Research on Short-term Wind Power Prediction Based on Generative Adversarial Networks

Xu Ji, Xueming Zhai

School of Control and Computer Engineering, North China Electric Power University, Baoding 071003, China

544939684@qq.com

Abstract

Aiming at the problem that the prediction accuracy of the existing prediction methods is not ideal, this paper adopts a short-term wind power prediction method based on combination analysis. This method uses the Generative Adversarial Networks as the system framework. Compared with the traditional neural network, this method is trained repeatedly by the interaction of the generative model and the discriminant model. Therefore, compared with the single prediction method, this method is more effective. The prediction accuracy of this method is high. In view of the chaotic characteristics of wind energy, such as disorder, randomness, instability and uncontrollability, chaotic networks can better represent the internal relationship between wind energy parameters and wind power than other types of neural networks. Therefore, this paper chooses chaotic neural network as the generation model of generative countermeasure neural network algorithm. In order to ensure the prediction accuracy of the combination method, BP neural network with good fitting performance of the non-linear function is selected as the discriminant model of the Generative Adversarial Networks.

Keywords

Wind power prediction; generative adversarial neural network; chaotic neural network; BP neural network.

1. Introduction

With the rapid development of the world economy and the increasingly serious environmental pollution, wind energy, as an important part of renewable energy, has become the focus of attention and technology research in the field of power generation. Wind power is the power of generating units. Because of the instability, fluctuation and intermittence of wind itself, the generation of wind farms is not stable. Therefore, in the process of grid-connected, it will have a great impact on the power system. To forecast wind power, on the one hand, the dispatching plan can be adjusted in time to reduce the operation cost, on the other hand, according to the output power of wind power, other conventional energy can be reasonably arranged to ensure the safe and stable operation of the power system. Therefore, wind power prediction plays an important role in the safe operation of power grid.

n recent years, scholars at home and abroad have done a lot of work on short-term prediction of wind power, which mainly includes two methods: statistical modeling technology and physical modeling technology, the former is mainly based on the time series of wind farm output power to predict; the latter is based on numerical weather prediction (NWP) as input and predicts wind power output according to power curve. The physical method does not need a lot of historical data, but the prediction accuracy is poor. The forecasting methods include auto regressive moving average (ARMA) [2], Kalman filter [3], local recurrent neural network [4], wavelet analysis [5] and support vector machine

(SVM) [6]. In addition, there is an improved combination forecasting method, which combines the advantages of several methods and has better forecasting effect. Practice has proved that the combined forecasting method is better than the single forecasting method, and the forecasting accuracy is higher.

In order to obtain high accuracy prediction results, this paper uses the combination method and Generative Adversarial Networks [7] as the basic algorithm framework for wind power prediction. In view of the chaotic characteristics of wind energy, such as disorder, randomness, instability and uncontrollability, chaotic networks can better represent the internal relationship between wind energy parameters and wind power than other types of neural networks. Therefore, this paper chooses chaotic neural network as the generation model of generative countermeasure neural network algorithm. In order to ensure the feasibility of the combined algorithm, BP neural network with good generality is selected as the discriminant model of the GAN.

2. Generative Adversarial Network Framework

2.1 Generative Adversarial Network

In December 2014, Ian J. Goodfellow et al. proposed a new framework, which is a generation model by estimating the confrontation process, namely, the Generative Adversarial Networks (GAN). Its idea comes from the "two-person zero-sum game" in game theory. Generative model and Discriminative model are the two sides of the game. Both of them are non-linear mapping functions. The whole system model is trained by back-propagation algorithm. Generating model G captures potential distribution and generates new data samples by generating model G through real samples. Discriminating model D judges the probability that samples originate from real wind power time series or time series generated by generating model. In the training process, GAN fixes any aspect and optimizes the other aspect, which is a direct alternating optimization process, such as: fixed generation model, optimized discrimination model; or fixed discrimination model, optimized generation model. The optimization purpose of the generating model is to get closer to the results of real wind power time series, and the optimization purpose of the discriminant model is to more accurately determine whether the input data is generated by the generating model. Through continuous optimization and iteration of the two models, the network structure of the two models is continuously improved, and the convergence of the generating model and the discriminant model is stopped. Generation model can fit the probability distribution of real data successfully. Discriminant model also has some shortcomings. The probability of judging whether the time series originates from the generated image or the real time series problem tends to be 0.5.

