Temperature prediction model for solar greenhouse based on improved BP neural network

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Abstract. In the production of solar greenhouse, indoor temperature is a very important index, which is closely related to the growth of crops. In order to solve the problem of hysteretic nature in solar greenhouse temperature regulation, a solar greenhouse temperature prediction model was proposed in this paper. The model took three indoor parameters including temperature, humidity and light intensity of current time in solar greenhouse as inputs and was built on the base of a kind of BP neural network algorithm which was improved by nearest neighbor algorithm, and accurate prediction results were obtained. The mean absolute error (MAE), mean relative error (MRE) and maximal absolute error (MaxE) of the predicted value of the model were 0.89℃, 4.66% and 2.23℃, respectively. All of the three indexes were greatly improved compared with the model without improvement. The model was able to predict the indoor temperature of the greenhouse accurately and as well provide technical support and decision support for the temperature regulation system of the solar greenhouse.

1. Introduction
Greenhouse is an important carrier of facility agriculture and also the most active part in the development of Intelligent Agriculture in China [1]. In solar greenhouse, indoor temperature is one of the most important indicators in production, and is closely related to the growth of crops. If the crops in greenhouse grow in unsuitable environment for a long time, the yield of crops will be reduced and in extreme cases, it can even cause the death of crops [2].

However, there is a hysteretic nature in the temperature regulation of solar greenhouse at present [3,4], and this nature is almost inevitable due to not only the physical distance between the sensor and the temperature regulating mechanism but also the starting time for the temperature regulating mechanism [5,9]. This delay exists whether automatic control or manual control is selected, and may cause the greenhouse crops to suffer from unsuitable growth temperature for a long time and the yield will be reduced. Therefore, if a greenhouse temperature prediction model can be established to predict the greenhouse temperature after a period of time, it would be able to provide important decision support for greenhouse temperature regulation and effectively solve the problems above.

Greenhouse environment is a complex, nonlinear and multi-input multi-output system. The parameters in greenhouse are closely combined and interact with each other [7]. Indoor temperature, light intensity and humidity are the three critical control variables in greenhouse environment control. The three factors together affect the growth of greenhouse crops [8]. Hu Jian and Li Weiqing had studied the relationship between indoor temperature and humidity during cooling process of greenhouse in summer. The results showed that the changes of indoor temperature and humidity interacted and restricted each other [9]. Lu Man and Li Yanbin explored the relationship between...
temperature and illumination intensity in greenhouse and came out with the results which showed that the two factors affected each other\cite{10}. It is obvious from the researches above that there is a complex and close relationship between those environmental factors in greenhouse which must be considered in the establishment of temperature prediction model.

Artificial neural network algorithm (ANN) is a kind of algorithm which simulates the structure and function of human brain through artificial neuron. It does not have to find the corresponding rules of inputs\cite{11} during building process of the model and the models based on ANN are robust and have strong adaptability. At present, BP neural network is one of the most widely used ANN, which has been widely applied in prediction of greenhouse environmental parameters in recent years.

He fen\cite{12} established a BP neural network model based on genetic algorithm optimization and predicted the air humidity of solar greenhouse in North China in winter with it. Zhu Chunxia\cite{13} took environmental factors which affect the humidity of greenhouse and state quantity of management equipment as inputs and predicted the humidity in solar greenhouse with a model based on BP neural network. In the aspect of temperature prediction, Ferreira\cite{14} and Xia Shuang\cite{15} established models based on RBF neural network respectively to predict indoor temperature of greenhouse. Xu Yu and his team predicted the temperature change trend in glass greenhouse based on complex neural network\cite{16}.

In order to solve the problem of complex coupling between the input factors of solar greenhouse, Wang Hongjun\cite{17} proposed a temperature prediction model for solar greenhouse by improving BP neural network with Bayesian regularization algorithm. Based on BP neural network, Wen Yongjing\cite{18} established a model which was able to predict greenhouse temperature in three different periods of a day under three different weather conditions.

While ANN was used to predict greenhouse indoor temperature, several problems were often encountered. Large training sample demand, insufficient prediction accuracy or complex network structure caused by large amount of input parameters were some of the most significant ones. In view of the problems above, this paper proposed a greenhouse temperature prediction model based on BP neural network which took indoor temperature, humidity and light intensity of greenhouse as inputs and output the indoor temperature of greenhouse after 20 minutes (time interval between two data acquisition). In order to deal with the situation that a great quantity of training samples was required during training process of BP neural network, this paper improved BP neural network through nearest neighbor algorithm. The improved model achieved better prediction results than the original model in experimental data set. Then the model’s test results were analyzed, and the improved model had been improved again according to the test results. After two improvements, a solar greenhouse temperature prediction model which could accurately predict the greenhouse temperature has finally been obtained. The prediction results of the model were able to provide technical support and decision support for greenhouse temperature regulation.

