

Research on the Prediction Model of Greenhouse Temperature Based on Fuzzy Neural Network Optimized by Genetic Algorithm

Lina Wang, Wenbin Dai, Jinjie Liu, Xiaohong Cui, Binrui Wang*

Abstract—Aiming at the complex nonlinear system of greenhouse, combined with the advantages of the genetic algorithm and fuzzy neural network algorithm, a fuzzy neural network temperature prediction method with the genetic algorithm is proposed. In the method, the initial parameters of the fuzzy neural network are optimized by the genetic algorithm, and the error of network prediction is taken as the target value to the genetic algorithm for the next-generation genetic algorithm. Combining the advantages of the two algorithms, better prediction results are obtained. In this paper, the forecast method was simulated by using the data of the Hangzhou meteorological station. The results show that the prediction decision coefficient $R^2 = 0.9724$. Therefore, it is proven that the method has good prediction accuracy and can effectively predict the greenhouse temperature.

Keywords—prediction of greenhouse temperature, genetic algorithm, fuzzy neural network

I. INTRODUCTION

WITH the improvement of modern agricultural science and technology, cultivating crops in a greenhouse environment has become popular. The control of some environmental factors in the greenhouse environment can eliminate the influence of time and region on the growth of most crops, which help to increase production and improve quality. There are many small environmental factors with close relations to each other in the greenhouse, where temperature plays an important role^[1-4], and it is difficult to control the temperature accurately. However,

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greenhouse is a complex nonlinear system, If the trend of temperature change is known, people can directly improve the effect of temperature control. Therefore, it is vital to apply an effective method to improve prediction accuracy of greenhouse temperature.

Regarding the method of temperature prediction, Xia Shuang et al. used a PSO-RBF model to predict the greenhouse temperature^[5]; Chen Xin et al. used the two-steps prediction method of the twice cluster analysis and the BP neural network to model the temperature of solar greenhouse^[6]; Ferreira P M et al. used linear-nonlinear structures in radial basis function neural networks to find an online learning method^[9]. In addition, the algorithm used in this paper has been applied in many fields and has achieved certain results. Fan Zheng et al. optimized the synthesis process of benzyl acrylate by using a fuzzy neural network-genetic algorithm^[10]; B.K.Patle et al. used the ANFIS and the genetic algorithm to optimize the setting of diesel engine^[11]; Soepangkat et al. carried out the grey fuzzy analysis and BPNN-GA to optimize drilling kevlar fiber reinforced polymer^[12]; Bozorgvar Masoud et al. used adaptive neuro-fuzzy intelligent controller based on magnetorheological damper and genetic algorithm to conduct semi-active seismic control of buildings^[13]; A. Quteishat et al. proposed a two-stage pattern classification and rule extraction system based on improved fuzzy minimum or maximum network and genetic algorithm rule extractor, and verified the stability of the system with a practical medical diagnosis task^[14]; Kaan Uyar et al. proposed a genetic algorithm-based training recurrent fuzzy neural network for heart disease diagnosis^[15].

Although the above research on greenhouse temperature prediction has acquired some results, which did not show excellent prediction accuracy. In addition, the success of the fuzzy neural network-genetic algorithm in various cases shows that the fusion algorithm has better prediction results and opens up a new way for the greenhouse research. Therefore, the following paper combines the fuzzy neural network algorithm with the genetic algorithm to predict greenhouse temperature and find a more accurate greenhouse temperature prediction method.

II. SYSTEM DESCRIPTION PROBLEM FORMULATION

Artificial neural network is a kind of algorithm, which is designed to imitate the human central nervous system to solve nonlinear and complex problems. Fuzzy

neural networks incorporate fuzzy rules in neural network algorithms, which can handle uncertain information through fuzzification [16]. The genetic algorithm has the ability to solve complex nonlinear optimization problems and can effectively solve the randomness of the initial parameters selection of fuzzy neural network, so as to increase the network training efficiency and the prediction accuracy of the training models [18]. This section mainly describes the basic principles of these algorithms.

A. Fuzzy neural network

Fuzzy neural network algorithm combines the neural network algorithm with a fuzzy algorithm. The fuzzy algorithm uses two concepts of the membership degree and the membership function. Membership degree stands for the elements belonging to fuzzy subset, and its size is between 0 and 1. T-S fuzzy system with the excellent adaptive capabilities is used in this paper, whose definition rules are as follows.