GAN framework is widely used in image generation, image enhancement and image restoration, but it has not been widely used in the field of wind power prediction. In view of the chaotic characteristics of wind energy, such as disorder, randomness, instability and uncontrollability, chaotic networks can better represent the internal relationship between wind energy parameters and wind power than other types of neural networks. Therefore, this paper chooses chaotic neural network as the generation model of generative countermeasure neural network algorithm. In order to ensure the feasibility of the combined algorithm, BP neural network with good generality is selected as the discriminant model of the GAN.

2.2 Training Network Structure for Wind Power Prediction

In the training process of the combined method of wind power forecasting for GAN, the training of chaotic neural network generation model and BP neural network discriminant model is carried out alternately, and there is no interaction between them.

The input variables of chaotic neural network and BP neural network are data sets composed of wind power time series every 72 hours and measured data of wind speed and air density. The time resolution is 15 minutes.

The training steps of chaotic neural network are as follows:

(1) Maximum Lyapunov exponent method is used to verify the chaos of wind power time series. If it is not chaotic, other neural networks are selected to form a GAN.

(2) The C-C method is used to reconstruct the phase space of wind power time series.

(3) Determine the delay time and embedding dimension.

(4) Determine the data set of input variables.

(5) Model training.

Logistic nodes in chaotic neural networks record the logical mapping between meteorological information and corresponding time wind power. The training flow chart of chaotic neural networks is shown in Fig. 2 .

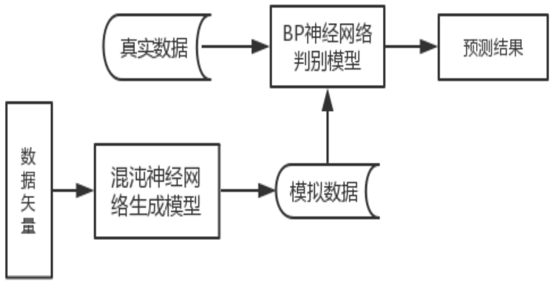


Fig. 1 GAN Topology

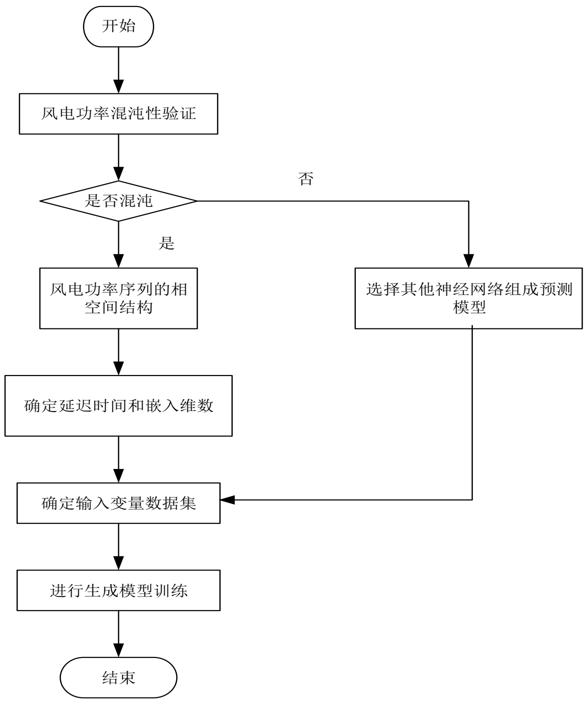


Fig. 2 Chaotic Neural Network Training Flow

2.3 Prediction Network Structure for Wind Power Prediction

In the process of predicting the GAN, the upgrade process of the generative model and the discriminant model is carried out alternately. Firstly, the discriminant model is fixed to make the generated model learn. The purpose is to generate a more realistic time series of wind power, so that the discriminant model can not judge whether the time series is a real time series or a prediction sequence generated by the model. The next step is to fix the generation model and make the discriminant model learn. The purpose is to determine the probability that the time series of wind power input is close to the real sequence. Its structure is shown in Fig. 3.

