represent the first order and second order derivatives of the input variables, f_{ANN} represent a static neural network to approximate an nonlinear function. For the wind power predicting system, $\boldsymbol{X}$ can be wind speed and wind direction, so $\dot{\boldsymbol{X}}, \ddot{\boldsymbol{X}}$ will be the first and second order derivatives of wind speed and wind direction. As the derivatives reflect the changing trends of the input variables and ANN reflect the nonlinear relation between the input and output, such kind of model can approximate most of the general nonlinear dynamic systems. Its application in wind power prediction is likely to obtain satisfactory results.

3. Experiment and discussion

Taking eleven wind turbines on a wind farm in Yancheng as a research object, we investigated the above mentioned two kind of ANN wind power predicting methods.

First, we investigated the static ANN predicting model. Take wind speed $V_1 \sim V_{11}$ and wind direction $D_1 \sim D_{11}$ as the input of a 22-25-1 structure ANN and the one hour predicting power Y as the output of the ANN as shown in Figure 1. The activated function of the hidden layer of the ANN is “tansig” and one of output layer is “purelin”. Then the ANN is trained with Levenberg-Marquardt training algorithm for 300 times and the training error are getting less than 10^{-6}. The trained ANN can then be used to constitute a predicting model and realize the power prediction in the wind farm.

As the predicting model shown in Figure 1 is without any of the dynamic units and is only composed of an ANN representing the nonlinear function, it is indeed a static ANN predicting model.

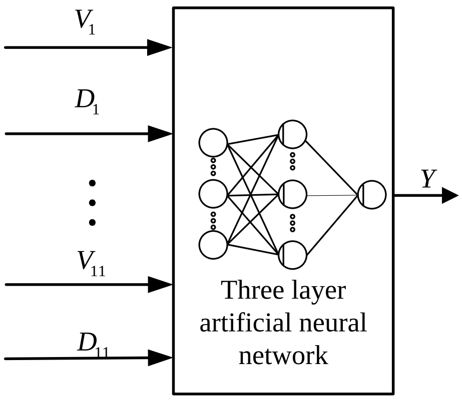

Figure 1. Static artificial neural network predicting model

The predicting result is shown in Figure 2, where the solid line represents the actual wind power and the dashed line represents the one hour predicting result.

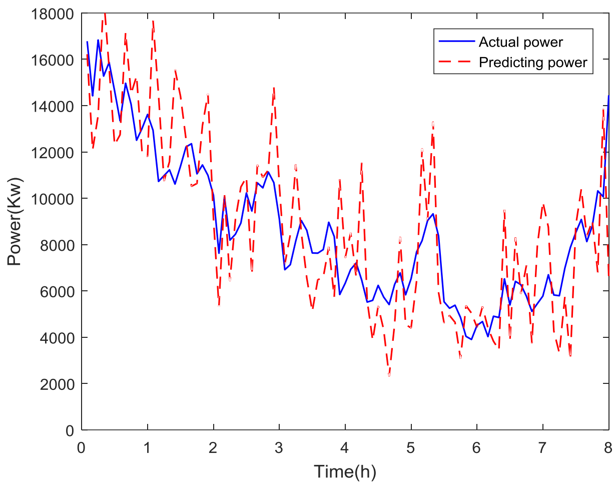

Figure 2. Wind power predicting result obtained by static neural network

The predicting result is also shown in Table 1 by relative mean square error(RMSE), which is calculated according to the following equation:

$$RMSE = \frac{1}{P_{rated}} \sqrt{\frac{1}{n} \sum_{i=1}^{n} (Y_i - P_i)^2} \times 100\% , \tag{3}$$

Where P_{rated} represents the rated capacity of the wind farm, Y_i represents the *i*-th predicting power, P_i represents *i*-th actual power, and *n* is the predicting number.

Meanwhile, to evaluate the predicting error when big changes occur, Max Relative Error (MRE) is also given in Table 1:

$$MRE = \frac{1}{P_{rated}} \max |Y_i - P_i| \times 100\% \tag{4}$$

From Table 1, one can see that the MRE of the predicting result of the static model is greater than 40% and the RMSE is also not small, so this kind of static ANN predicting model is not suitable for the wind power regulation.

To improve the predicting accuracy, we constructed a dynamic ANN predicting model according to (2).