For the fuzzy reasoning case of R^i is as shown:

R^i : If x_1 is A_1^i , x_2 is A_2^i, \dots, x_k is A_k^i then $y_i = p_0^i + p_1^i x_1 + \dots + p_k^i x_k$

Where A_j^i is the fuzzy set; p_j^i ($j = 1, 2, \dots, k$) is the fuzzy system variables; y_i is the fuzzy output which is obtained from the fuzzy rules. The fuzzy input part (if part) typed as fuzzy variables, and the fuzzy output part (then part) typed as definite variables. The whole inference process indicates the linear relationship between outputs and inputs.

Assuming the input $x = [x_1, x_2, \dots, x_k]$. The membership degree of input x_j is calculated as followed:

$$\mu A_j^i = \exp\left(-\frac{(x_j - c_j^i)^2}{b_j^i}\right) \quad j = 1, 2, \dots, k; \quad i = 1, 2, \dots, n \quad (1)$$

In this formula, c_j^i and b_j^i are the center variables and width variables of the membership function; k and n is the number of input variables and number of fuzzy subsets.

In the fuzzy membership degree calculating process, the fuzzy operator is used as the multiplication operator:

$$w^i = uA_j^1(x_1) \times uA_j^2(x_2) \times \dots \times uA_j^k(x_k) \quad i = 1, 2, \dots, n \quad (2)$$

According to the results, the output y_i is calculated:

$$y_i = \sum_{i=1}^n w^i (p_0^i + p_1^i x_1 + \dots + p_k^i x_k) / \sum_{i=1}^n w^i \quad (3)$$

The learning methods of the network are as follows:

(1) Error calculation

$$e = \frac{1}{2} (y_d - y_c)^2 \quad (4)$$

Where y_d is the network expected output; y_c is the actual output; e is the error between y_d and y_c .

(2) System correction

$$p_j^i(k) = p_j^i(k-1) - \alpha \frac{\partial e}{\partial p_j^i} \quad (5)$$

$$\alpha \frac{\partial e}{\partial p_j^i} = (y_d - y_c) w^i / \sum_{i=1}^m w^i \cdot x_j \quad (6)$$

Where p_j^i is the weights of the neural network; α is the learning rate; x_j is the input of the network; w^i is the continuous product of membership degree of the input.

(3) Parameter modification

$$c_j^i(k) = c_j^i(k-1) - \beta \frac{\partial e}{\partial c_j^i} \quad (7)$$

$$b_j^i(k) = b_j^i(k-1) - \beta \frac{\partial e}{\partial b_j^i} \quad (8)$$

In the formula, c_j^i and b_j^i are the center variables and width variables of the membership function.

B. Genetic algorithm

The genetic algorithm encodes the parameters of the problem as chromosomes and uses the iterative method to carry out the selection, crossover and mutation to exchange the information of chromosomes in the population. Finally, it generates the chromosomes that meet the optimization objectives. Chromosomes corresponding to the data are usually one-dimensional string structure data. The values of genes corresponding to each position in the string are the values of the parameters. Each chromosome represents a sample individual. The adaptation degree of individual from populations to the environment is called fitness. The larger the fitness the larger the likelihood that the gene will be retained and passed on to the next generation [17].

The genetic algorithm steps are as follows:

a) Code

There are many coding methods of the genetic algorithm. Following paper adopts binary coding. Code the value range of the selected parameters into the corresponding binary code to complete the coding.

b) Generation of the initial population

N individuals are randomly selected for inheritance.

c) Fitness assessment

According to the required optimal solution, the corresponding fitness function is written. In this paper, the error after the algorithm training is selected as the fitness function, and the minimum value is taken as the objective to find the optimal initial value.

d) Choice

According to fitness, each individual is given a different probability of inheritance to the next generation. After selection, the parameters closest to the optimal solution can be passed to the next generation with a greater probability.

e) Crossover and mutation

It increases the possibility of finding other optimal solutions to avoid the situation that the population deviates from the category of the optimal solution during initializing.