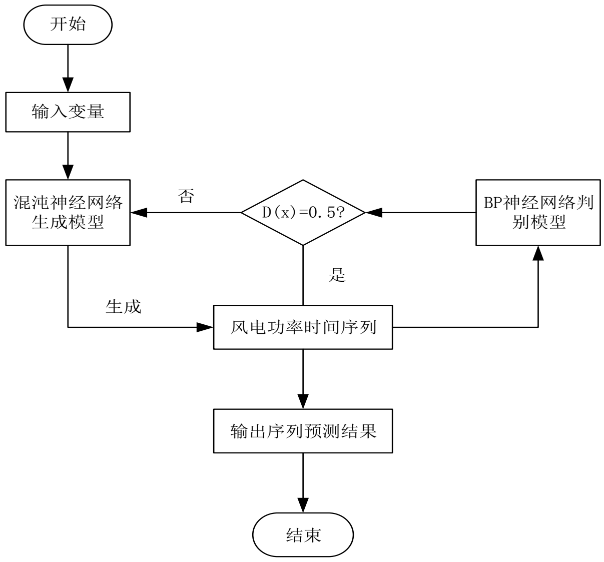


Fig. 3 GAN Prediction Architecture

The input variables of the chaotic neural network model are the 24-hour wind power series, wind speed and air density data before the prediction point. The time resolution is 15 minutes, and the output is the 72-hour wind power series of the prediction point. The input variable of the BP neural network discriminant model is the next 72 hours wind power series generated by chaotic neural network. The output value is the probability $D(x)$of the input variable approaching the real time series. The probability value is fed back to the chaotic neural network generation model as the return value. When $D(x)$approaches zero, the weights and iterations of the generated model are adjusted and optimized; when $D(x)$approaches 1, the weights and iterations of the discriminant model are adjusted and optimized.

In the process of forecasting, the generation model and the discriminant model are optimized alternately to reach the goal of approaching each other. When the $D(x)$value is equal to 0.5, the model achieves the global optimal solution. At this time, the time series generated by the chaotic neural network is the forecasting result of the forecasting model.

3. Wind Power Time Series Generation Model Based on Chaotic Neural Network

Because of the instability, intermittence and fluctuation of wind force, time series can not be expressed by simple numerical methods, and the intrinsic dynamic mechanism of time series can not be accurately expressed. Because of the superposition of many factors, the output power of wind farm is non-linear. Wind power time series has inherent randomness, sensitivity of initial value and irregular order, which accords with the characteristics of chaos theory. Therefore, this paper uses chaotic neural network as the generation model of GAN. In order to confirm that chaotic neural network is indeed suitable for wind power prediction, it is necessary to verify the chaos inherent in it. Then the phase space of wind power time series is reconstructed and a chaotic neural network generation model based on phase space is established to generate the time series of wind power.

3.1 Chaos Verification of Wind Power Time Series

The time series of wind farm output power is non-linear or even chaotic under the interaction of many factors. In addition, due to the influence of other inherent uncertainties, it is difficult for simple numerical methods to accurately describe the inherent dynamic mechanism of the time series. According to the influence factors of power output of wind farm, the error band prediction model of artificial neural network is established to predict the output power of wind farm, and good results are obtained. The chaotic property of power output time series of wind farm is verified in literature [9]. The error performance of prediction algorithm of chaotic neural network is analyzed in literature [10]. The chaotic neural network has better prediction performance. 。

In this paper, the maximum Lyapunov exponent method is used to verify the chaos of wind power time series. Lyapunov exponent is a quantitative method for describing the local stability of dynamic system orbit. This method takes time as a measure to measure the degree of attraction or separation of two phase trajectories with different initial values in phase space. Definition: Let a point $x(0)$and a radius $\varepsilon(0)$ in the phase space, and the neighborhood corresponding to the point be expanded or contracted into a hyperellipsoid with the change of the dynamic system. The axis of the hyperellipsoid in each direction is $\varepsilon_i(t)$, and the Lyapunov exponent of the point $x(t)$ in the second direction is as follows:

$$\lambda_i = \lim_{t\to\infty} \lim_{\varepsilon(0)\to 0} \frac{1}{t} \ln \frac{\varepsilon_i(t)}{\varepsilon(0)} \tag{1}$$

The maximum Lyapunov exponent is greater than 0. 0055. From this, we can see that the time series of wind power is chaotic, and the chaotic neural network algorithm is suitable for the time series of wind power.

