Short-term Wind Power Forecast Based on GA-Elman Neural Network and Nonlinear Combination Model

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Abstract. The accuracy of short-term wind power forecast is important to the operation of power system. Based on the real-time wind power data, a wind power prediction model using Elman neural network is proposed. In order to overcome such disadvantages of Elman neural network as easily falling into local minimum, this paper put forward using Genetic algorithm (GA) to optimize the weight and threshold of Elman neural network. At the same time, it’s advisable to use Support Vector Machine (SVM) to comparatively do prediction and put two outcomes as input vector for generalized regression neural network (GRNN) to do nonlinear combination forecasting. By analyzing the measured data of wind farms, indicate that the nonlinear combination of forecasting model can improve forecast accuracy.

Introduction

In recent years, wind power has become internationally recognized as the lowest cost of development, one of the most popular renewable energy. The electricity grid balance must be maintained between consumption and generation, otherwise disturbances may occur. While wind generation is generated from wind and, in contrast to conventional generation systems, is not easily dispatchable. As a result of wind power inherent randomness, volatility and intermittent, the future short-term power generation plan seem to be difficult, for managing the variability of wind generation is the key aspect associated to the optimal integration of renewable energy into electricity grids[1]. The safe and stable operation impaction of the power system restricts the prospect of wind power. In order to meet the demand of power supply and ensure stable operation to grid, power supplying must be effective planning and scheduling. The main way to solving this problem is forecasting the short-term wind power.

Elman neural network is a typical dynamic neural network[2]. On the basis of feed-forward network by storing the internal state mapped the dynamic characteristics of functions, enabling the system has the ability to adapt to the time-varying characteristics. Compared to the traditional neural network, Elman neural network can be more vivid and more directly to reflect the dynamic characteristics of the system. So
it is a very effective tool for the prediction. Structure of Elman neural network characteristic is shown in figure 1.

Fig. 1: Elman neural network structure

Elman neural network is generally divided into four layers: an input layer, a hidden layer, an output layer and a return layer. Characterized as one of the input layer, hidden layer and output layer are similar to feedforward networks, specifically, the input layer making the signal transmission, the output layer is a linear weighting function, following a layer known as return layer, the role of the output value is stored previously hidden layer unit and return back to the network input.

Elman neural network is characterized by output layer, hidden layer and the forward feedback as the system input. The network is very sensitive to the historical data, while the internal feedback network is added to improve the ability to handle dynamic network of information, which can effectively carry out dynamic modeling. Furthermore, Elman neural network can approximate any nonlinear work, and has better accuracy, while not need to consider whether the impact of external noise on the system. In other words, regardless of the external noise affect, we can build system and do simulation by the provided datas.

The Equation in nonlinear state for Elman neural network is shown as follows:

\[ y(k) = g(w^3x(k)) \]  
\[ x(k) = f(w^1x(k) + w^2(u(k-1))) \]  
\[ x_c(k) = x(k-1) \]

In the formula, \( y \) represents the output node vector; \( x \) represents the hidden layer node vector; \( u \) represents the r-dimension input vector; \( x_c \) represents feedback state vector; \( w^3 \) represents the weights between hidden layer to output layer; \( g \) represents the transfer function of the output neurons and linear combination of the hidden layer output; \( f \) represents the transfer function of hidden layer neurons.

It is necessary to explain that Elman neural network also take BP algorithm to amend weights, and the error function as followed:

\[ E(w) = \sum_{i=1}^{N}(y_i(w) - \tilde{y}_i(w))^2 \]

In the formula, \( \tilde{y}_i(w) \) is the target output vector.

**GA-Elman neural network**

Elman neural network using a gradient descent method to fit weights and thresholds, so the weakness of this method is easy falling into local minimum. Therefore, this paper propose using GA to optimize the initial weights and thresholds. GA-Elman neural network consists of those steps. First, determine the fitting function of the input and output parameters of Elman neural network, thus ensuring GA to optimize the weights and thresholds, the length of the individual, the
population included in each individual weights and thresholds effectively. Use the fitness function to calculate the fitness value of the individual, through selection, crossover and mutation genetic algorithm operation, the individual will be found adapted to the corresponding values. Examples can be found through process, and Elman neural network will obtain the initial weights and thresholds networks using genetic algorithms, then we can get a better prediction result.

The main steps are as follows:

**Steps 1:** Initialize population $P$, including cross-scale, cross probability $P_c$, mutation probability $P_m$, corresponding weights and thresholds of the network.

**Steps 2:** Evaluation function is calculated and classified for each individual. Select the network based on the probability value calculated.

$$P_i = \frac{f}{\sum f_i}$$  \hspace{1cm} (5)

In the formula, $f_i$ is the fitness value of $i$, measured by the error of squares $E$:

$$f_i = \frac{1}{E(i)}$$  \hspace{1cm} (6)

$$E(i) = \sum_k \sum_j (d_j - y_j)^2$$  \hspace{1cm} (7)

In the above formula, $i$ is the number of chromosomes, $j$ is the output nodes, $k$ is a sample to the study, $y_j$ is the actual output value, and $d_j$ is the output of the network expected.

**Steps 3:** By using crossover operation on the individuals $G_i$ and $G_{i+1}$, producing new individuals $G'_i$ and $G'_{i+1}$, and there is no cross-operating individuals are copied.

