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A dynamic prediction model for wind farm power generation based on RBF neural network

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Abstract. As a renewable energy, wind power is considered to be an important non-exhaustible energy in the times of energy crisis. Therefore, in electric power system, wind turbine generators have become important generation alternatives. As wind power penetration increases, power forecasting is crucially important for integrating wind power into a conventional power grid. A short-term wind farm power output dynamic prediction model is presented using RBF neural network with error discriminant function. Based on the wind data from a wind farm in Inner Mongolia of China, a power forecasting map is illustrated, and the errors of the model are analyzed to present the differences between dynamic model and conventional prediction model.

Introduction

In the wind farm, the power generated by a wind turbine generator varies randomly with time due to the variability of wind speed. Uncertainty of the wind power and the increase of wind power penetration will affect system stability and run the risk of blackouts. The fluctuation of wind speed results in rapid changes in the electric power generated by electric wind turbines; the forecasting model will inevitably be non-linear. Unlike other forecasting models, the model input variables of wind power prediction model are not only historical wind power output but also major factors effecting wind power in order to improve prediction accuracy. Many different approaches have been used to forecast wind farm power, such as an Auto Regressive Moving Average Model (ARMA) [1], Kalman Filter Model [2], Time Series Analysis Model [3], and Artificial Neural Networks [4]. Comparing the ANN approach with other methods, it is found that ANN is more suitable due to its ability of modeling complex nonlinear systems. However, the conventional ANN is a static model which cannot handle the variation of wind power with time. Therefore, the dynamic training mechanism should be added to the conventional ANN. Radial Basis Function (RBF) neural network is one of the widely used neural networks due to its fast convergence and good generalization property [5]. This paper presents a wind power dynamic prediction model based on RBF neural network with error discriminant function, which is shown to outperform the conventional ANN model, and case studies demonstrate that the prediction model has a good agreement with the measured data.

Major Factors Effecting Wind Power

Wind farm output power comes from wind power captured by wind turbines. Essentially, wind energy is kinetic energy, and it can be calculated by:

$$E = \frac{1}{2} m v^2 \, (Joules) \tag{1}$$

where m is the air mass (kg) and v is the air speed in the upstream wind direction at the entrance of rotor blades (m/sec).

Wind power can be derived from kinetic energy of wind using

$$P = \frac{dE}{dt} = \frac{1}{2}\frac{dm}{dt} \cdot v^2 = \frac{1}{2}(\rho \cdot Av)v^2 = \frac{1}{2} \cdot \rho A v^3 \, (Watts) \tag{2}$$

where v is the air speed in the upstream wind direction at the entrance of rotor blades (m/sec), ρ is air density (kg/m^2), A is area swept by rotor blades (m^2).

Following the same principle, the actual power extracted from wind turbine blades can be obtained using (2), where the air mass flow rate through wind turbine blades dm/dt has changed; equation (3) shows the new air mass flow rate:

$$\frac{dm}{dt} = \rho \cdot A \cdot (\frac{v + v_0}{2}) \tag{3}$$

where v_0 is the air speed in the downstream wind direction at the exit of the rotor blades (m/sec).

So the mechanical power extracted from wind turbine blades can be obtained using (2) and (3):

$$\begin{aligned} P_0 &= \frac{1}{2} \cdot \frac{dm}{dt} v^2 - \frac{1}{2} \cdot \frac{dm}{dt} v_0^2 = \frac{1}{2} \cdot \frac{dm}{dt} (v^2 - v_0^2) = \frac{1}{2} \cdot (\rho \cdot A \cdot \frac{v + v_0}{2})(v^2 - v_0^2) \\ &= \frac{1}{2} \cdot \rho \cdot A \cdot v^3 \cdot \frac{(1 + \frac{v_0}{v})[1 - (\frac{v_0}{v})^2]}{2} = \frac{1}{2} \cdot \rho \cdot A \cdot v^3 \cdot C_p(Watts) \end{aligned} \tag{4}$$

where C_p is the rotor efficiency, and it is shown by equation (5)

$$C_p = \frac{(1 + \frac{v_0}{v})[1 - (\frac{v_0}{v})^2]}{2} = \frac{P_{rotor}}{P_{wind}} \tag{5}$$

where $v_0/v=x$, so we can get its maximum value as follows.