The key point of phase space reconstruction for noisy time series is to determine the time delay_and embedding dimension M. Otherwise, the quality of reconstructed phase space will be greatly affected. There are two viewpoints in determining time delay_and embedding dimension m: one is that_and M can be independently determined. The methods of determining time delay_are autocorrelation function method [19], mutual information method [20], average displacement method [21]. The methods of determining embedding dimension m are: False Nearest Neighbors (FNN) [22], singular value decomposition method Lar value decomposition, SVD [23], etc. The other holds that τ and m are interdependent and can be established at the same time, including time window method [24], C-C method [25]. It is generally believed that there is no essential difference between the two views. The key may be that the sensitivity of the measured data to the parameters is different when the delay time_and the embedding dimension m are determined by specific methods. In this paper, C-C method is used.

$$\bar{S}(t) = \frac{1}{j(m-1)} \sum\nolimits_{m=2} \sum\nolimits_{j=1} S(m, r_j, t) \tag{2}$$

$$\Delta\bar{S}(t) = \frac{1}{m-1} \sum\nolimits_{m=2} S(m, t) \tag{3}$$

The optimal delay time τ is determined by the first zero of $\bar{S}(t)$ or the first minimum of $\Delta\bar{S}(t)$. The maximum time window τ_ω is determined by the minimum of $S_{cor}(t)$, and the optimal embedding dimension m is determined by $\tau_\omega = (m-1)\tau$.

In this paper, the time series of wind power is used to reconstruct phase space. The results of $\Delta\bar{S}(t)$ and $S_{cor}(t)$ obtained by C-C method are shown in Fig. 4.

As can be seen from Figure 4, when the value of τ is 4, $\Delta\bar{S}(t)$ obtains the first minimum, so the delay time τ is 4, and $S_{cor}(t)$ obtains the minimum when t is 98, so the embedding dimension m is 26.

3.2 Training of Chaotic Neural Network and Generation of Wind Power Time Series

Because chaotic neural network has strong fitting ability for non-linear system, which is a point compared with traditional neural network, this paper takes chaotic neural network as the generation model of GAN. In the structure of chaotic neural network, in its hidden layer, each node will have an adjoint neuron attached to it based on logical mapping. The hidden layer of chaotic neural network is a two-layer structure, which is the main characteristic of chaotic neural network. In addition, it has strong non-linear fitting ability, fault tolerance and self-learning ability. Its structure is shown in Fig. 5.