**Steps 4:** The algorithm utilizing mutations $P_m$ generating new individuals $G'_i$ to replace $G_j$. Enter the new entity to $P$, calculate and get new individual evaluation function.

**Steps 5:** Determine whether the algorithm ends, or go on the next round from step 3 operation.

**Steps 6:** End algorithms. After reaching a predetermined performance indicators, network connections get right individuals solved and give the best final optimized weight.

**Steps 7:** The connection on network optimized weight, distributing to Elman neural network to obtain the output.

**Nonlinear combination based on GRNN**

The basic idea of the combination for different prediction models and methods is that combining the information provided by the various ways, which by means of weighted value to get the right combination. Because each method of forecasting models are not identical, the combination forecasting method can maximize the advantages of various single forecasting method, thus it can be convinced that a combination forecasting model can effectively improve the prediction accuracy on the whole.

The theoretical foundation of the GRNN is nonlinear regression analysis. The dependent variable $Y$ relative to the regression analysis is the calculation of independent variable $x$ maximum probability value of $y$. Assuming random variables $x$ and $y$ represent the joint probability density function of random variable of $f(x, y)$, the observation value of $x$ is $X$, then the regression of relative to the $X$ as follows:

$$\hat{Y} = E(Y/X) = \frac{\int f(X,y)dy}{\int f(X,y)dy}$$  \hspace{1cm} (8)
\( \hat{Y} \) is under the condition of the input \( X \), reflect the output forecasts for \( Y \). Using Parzen nonparametric estimation, through a sample data set \( \{x_i, y_i\}_{i=1}^n \) to estimate the density function \( \hat{f}(X, y) \).

\[
\hat{f}(X, y) = \frac{1}{n(2\pi)^{P/2} \sigma^P} \sum_{i=1}^n \exp \left[ -\frac{(X - X_i)^T (X - X_i)}{2\sigma^2} \right] \exp \left[ -\frac{(Y - Y_i)^2}{2\sigma^2} \right]
\]  

(9)

For the formula, \( x_i, y_i \) is the random variable \( x \) and \( y \) sample observations, \( n \) is the size of sample, \( P \) is the dimensions of the random variable \( x \), \( \sigma \) is the width of the gaussian function coefficient, called smooth factor here.

This paper proposes a nonlinear combination forecasting method based on GRNN. In approximation, classification ability and learning speed, GRNN has strong advantages, at the same time it has strong nonlinear mapping ability and flexible network structure with a high degree of fault tolerance. Make the results from GA -Elman model and SVM prediction as the input vectors for GRNN, the combined forecasting model is shown in figure 2.

Fig. 2: GRNN nonlinear combination models

**The example analysis**

**Simulation experiment.** In order to verify the effectiveness of the GRNN nonlinear combination model, a time series is selected of wind power output from a wind farm in Inner Mongolia to predict. Step length of prediction is 15min. The measured data is from July 1, 2013 to July 29, 2013 of the wind farm, whose size is 2784. Set the parameters of GA algorithm: Population size is 30, Number of evolution is 100, crossover probability is 0.4, mutation probability is 0.01. Learning rate is 0.1, the largest number of training is 1000, train target is 0.001. The measured data of July 30 is set as the test-out samples. Simulation results is shown in figure 3.

![Fig. 3 Simulation results of GRNN](image)
We can draw the conclusion from the Figure 3: Because of the wind speed fluctuations, the wind power output is nearly to zero in some time, while the power fluctuation range is unignorable. The GRNN model not only can approximate actual power values, but also trace the power change trend effectively and exactly. The accuracy of prediction was improved, and the occurrence of the prediction error is reduced effectively. In order to show the precision of the GRNN model, it’s suggested to use GA-Elman and SVM to establish the short-term wind power prediction model respectively. Training sample is the same, test samples are the data on July 30. The simulations results which were established by GA-Elman and SVM as shown in figure 4.

![Fig.4 Simulation results of GA-Elman and SVM](image)

The conclusion can be drawn that in the above three kinds models, the precision of using GRNN nonlinear combination model is the highest.  
**The error analysis.** Choose error indicator for evaluation is of great significance. This paper put forward using the Root Mean Square Error (RMSE) as the indicator of wind power prediction. Results is shown in table 1.

<table>
<thead>
<tr>
<th>prediction methods</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>GA-Elman</td>
<td>0.3074</td>
</tr>
<tr>
<td>SVM</td>
<td>0.2732</td>
</tr>
<tr>
<td>GRNN model</td>
<td>0.1637</td>
</tr>
</tbody>
</table>

The table shows that the accuracy of GRNN prediction model is improved significantly. However, complexity of nonlinear combination model is enhanced on the other hand.

**Conclusions**

In order to meet the real-time and high precision, which is the characteristics of short-term wind power prediction, it can be concluded from the simulation that GA-Elman model and SVM model do a good job, while the combination of them by GRNN model educing the advantages and disadvantages of two methods and inosculating them. The simulation experiment proves it, showing that the nonlinear combination forecasting model has higher prediction accuracy in the short-term wind power prediction.

As a renewable energy, wind power provide us opportunity to deal with environmental and resource issues. So the problems from the development of it worthy of our sustained and in-depth discussion and research.

**References**