Differentiating (5) with respect to x,

$$\frac{dC_p}{dx} = \frac{d}{dx}[\frac{(1+x)(1-x^2)}{2}] = \frac{d}{dx}[\frac{1 - x^3 - x^2 + x}{2}] = \frac{1}{2}[-3x^2 - 2x + 1] = 0 \tag{6}$$

From equation (6), the extremum is found to be x=1/3, so $C_{p.\max}$ can be derived:

$$C_{p\cdot\max}(x = \frac{1}{3}) = \frac{P_{rotor}}{P_{wind}} = 0.593 \tag{7}$$

The maximum value of the mechanical power extracted from wind turbine blades can be derived using (4) (7), thus

$$P_{wind\cdot\max} = \frac{1}{2} \rho A v^3 \cdot C_{p\cdot\max} = \frac{1}{2} \rho A v^3 \cdot 0.593(Watts) \tag{8}$$

We know that C_p is a function of wind speed, turbine speed and turbine blade parameters, such as pitch angle, angle of attack. Therefore, in variable speed wind turbines, rotor speed is varied to hold C_p at its maximum value. Therefore, output power of a wind turbine generator, P is proportional to $P_{wind.\max}$. For a fixed wind turbine, the area swept by the rotor blades is constant, so P is proportional to the air density ρ, and the air speed in the upstream wind direction at the entrance of rotor blades v, and ρ is determined mainly by air temperature. Therefore, the major factors affecting wind farm electric output are simplified to air speed and air temperature.

Wind Farm Modeling

Wind farms consist of several wind turbine generators (WTGs) and the power output of a wind farm is the total power of each turbine. In order to predict the electric power of wind farm, we divide a wind farm into several wind turbine generation units, and the power of each unit is predicted individually and then the outputs of all units are aggregated to calculate the wind farm power. Therefore, it is crucially important to establish the prediction model of output power of single wind turbine generator.

Because the forecast is used by the operational department of power system, the historical power output collected by the Energy Management System (EMS) would be included in the model input, while the wind power is selected as the model output. As mentioned in previous section, the major factors affecting wind turbine output are air speed and air temperature, so they can be used as model input, and can be obtained from a Supervisory Control and Data Acquisition (SCADA) system installed at a wind farm. Figure 1 illustrates the data flow.

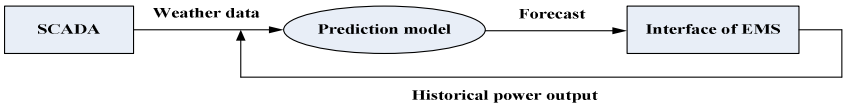

Figure 1. The sketch map of data flow

To establish the wind power prediction model, the inputs were formed by time series of historical data of wind power, air speed and air temperature. So the input/output pattern can be represented as $\boldsymbol{M}(\boldsymbol{X}, Y)$, $\boldsymbol{X}$=[$v(s)$, $v(s\text{-}1)$…$t(s)$, $t(s\text{-}1)$ … $p(s)$, $p(s\text{-}1)$], Y= $p(s+1)$. The number of hidden layer nodes can be confirmed by the performance of network training.

The network consists of n input nodes, m hidden layer nodes, and a single output node. The hidden layer nodes are connected to the output node in a feedforward fashion via weights W_m. In the prediction model, the parameters of the network are updated after error discrimination while the network is trained. In the testing section, the parameters of the network are adjusted according to adjusting training datasets while error discriminant function doesnot satisfy the prediction accuracy. The structure of the model is shown in Figure 2.

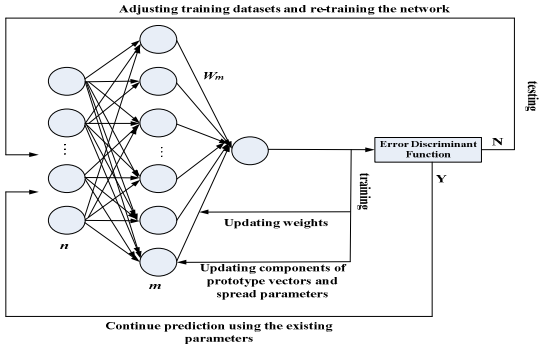

Figure 2. The structure of the model

In this model, the input space is divided into m subclasses and a prototype vector for each subclass is assigned by Fuzzy C-Means (FCM) clustering algorithm. The neurons in the hidden layer of network have a Gaussian activity function and their input-output relationship is shown by equation (9):

$$y_i = g_i(x) = \exp(-\frac{\|\mathbf{x} - \mathbf{c}_i\|^2}{2\sigma_i^2}) \tag{9}$$

where $\mathbf{x}$ is the input vector (=[x_1, x_2, x_3, … , x_k]), k is the dimension of the input vector, $\mathbf{c}_i$ is the prototype vector corresponding to the i'th hidden neuron, whose initial value is determined by FCM clustering (=[c_{1i}, c_{2i}, c_{3i},…, c_{ki}]) and σ_i is the spread parameter which is initialized as the standard deviation of the vectors in the subclass after clustering.