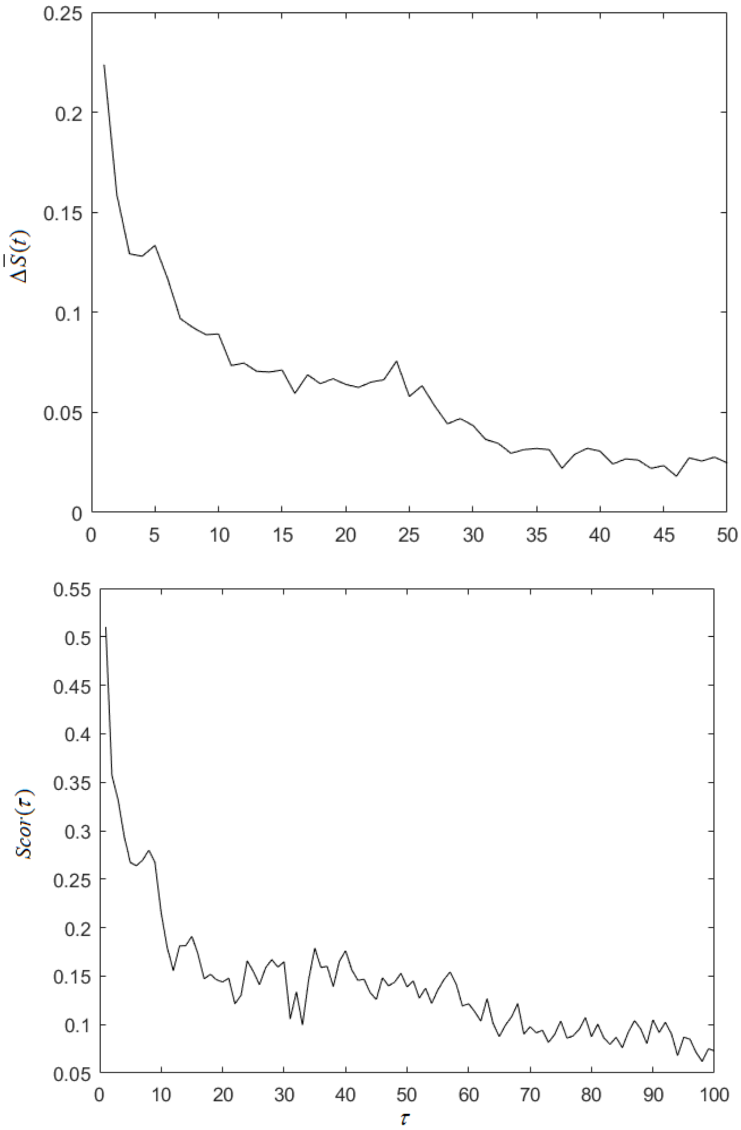


Fig. 4 $\Delta\bar{S}(t)$ and $S_{cor}(t)$ versus delay time τ

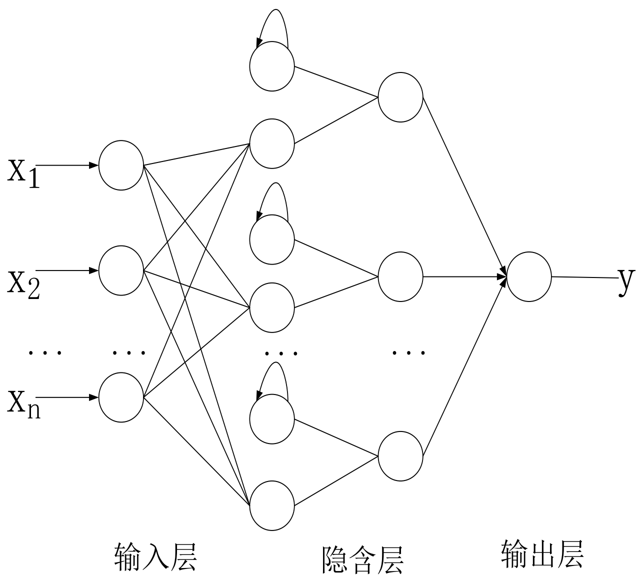


Fig. 5 Topology of Chaotic Neural Networks

The first layer consists of F neurons and B neurons. F neurons receive all input signals and B neurons receive their own dynamic feedback.

The second layer consists of output neurons of the hidden layer, called H neurons. The main function of H neuron is to process the output signals of F neuron and B neuron and then input them into the output layer.

In the training process, the optimal delay time $\tau = 18$, embedding dimension m=6, and time resolution of wind power series are 15 minutes after phase space reconstruction of 72-hour wind power time series. That is to say, 288 data are recorded every 15 minutes, so the phase space vectors of time series after phase space reconstruction are $N = n - 1 - (m-1)\tau = 187$. At the same time, the wind speed and air density in 72 hours are used as input parameters of the chaotic neural network, and the time resolution is 15 minutes. The purpose of the training is to enable the chaotic neural network to reveal the intrinsic relationship between meteorological information and time series of wind power.

In the process of generating wind power time series, the input variables are wind power series, wind speed and air density data 24 hours before the predicted point. The wind power of the predicted point in the next 72 hours is generated. The generated time series is used as the input parameters of the BP neural network discriminant model to determine the probability that the time series is close to the real time series.

4. Discriminant Model of Wind Power Time Series Based on BP Neural Network

In order to obtain good prediction results, according to the principle of GAN, it is necessary to add a discriminant model. At this time, this paper chooses BP neural network, which is widely used, because it has strong mapping ability and can approximate any non-linear function.

In order to ensure the feasibility of the combined algorithm, the BP neural network with high generality is used as the discriminant model of the GAN. BP neural network learning algorithm includes two aspects: signal forward propagation, the direction from input layer to output layer when calculating output value; error back propagation, according to the direction of error negative gradient from output layer to input layer, adjust the weight and threshold [26,27].

BP neural network is a discriminant model of GAN. The input parameters are the time series of wind power generated by chaotic neural network. Its function is to judge the rationality of the input wind power series. The output results are the probability that the input parameters are the real wind power series. In the framework of GAN, the output results are fed back to the generating model in the form of return value. When the return value approaches zero, the number and weight of iterations are optimized so as to make the generated time series closer to the real time series. On the contrary, when the return value approaches 1, the discriminant model is optimized to improve its discriminant ability. In this way, the generated model, i.e. chaotic neural network, can produce more optimized prediction results.