III. MODELING AND TEMPERATURE PREDICTION METHODS

Based on the principle of the algorithms, two prediction models are constructed by using two kind of fuzzy neural network algorithm. After genetic algorithm optimization and prediction simulation to compare the prediction results errors.

A. Data selecting

The training data were obtained from the meteorological stations of temperature, relative humidity and accumulated radiation from 2010 to 2019. The data used to predict the test are the daily average temperature, average surface temperature, average relative humidity and cumulative radiation from Hangzhou meteorological station in 2016.

B. Modeling of Fuzzy Neural Networks

The average daily temperature of Hangzhou in the past ten years is taken as the output value of the training. While the daily average cumulative radiation (corresponding parameter P1), daily average air relative humidity (corresponding parameter P2), and daily average surface temperature (corresponding parameter P3) are taken as the training inputs of the fuzzy neural network. The temperature data in the test data is also used as the expected value, and the rest of the test data is used as the test input value. Data order is disrupted before training to get a better

prediction model.

The input is set to 3; the output is set to 1; the number of determined membership function is set to 7; the network structure is set to 3-7-1. Based on the parameter settings, the center c of the fuzzy membership function, width b and coefficient $p_0 \sim p_3$ are randomly initialized. The learning goal is set to 0.001; the learning rate is set to 0.05; the maximum training period is set to 200.

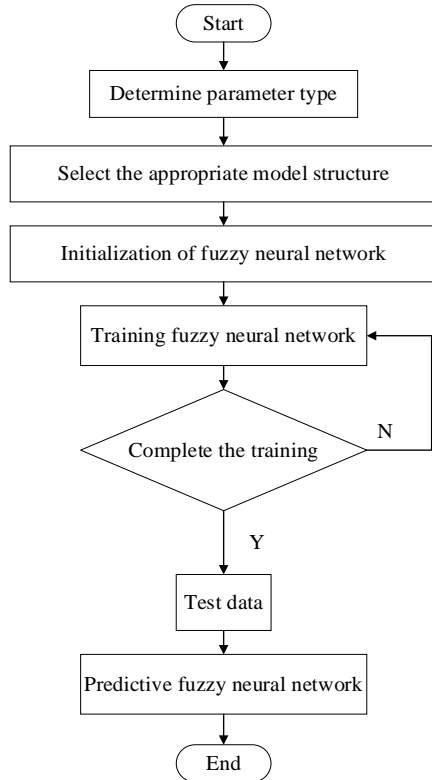


Fig. 1. The process of Fuzzy Neural Networks

C. Establishment of a Fuzzy Neural Network Model Based on Genetic Algorithm

According to the number of nodes determined by the former model, this model selects the learning target, learning rate, sample coefficient ($p_0 \sim p_3$), the center c , and width b in the Fuzzy Neural Network Algorithm as 8 genes of the individual to be screened generation by generation. After 200 network iterations, the optimal parameters are taken as the initial input parameters of fuzzy neural network. After Repeating network training to obtain the final prediction model.

IV. RESULTS AND ANALYSIS

A. Training and forecasting results

According to the established model, the Matlab R2019b software was used for programming and simulation. And the results of training and testing of two models are obtained as follows:

B. Forecast Decide Coefficient R^2

This paper uses the R^2 (determination coefficient) as the forecast decide coefficient.

$$R^2 = \frac{Cov(X,Y)}{\sqrt{D(X)}\sqrt{D(Y)}} \quad (9)$$

Where X is the predicted values and Y is expected value in simulation, which are the criterion of prediction accuracy. The coefficient of determination is from 0 to 1. The closer it is to 1, the higher the fitting degree of the curve and the higher the accuracy of prediction. Reversely, the closer it is to 0, the worse the accuracy of prediction.

