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. However, Elman neural network is taking the gradient descent method to update the weights and thresholds, which is easy to falling into local minimum. Therefore, this paper put forward using genetic algorithm (GA) to optimize the initial weight and threshold to avoid falling into local optimum. Because it has the future of parallel search, ensuring that the algorithm is fast and stable. Simulation shows that the accuracy of optimized model prediction has been improved.

To reduce the error of single forecasting model, using SVM to comparatively do prediction[3], and link them by GRNN to do the nonlinear combination. In order to test the adaptability of the new combination forecast model, utilize the model to forecast short-term wind power, and achieved good prediction. Simulation results show that the prediction accuracy of nonlinear combination model has been greatly improved.

Elman neural network[4-5]

Elman neural network is a typical dynamic neural network, which is characterized by the structure of a feedforward artificial network. By storing the internal state of the dynamic nature, the system 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.
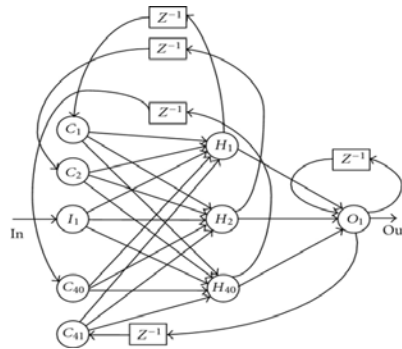

Fig. 1: Elman neural network structure

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:

$$y(k) = g(w^3 x(k)) \tag{1}$$

$$x(k) = f(w^1 x_c(k) + w^2(u(k-1))) \tag{2}$$

$$x_c(k) = x(k-1) \tag{3}$$

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:

$$E(w) = \sum_{k=1}^{n} (y_k(w) - \tilde{y}_k(w))^2 \tag{4}$$

In the formula, $\tilde{y}_k(w)$ is the target onput 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 useing GA to optimize the initial weights and thresholds[6]. 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.

$$P_i = \frac{f}{\sum_i^N f_i} \tag{5}$$

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

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

$$E(i) = \sum_k \sum_j (d_j - \gamma J_j)^2 \tag{7}$$

In the above formula, i is the number of chromosomes, j is the output nodes, k is a sample to the study, γJ is the actual output value, and d 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'_j 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:

$$\hat{Y} = E(y/X) = \frac{\int_{-\infty}^{\infty} y f(X, y) dy}{\int_{-\infty}^{\infty} f(X, y) dy} \tag{8}$$

$\hat{Y}$ 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 $\hat{f}(X, y)$.

$$\hat{f}(X, y) = \frac{1}{n(2\pi)^{\frac{p+1}{2}} \sigma^{p+1}} \sum_{i=1}^{n} \exp\left[-\frac{(X - X_i)^T (X - X_i)}{2\sigma^2}\right] \exp\left[-\frac{(X - Y_i)^2}{2\sigma^2}\right] \qquad (9)$$

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, σ 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.
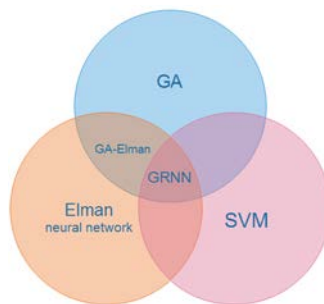

Fig. 2: GRNN nonlinear combination models

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.
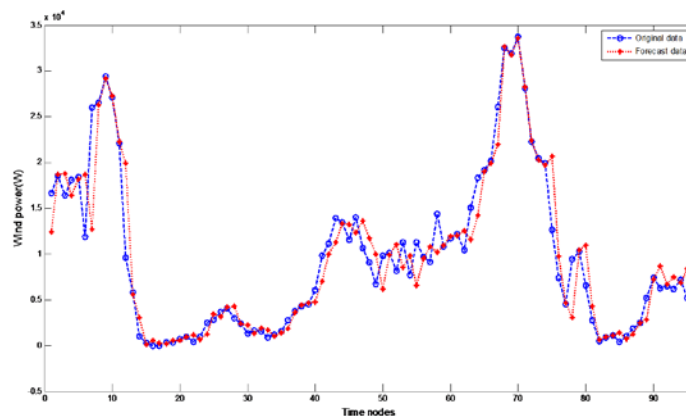

Fig.3 Simulation results of GRNN

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.
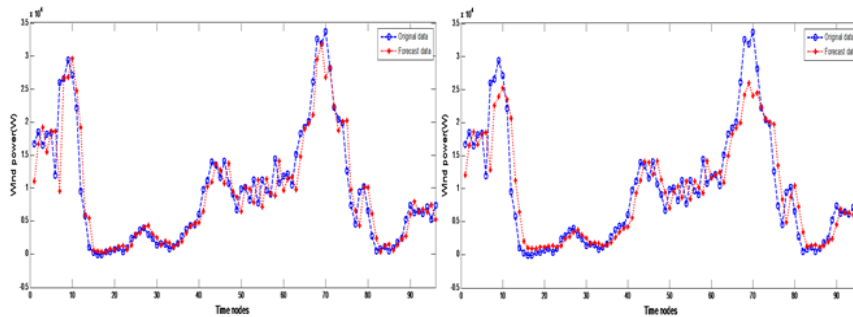

Fig.4 Simulation results of GA-Elman and SVM

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 useing the Root Mean Square Error (RMSE) as the indicator of wind power prediction. Results is shown in table 1.

Table 1 Prediction error of three methods

prediction methods	RMSE
GA-Elman	0.3074
SVM	0.2732
GRNN model	0.1637

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

[1]Costa, Alexandre, et al. "A review on the young history of the wind power short-term prediction." Renewable and Sustainable Energy Reviews 12.6 (2008): 1725-1744.

[2]De Giorgi, Maria Grazia, Antonio Ficarella, and Marco Tarantino. "Error analysis of short term

wind power prediction models." Applied Energy 88.4 (2011): 1298-1311.

[3]Liu, Yongqian, et al. "Short-term wind-power prediction based on wavelet transform–support vector machine and statistic-characteristics analysis." Industry Applications, IEEE Transactions on 48.4 (2012): 1136-1141.

[4]Cheng, Yuan-chu, Wei-Min Qi, and Wei-you Cai. "Dynamic properties of Elman and modified Elman neural network." Machine Learning and Cybernetics, 2002. Proceedings. 2002 International Conference on. Vol. 2. IEEE, 2002.

[5]Gao, X. Z., X. M. Gao, and S. J. Ovaska. "A modified Elman neural network model with application to dynamical systems identification." Systems, Man, and Cybernetics, 1996., IEEE International Conference on. Vol. 2. IEEE, 1996.

[6]Ding, Shifei, et al. "Research on using genetic algorithms to optimize Elman neural networks." Neural Computing and Applications 23.2 (2013): 293-297.

[7]Marvuglia, Antonino, and Antonio Messineo. "Monitoring of wind farms' power curves using machine learning techniques." Applied Energy 98 (2012): 574-583.

[8]Yang, Hong, et al. "Forecast of short-term wind speed in wind farms based on GA optimized LS-SVM." Power System Protection and Control 39.11 (2011): 44-48.