And neuron in the output layer has an S-shaped transfer function known as the "sigmoid activation function", so the output could be calculated using the following equation:

$$f(z) = \frac{1}{1+e^{-z}} \tag{10}$$

where

$$z = \sum_{i=1}^{m} y_i W_i \tag{11}$$

In the model, the parameters including kernel vectors, spread parameters and the connection weights of output layer are adjustable. Before starting the training, total sum-squared error (TSSE) is defined as the cost function and through the training process we will try to minimize it. It is shown as follow:

$$\text{TSSE} = \sum_q E_q = \sum_q (t_q - f(z)_q)^2 \qquad (q=1, ..., Q) \tag{12}$$

where t_q is the desired output with q'th training pattern, Q is the number of training patterns.

Let E be the simplified notation for E_q as equation (13):

$$E = (t - f(z))^2 \tag{13}$$

In the training process, backpropagation algorithm is used to train the model. Firstly, the parameters in the network are initialized. Next step is the calculation in forward pass, the input $\boldsymbol{x}$ and desired output t are inserted and the network output is computed by proceeding forward through the network, layer by layer. After comparing the output with the desired, in the backward pass, the error gradients versus the parameters including $\partial E/\partial W_i$, $\partial E/\partial c_i$ and $\partial E/\partial \sigma_i^2$ are calculated starting from the output layer and proceeding backwards as follows:

$$\frac{\partial E}{\partial W_i} = -2(t - f(z)) f(z)(1 - f(z)) y_i \tag{14}$$

$$\frac{\partial E}{\partial c_{ji}} = -2(t - f(z)) f(z)(1 - f(z)) W_i \frac{y_i}{\sigma_i^2}(x_j - c_{ji}) \tag{15}$$

$$\frac{\partial E}{\partial \sigma_i^2} = -2(t - f(z)) f(z)(1 - f(z)) W_i y_i \left(\frac{\|\mathbf{x} - \mathbf{c}_i\|^2}{2\sigma_i^4}\right) \tag{16}$$

After the calculation, the parameters are updated as equation (17) to (19):

$$W_i(n+1) = W_i(n) - \eta_1 \frac{\partial E}{\partial W_i} \tag{17}$$

$$c_{ji}(n+1) = c_{ji}(n) - \eta_2 \frac{\partial E}{\partial c_{ji}} \tag{18}$$

$$\sigma_i^2(n+1) = \sigma_i^2(n) - \eta_3 \frac{\partial E}{\partial \sigma_i^2} \tag{19}$$

where η_1, η_2, η_3 are learning rate factors in the range [0,1].

Finally, repeat the algorithm for all training inputs.

Once the training of the neural network is completed, the parameters of the model are confirmed. In prediction process, based on our experience, root-mean-square error (RMSE) of all prediction results is defined as the error discriminant function F in order to avoid the exceptional data, which is shown as equation (20):

$$F = \sqrt{\frac{\sum_r (t_r - f(z)_r)^2}{R}} \qquad (r=1, ..., R) \tag{20}$$

where R is the number of prediction results after completing R'th prediction.

The forecasting process is divided into two steps. Firstly, using the confirmed structure and parameters to predict the wind power until the error discriminant function is not satisfying the prediction accuracy, the training datasets are adjusted to update the parameters of the model and continue the prediction.

Case Study

In this section, we give an example of the wind power prediction with real measured data obtained from a wind farm in Inner Mongolia of China. The measured data from 8 days are used as original data. The data arising from the first 3 days are used to initialize the model and train the network. And the data arising from the last 5 days are used in the forecasting process.

We use the data during the latest 3 prediction periods as input to the network to predict wind power over the next period. In this paper, the period is regulated in an hour. After running the program several times, we confirm the most suitable number of hidden layer nodes is 20. In this example, a static prediction model and a dynamic prediction model are each used to predict the wind power output and we can compare the performance and error of each model. The dynamic model is designed as follows:

Firstly, the model is initialized by the data collected from the first 3days. FCM clustering algorithm is used to assign the kernel vector to each neuron in hidden layer. As mentioned above, the most suitable number of hidden layer units is 20, so the number of clusters m is 20. We should initialize m fuzzy clusters and calculate the membership degrees u_{ik} satisfying the follow constraints:

$$0 < \sum_{k=1}^{n} u_{ik} < n(i = 1,2,\cdots m) \tag{21}$$

and

$$\sum_{i=1}^{m} u_{ik} = 1(k = 1,2,\cdots n) \tag{22}$$

Then calculate the new values for cluster centers as the equation (23):

$$c_{ki} = \frac{\sum_{k=1}^{n} (u_{ik})^{l} x_k}{\sum_{k=1}^{n} (u_{ik})^{l}} \tag{23}$$

where l is the weighting exponent, $1 \le l < \infty$.