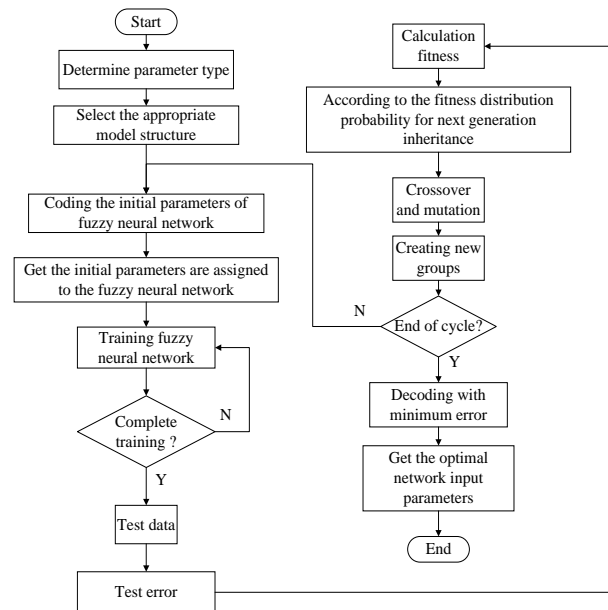


Fig. 2. The overall process of the fuzzy neural network optimized by genetic algorithm

C. Comparative Analysis of Algorithm

Fig. 3 and Fig. 4 are the training and test results of the fuzzy neural network. And the error between the predicted value and the expected value fluctuates slightly around the 0. The model prediction accuracy of the sample training is higher, while the error value fluctuates greatly around the 0 in the test result. $R^2 = 0.9545$, which means that the algorithm has a good accuracy but is not enough to ignore the error; After genetic algorithm optimization, the training results are shown in Fig. 5. It indicates that the error curve is more stable and close to the 0. The test results in Fig. 6 show that the test error only fluctuates slightly above and below 0. Compared with the fuzzy neural network, the prediction accuracy has been greatly improved.

V. ILLUSTRATIVE RESULTS AND DISCUSSION

The accurate prediction of greenhouse temperature can bring the possibility of accurate greenhouse temperature control, which not only leads to the increase of crop yield, but also broadens the variety of crops cultivated in the greenhouse. This means that effective methods for the accurate prediction of greenhouse temperature can promote the further development of the greenhouse field. In this paper, the fuzzy neural network greenhouse temperature prediction method based on the genetic algorithm optimization increases the autonomous optimization of the genetic algorithm and can constantly find and memorize the optimal initial parameters in learning and training processions. Finally, determining the optimal parameters to establish a prediction model and improve the accuracy of prediction provides a new method and way for the development of intelligent greenhouse.