5. Realization of Prediction Combination Method for GAN

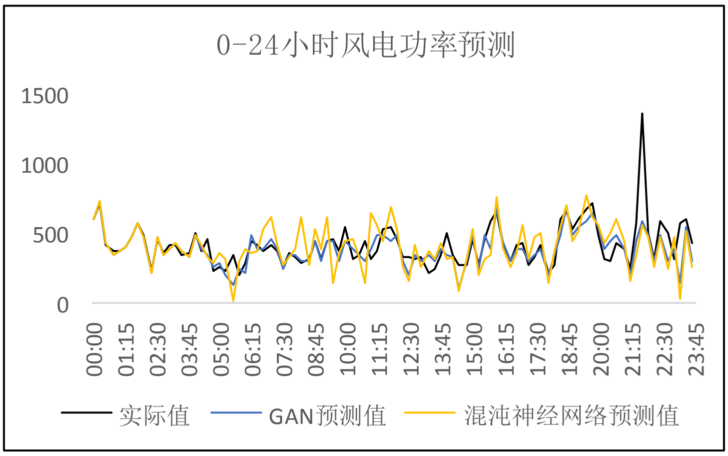
In the process of predicting the GAN, the upgrade process of the generative model and the discriminant model is carried out alternately. Firstly, the discriminant model is fixed to make the generated model learn. The purpose is to generate a more realistic time series of wind power, so that the discriminant model can not judge whether the time series is a real time series or a prediction sequence generated by the model. The next step is to fix the generation model so that the discriminant model can be learned. The purpose is to determine whether the time series of wind power input is the real sequence.

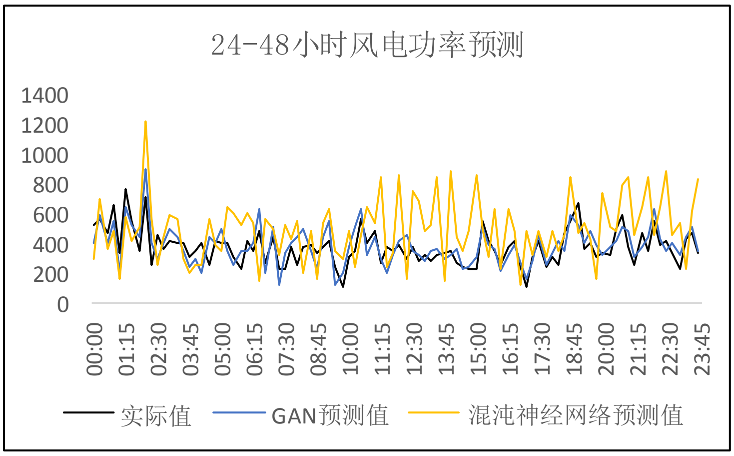
The two models learn alternately to improve their performance until the prediction time series generated by the model is very close to the real time series. When the discrimination model can not distinguish whether it is a real time series, the algorithm completes. At this time, the time series generated by the model is the prediction time series of wind power.

It should be noted that the number of iterations of the generated model and the discriminant model should not be too large, and the number of iterations of the generated model is higher than that of the discriminant model. If the number of iterations is too different, the discriminant ability of the discriminant model is too low, and it will enter the end state of the algorithm too early. At this time, the accuracy of the generated time series may not achieve the desired effect. In addition, if the number of iterations of the discriminant model is higher than that of the generated model, the discriminant ability of the discriminant model will be too strong, which will make the algorithm unable to end and fall into a dead cycle.

In the process of GAN training, the discriminant model D is trained to maximize the probability that the data originate from the real data, and the generated model G is trained to minimize. By alternating iteration method, the model G is fixed to maximize the discriminant probability of D, and the model G is optimized to minimize the discriminant probability of D. When and only if $P_{data} = P_g$, the global optimal solution is obtained.

Based on the wind power data of a wind farm in Ningxia, China, the input variables of the model chaotic neural network are generated as the 24-hour wind power series, wind speed and air density data before the prediction point. The wind power of the prediction point in the next 72 hours is predicted, and the time resolution of the prediction is 15 minutes. The number of iterations to generate the model is 60 and the number of iterations to discriminate the model is 50, and the final result is obtained when the model is upgraded alternately three times. The error rate is calculated and compared with the prediction result made by a single chaotic neural network. The prediction results are compared with those of chaotic neural networks as shown in Fig. 6, and the error rates are compared as shown in Fig. 7.