In this model, we take the wind speed $V_1 \sim V_{11}$ and wind direction $D_1 \sim D_{11}$ and their first order derivatives $\dot{V}_1 \sim \dot{V}_{11}$, $\dot{D}_1 \sim \dot{D}_{11}$ and second order derivatives $\ddot{V}_1 \sim \ddot{V}_{11}$, $\ddot{D}_1 \sim \ddot{D}_{11}$ as the inputs of a 66-90-1 structure ANN and the one hour predicting power as the output, as shown in Figure 3. In the figure, the derivatives are obtained by the differentiators *S*.

Set the activating functions of hidden layer and output layer as same as the ones used in Figure 1 and train the ANN with Levenberg-Marquardt algorithm for 300 times, the dynamic ANN predicting model are finally constructed.

The ultimate dynamic ANN model can be expressed as follows:

$$Y = f_{ANN}(V_1, \dot{V}_1, \ddot{V}_1, D_1, \dot{D}_1, \ddot{D}_1, ..., V_{11}, \dot{V}_{11}, \ddot{V}_{11}, D_{11}, \dot{D}_{11}, \ddot{D}_{11}) \tag{5}$$

The predicting result of the model is as shown in Figure 4, and the detailed RMSE and MRE are shown in Table 1.

From Figure and Table, one can see that the RMSE and MRE of the dynamic ANN model are both smaller than those of the static one. This is because the derivatives existed in the dynamic model. As these derivatives reflect the changing trends of the wind speed and wind direction, the future information of the wind power are implied in this model and it can surely give out the predicting wind power more accurately than the static model.

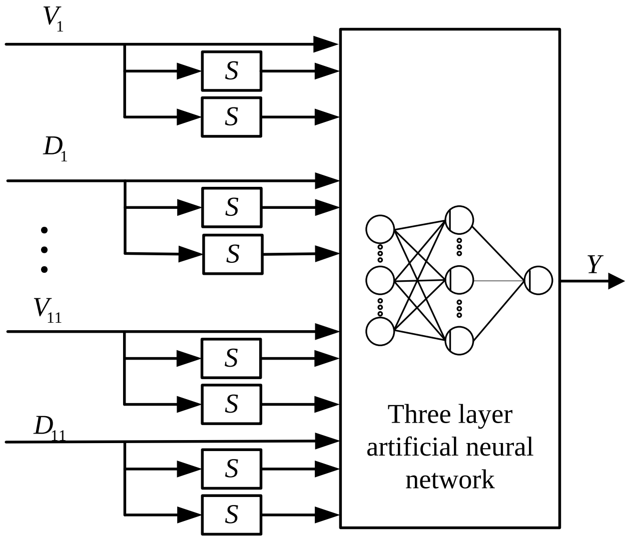

Figure 3. Dynamic artificial neural network predicting model composed of a three layer feedforward neural network and differentiators S

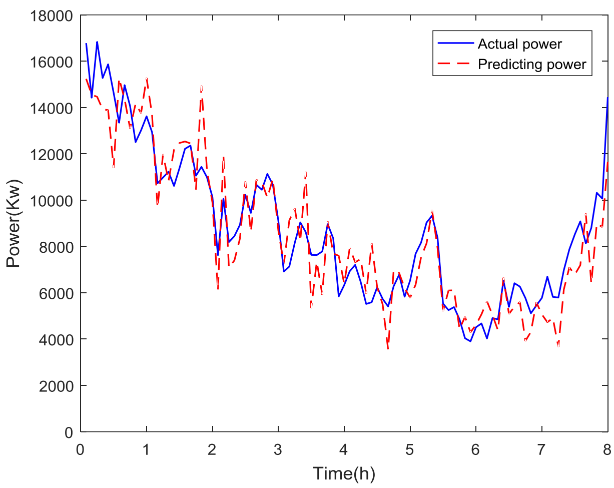

Figure 4. Wind power predicting result obtained by dynamic ANN model

Table 1. Data error comparison between two predicting methods

Predicting model	RMSE%	MRE%
Dynamic	7.1	18.0
Static	12.9	43.5

4. Conclusion

Static ANN wind power predicting model can give relatively good predicting result when the wind speed and direction are relatively steady while the predicting result will deteriorate when large changes of wind speed or direction occur. This will decrease the steadiness of the power system and sometimes will lead to the wind power abandon. To solve this problem, we presented a dynamic ANN wind power predicting model, which is composed a multilayer feedforward ANN and a series of differentiators. As the derivatives can be obtained by the differentiators, the trends or the future information of the wind speed and direction appeared in the model, which will definitely make the predicting result more accurate. The experimental results show that the dynamic ANN predicting model can not only reduce the RMSE but also the MRE and make it suitable to be used as a reference of peak load regulation.

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