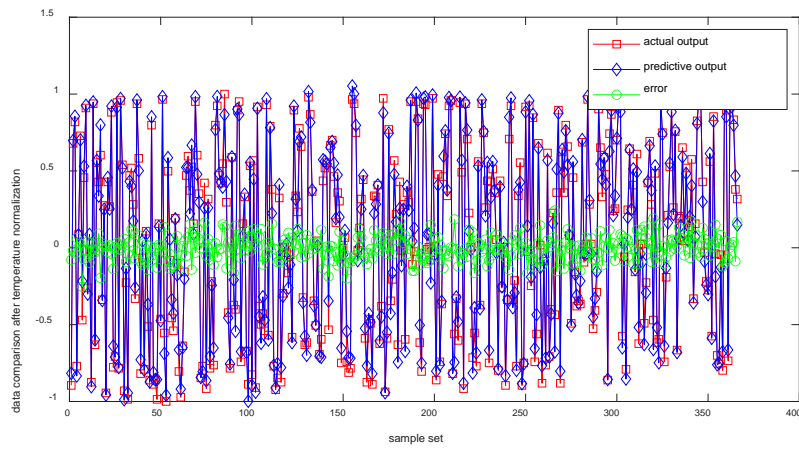


Fig. 3. Training results of fuzzy neural network

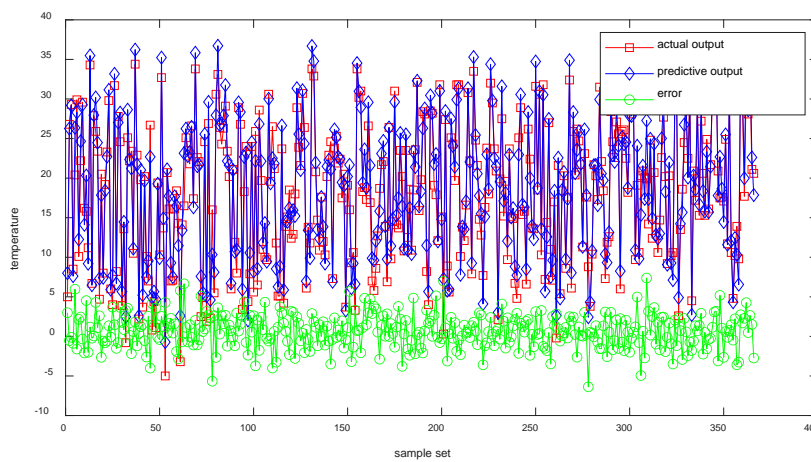


Fig. 4. Test results of fuzzy neural network

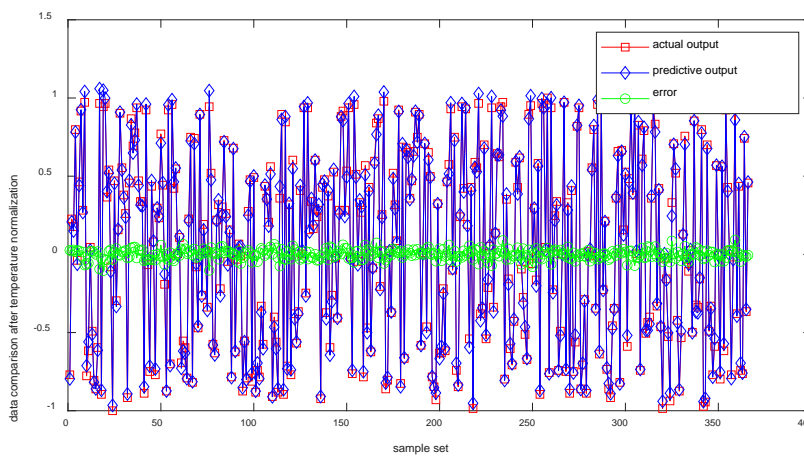


Fig. 5. Training results optimized by genetic algorithm

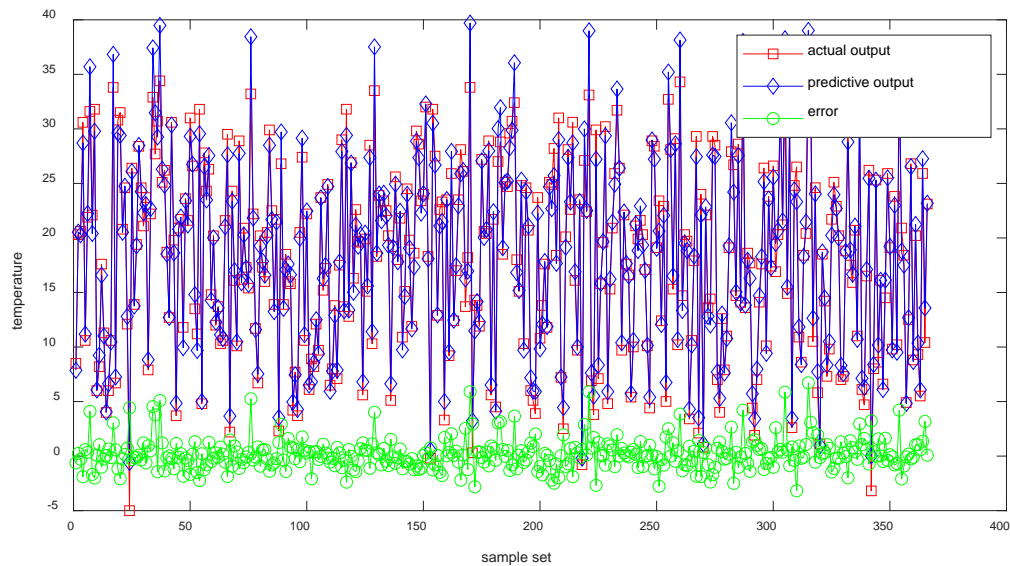


Fig. 6. Test results optimized by genetic algorithm

REFERENCES

- [1] Liu Zhi-peng, Dai Hai-yan, Sun Qi, Su Hua. Temperature prediction of solar greenhouse based on stepwise regression analysis[J]. Jilin agriculture, 2017 (20):96.
- [2] Zhang kun-ao, Zhao Kai. Prediction of greenhouse temperature based on improved CFA PSO-RBF neural network[J]. Computer application and software, 2020, 37(06):95-99+107.
- [3] Zhang Li-you, Ma Jun, Jia Hua-yu, Wang Xi, Zhang Zhao-xia. Greenhouse temperature prediction method and adaptive control system design based on online sequential extreme learning machine[J]. Jiangsu agricultural sciences, 2018, 46(14):226-230.
- [4] Zhou Xiang-yu, Cheng Yong, Wang Jun. Temperature prediction method of agricultural greenhouse based on improved deep belief network [J]. Computer application, 2019(04):1053-1058.
- [5] Xia Shuang, Li Li-hong. Application of PSO-RBF neural network in greenhouse temperature prediction [J]. Computer engineering and design, 2017, 38(03):744-748.
- [6] Chen Xin, Tang Xiang-lu, Li Xiang, Liu Tian-qi, Jia Lu, Lu Tao. A two-step temperature prediction method for solar greenhouse based on quadratic clustering and neural network [J]. Acta agriculturalis Sinica, 2017, 48(S1):353-358.
- [7] Qin Lin-lin, Ma Jiao, Huang Yun-meng, Wu Gang. Predictive control of greenhouse temperature hybrid system based on accumulated temperature theory [J]. Acta agriculturalis Sinica, 2018, 49(10):347-355.
- [8] Kothari S, Panwar NL. Steady state thermal model for predicting microclimate inside the greenhouse. Journal of the Institution of Engineers (India): Agricultural Engineering, 2007, 88:52.
- [9] Ferreira P M, Faria E A, Ruano A E. Neural network models in greenhouse air temperature prediction[J]. Neurocomputing, 2002, 43(1-4):51-75.