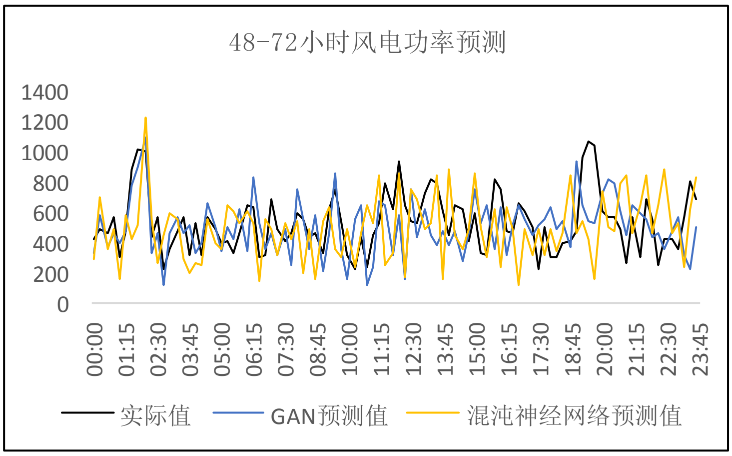


Fig. 6 Wind Power Prediction of GAN and Its Comparison with Chaotic Neural Network

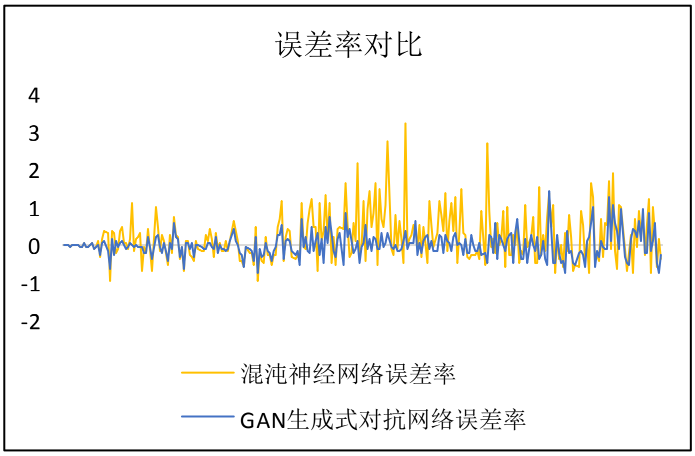


Fig. 7 Error Rate Comparison between Prediction Model of GAN and Prediction Results of Chaotic Neural Network

From the graph, it can be seen that the average error rate of the GAN algorithm is 12.35298%, which meets the international standard that the error rate is less than 15%. It is proved that the GAN generating countermeasure network composed of chaotic neural network and BP neural network is suitable for wind power prediction. Compared with the single chaotic neural network algorithm, the combined method can achieve higher prediction accuracy.

6. Conclusion

In this paper, GAN is used as the algorithm framework of wind power prediction, chaotic time series is established to verify the chaos of wind power time series, and chaotic neural network is used as the generating model to realize the prediction of wind power. BP neural network is used as the discriminant sequence of the hybrid analysis method, its role is to improve the prediction accuracy. Compared with the single chaotic neural network algorithm, the combined method has better prediction accuracy.

Further work includes: researching similar samples to improve the prediction accuracy, and on this basis, enhancing the integrity and accuracy of wind power description; optimizing the prediction model so that it can get the same or even higher prediction accuracy with fewer iterations.

References

[1] Li Zhi, Han Xueshan, Han Li, Kang Kai. Method of ultra-short-term prediction of wind power in regional power grids[J]. Automation of Electric Power Systems, 2010, 34(07): 90-94

[2] Tian Bo, Pu Zai-lin, Guo Dan, Wang Hui.Study on ultra-short-term wind power prediction based on ARMA-GARCH model[J].Electrical Measurement & Instrumentation,2016,53(17):12-17.

[3] Kariniotakis G, Pinson P, Siebert N, et al. State of the art in short-term prediction of wind power-from an offshore perspective[C]//Proceedings of the Ocean Energy Conference: Offshore Wind Energy, Marine Currents And Waves, October 15-15, 2008, Brest, France.

[4] Barbounis T G, Theocharis J B. Locally recurrent neural networks for wind speed prediction using spatial correlation[J].Information Sciences,2007,177(24):5775-5797.

[5] CHITSAZ H, AMJADY N, ZAREIPOUR H. Wind power forecast using wavelet neural network trained by improved clonal selection algorithm[J]. Energy Conversion & Management, 2015, 89(1): 588-598.

[6] Li Yanqing, Yuan Yanwu, Guo Tong. Ultra-short-term wind power combination forecast based on AMD-ICSA-SVM[J].Power System Protection and Control, 2017, 45(14): 113-120.