After the calculation, update the fuzzy membership degree as follow:

$$u_{ik} = [\sum_{j=1}^{m} (\frac{x_k - c_{ki}}{x_k - c_{kj}})^{\frac{2}{l-1}}]^{-1} \tag{24}$$

Repeat the equation (23) to compute the new centers until meeting the end condition as follow equation:

$$\left\| \mathbf{c}_{i,t} - \mathbf{c}_{i,t-1} \right\| < \varepsilon \tag{25}$$

where $\mathbf{c}_i = [c_{1i}, c_{2i}, c_{3i}, \ldots, c_{ki}]$, it is the kernel vector of the i'th hidden node.

After clustering, the standard deviation of the vectors in the subclass is calculated as the spread parameter σ_i and the weight matrix $\boldsymbol{W} = [W_1, W_2, W_3 \ \ldots \ W_m]$ is initialized. After the initialization, we should train the model using equation (14) to (19).

In prediction process, we predict the wind power output using the trained model until the error discriminant function doesn't meet the forecast accuracy. Then the training datasets are adjusted to the input/output patterns of the latest 3 days and the model is trained again. The prediction is carried on after the parameters of the model are updated. In this paper, the forecast accuracy is regulated as 1×10^{-5}.

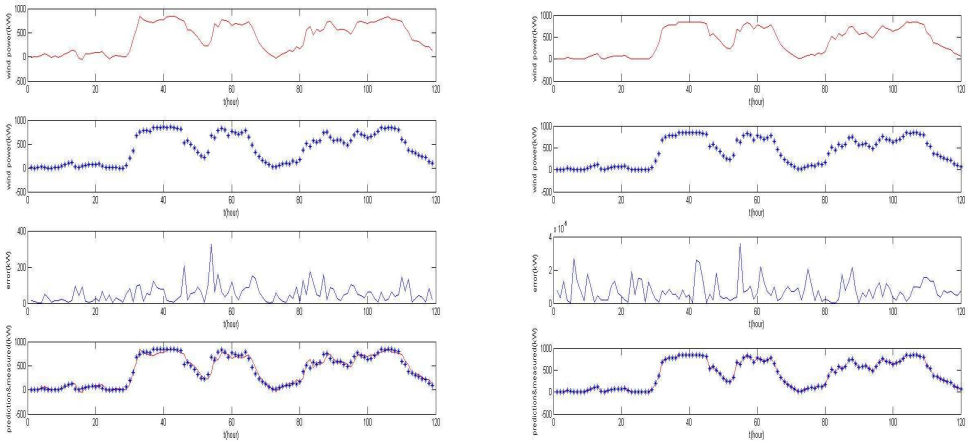

Figure 3. The prediction results of conventional model and dynamic model

Figure 3 shows the results of 1-hour wind power prediction with two types of model which are conventional static model and dynamic model. Red line represents real measured power and blue dots represent the predicted power at prediction points. In Figure 3, the output of the prediction model and actual wind power output are compared and the root-square errors are represented in the graph. Comparing the two graphs, we find the result in the right graph is superior to that in the left graph. In the right graph, the predicted and measured values are almost entirely consistent. But in the right graph, the root-square errors are too large to meet the needs of operational department in power system except the root-square errors at the beginning of prediction.

The maximal power output of the wind turbine generator is 850kW. After the prediction, the RMSE of all results in each model is calculated. The Table 1 shows the RMSE of each model. From the errors in Table 1, we observe that the dynamic model can supply the minimum error and meet the needs of operational department in power system.

Table 1. Comparison of prediction errors of wind power with different model

Model type	Conventional RBF model	Dynamic RBF model
RMSE	73.4121	9.9×10^{-7}

Summary

Based on the historical data of a wind farm, the application of a conventional RBF neural network and a dynamic RBF neural network with error discriminant function for wind power prediction are compared. It has been found that wind power can be successfully predicted using dynamic prediction model. With more parameters, the model can forecast power output better. Further studies will be carried out to improve this dynamic model, such as considering effects of other factors which are wind direction, humidity, etc.

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