- [10] Fan Zheng, Ji Pan-pan, Li Chao, Liu Zhuang, Zhao Yi-gang, Jing Xiao-yan. Optimization of synthesis process of benzyl acrylate by fuzzy neural network genetic algorithm [J]. Acta Chem Sinica, 2019, 70 (11):4315-4324.
- [11] B.K. Patle, Ganesh Babu L, Anish Pandey, et al. A review: On path planning strategies for navigation of mobile robot[J]. Defence Technology, 2019, 15 (4) :582-606.
- [12] Soepangkat, Bobby O. P., Pramujati, Bambang, Effendi, Mohammad Khoirul, et al. Multi-objective Optimization in Drilling Kevlar Fiber Reinforced Polymer Using Grey Fuzzy Analysis and Backpropagation Neural Network-Genetic Algorithm (BPNN-GA) Approaches[J]. International Journal of Precision Engineering and Manufacturing, 2019, 20 (4) :593-607.
- [13] BozorgvarMasoud, ZahraiSeyed Mehdi. Semi-active seismic control of buildings using MR damper and adaptive neural-fuzzy intelligent controller optimized with genetic algorithm[J]. Journal of Vibration and Control, 2019, 25 (2) :273-285.
- [14] A. Quteishat, C. P. Lim and K. S. Tan, "A Modified Fuzzy Min-Max Neural Network With a Genetic-Algorithm-Based Rule Extractor for Pattern Classification," in IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, vol. 40, no. 3, pp. 641-650, May 2010.
- [15] Kaan Uyar, Ahmet İlhan, Diagnosis of heart disease using genetic algorithm based trained recurrent fuzzy neural networks, Proceedings Computer Science, Volume 120, 2017, Pages 588-593.
- [16] E. Kayacan, E. Kayacan and M. Ahmadiéh Khanesar, "Identification of Nonlinear Dynamic Systems Using Type-2 Fuzzy Neural Networks—A Novel Learning Algorithm and a Comparative Study," in IEEE Transactions on Industrial Electronics, vol. 62, no. 3, pp. 1716-1724, March 2015.
- [17] Fernandez, M., Caballero, J., Fernandez, L. et al. Genetic algorithm optimization in drug design QSAR: Bayesian-regularized genetic neural networks (BRGNN) and genetic algorithm-optimized support vectors machines (GA-SVM). Mol Divers 15, 269–289 (2011).
- [18] Pejman Tahmasebi, Ardeshir Hezarkhani, A hybrid neural networks-fuzzy logic-genetic algorithm for grade estimation, Computers & Geosciences, Volume 42, 2012, Pages 18-27