[7] Goodfellow I J, Pouget-Abadie J, Mirza M, et al. Generative adversarial networks [J]. Advances in Neural Informa-tion Processing Systems, 2014, 3: 2672-2680.

[8] Fan Gaofeng, Wang Weisheng, Liu Chun, et al. Wind Power Prediction Based on Artificial Neural Network[J]. Proceedings of the CSEE, 2008(34): 118-122.

[9] Wang C , Zhang H , Fan W , et al. A new wind power prediction method based on chaotic theory and Bernstein Neural Network [J]. Energy, 2016, 117:259-271.

[10] Abedinia O, Amjady N. Short-term wind power prediction based on Hybrid Neural Network and chaotic shark smell optimization[J]. International Journal of Precision Engineering and Manufacturing-Green Technology, 2015, 2(3):245-254 .

[11] Zhang Xueqing, Liang Jun. Chaotic characteristics analysis and prediction model of wind power power time series[J]. Acta Phys. Sin., 2012, 61(19):000070-81.

[12] Jian Xiangchao, Zheng Junli. Evaluation criteria and performance analysis of chaotic neural network prediction algorithm[J]. Journal of Tsinghua University(Science and Technology), 2001(07): 43-46.

[13] Niu Chenguang, Liu Cong. Short-term wind power prediction model based on neural network reconstruction based on phase space reconstruction[J]. China Electric Power, 2011, 44(11): 73-77.

[14] Zhang Y, Jiping L U, Meng Y, et al. Wind Power Short-term Forecasting Based on Empirical Mode Decomposition and Chaotic Phase Space Reconstruction [J]. Automation of Electric Power Systems, 2012.

[15] Hu Yu, Chen Tao. Phase space reconstruction technique of chaotic attractors based on C-C algorithm[J]. Journal of Electronic Measurement and Instrument, 2012, 26(5): 425-430.

[16] Lei D, Wang L, Shuang G, et al. Prediction of Wind Power Generation based on Chaotic Phase Space Reconstruction Models [C]// International Conference on Power Electronics & Drive Systems. 2008.

[17] Du D Y, Chen B F. Ultra-Short-Term Forecasting Based on Phase Space Reconstruction and Wind Power Wind [J]. Applied Mechanics & Materials, 2015, 713-715: 1444-1447.

[18] Ouyang T, Zha X, Liang Q, et al. Short-term wind power prediction based on kernel function switching [J]. Electric Power Automation Equipment, 2016.

[19] Jiang Yuechun, Zhang Bingjiang, Xing Fangfang, et al. Multi-step prediction of ultra-short-term wind power based on chaotic time series GA-VNN model[J]. Power System Technology, 2015, 39(8): 2160-2166.

[20] Wei G, Tao X, Lu Z. An integrated chaotic time series prediction model based on efficient extreme learning machine and differential evolution[J]. Neural Computing & Applications, 2016, 27(4): 883-898.

[21] Wu Z Q, Jia W J, Zhao L R, et al. Maximum wind power tracking for PMSG chaos systems - ADHDP method [J]. Applied Soft Computing, 2015, 36(C): 204-209.

[22] Barbounis T G, Theocharis J B, Alexiadis M C, et al. Long-term wind speed and power forecasting using local recurrent neural network models [J]. IEEE Transactions on Energy Conversion, 2006, 21(1): 273-284.
[23] Wang Lizhen, Liao Xiaozhong, Gao Shuang, et al. Chaotic attribute analysis of power-time series of wind power generation in large-scale wind farms with grid-connected[J]. Journal of Beijing Institute of Technology, 2007, 27(12): 1077-1080.
[24] Li Y, Deng S, Di X. A novel Hash algorithm construction based on chaotic neural network[J]. Neural Computing & Applications, 2011, 20(1): 133-141.
[25] Li Lingling, Li Zongli, Li Junhao, et al. Short-term prediction of wind power based on chaotic radial basis function[J]. Power Supply Technology, 2014(12): 2328-2330.
[26] Cui M, Sun Y, Deping K E. Wind Power Ramp Events Forecasting Based on Atomic Sparse Decomposition and BP Neural Networks [J]. Automation of Electric Power Systems, 2014.
[27] Li J, Mao J. Ultra-short-term wind power prediction using BP neural network [C]// Industrial Electronics & Applications. 2014.