2. Materials and methods

2.1. Acquisition of experimental data

The experimental data used in this paper were all collected from the solar greenhouse of Zhuozhou teaching experiment field of China Agricultural University. The field was located in Zhuozhou, Hebei Province which belongs to the semi humid area of the eastern monsoon warm and humid zone. The four seasons are distinct in this area with remarkable continental climate characteristics and is suitable for the growth of various kinds of crops. The annual average sunshine of the field is more than 2500 hours, which can reach the requirements of two harvest a year. All the solar greenhouses in the experiment field are equipped with advanced measuring sensors and greenhouse environment controllers, and operated by professionals. The measurement of indoor temperature, humidity, light intensity and other environmental data of solar greenhouse is accurate and reliable.

The greenhouse selected in this paper had earthy ground and the crops in it was tomato. The greenhouse environmental data were collected continuously from March 2018 to May 2018 through sensors arranged 2.0 meters high away from the ground. The data were collected every 20 minutes,
and 6160 groups of data were selected from the collected data for subsequent experiments. Because the time interval between the two data acquisition is 20 minutes, the temperature predicted by the model proposed in this paper was the indoor temperature 20 minutes after current time.

2.2. Research method

2.2.1. Temperature Prediction Model Based on BP Neural Network. BP neural network is a kind of multilayer feedforward neural network which is widely used at present. It has the functions of prediction, classification and function approximation. Because of its simple structure and low computation requirement, BP neural network is suitable dealing with complex nonlinear system\[19\]. BP neural network generally adopts three-tier structure, which includes input layer, hidden layer and output layer, and the adjacent layers are connected by weight. The algorithms in this paper were discussed in three-tier structure.

Considering of the complex coupling relationship between greenhouse temperature, humidity and illumination, the model took temperature of current time, humidity and illumination intensity as inputs of the neural network and the output was greenhouse temperature at target time (20 minutes later).

The input layer of the network consists of three neurons, which represented indoor temperature $K$ (℃), humidity $R$ (%) and light intensity $I$ (lux) of the greenhouse at current time. The output layer included only one neuron, which represented the greenhouse temperature $T$ (℃) 20 minutes later.

The inputs were recorded as $X = (K, R, I)$. Where $K$, $R$ and $I$ represent temperature, humidity and light intensity, respectively. The output was marked as $T$ in degrees Celsius. The relationship between input and output could be expressed as $T = W \ast X + B$. Where $W$ represented weights of neural network and $B$ represented neural network threshold. The number of neurons in hidden layer determines the accuracy and learning speed of neural network. This number was usually determined by empirical formulas. The two most commonly used empirical formulas\[20\] were as follows:

$$t = (n + m)^{1/2} + a$$

$$t = \log_2 n$$

Among them, $t$ represents the number of neurons in hidden layer, $n$ represents the number of input units, $m$ is the number of output units and $a$ is a constant between 1 and 10. In order to avoid making the network structure too complex, the second formula was chosen in this paper. The number of input layer was 3 therefore $t$ should be 2 according to the second formula above. The structure diagram of neural network in this paper was shown in Figure 2:

![Figure 1. Structural Chart of BP Neural Network](image)

In this paper, gradient descent method is used to update the weight of the network. In order to improve the probability of finding the optimal solution, the method of random initialization was selected to assign the initial weight which means the initial weight of neural network would be a
random number generated by random function between 0 and 1. The maximum allowable error of neural network determines the accuracy of training results. The smaller this parameter is, the better the fitting effect of the neural network will be. However, if the maximum allowable error is too small, it will reduce the training speed of the neural network and sometimes can even make the network unable to convergence. Therefore, considering the prediction accuracy and training speed of the network, the maximum allowable error was set as 0.001 in this paper.

The learning rate of neural network is generally set in the range of 0.8 to 0.99. The smaller the learning rate is, the more accurate the result of neural network training will be, but it will increase the number of iterations, finally resulting in longer training time. Considering of the accuracy of the result and training time of the model, the learning rate was set to 0.9 in this paper. The activation function of the model was sigmoid function which was widely used in BP neural network[21]. According to the number of nodes and the structure of the neural network model selected in this paper, the maximum number of iterations was set as 10000.

2.2.2. Model improvement based on nearest neighbor algorithm. Traditional BP neural network is easy to be affected by the number of training samples in training process[22]. If the number is few, the calculation accuracy of the trained neural network is likely to be insufficient and it may cause a big gap between the predicted value and the measured value. In the case of greenhouse temperature control, this gap may lead to overheating or underheating.

Generally, if the number of samples is insufficient, the common method is to increase the number of sample points by manually manufacturing data[23]. While these artificial sample points may not fit the original data set well and will not only cost more time during training process but also reduce the prediction accuracy of the neural network as well.

In consideration of the complexity of the coupling relationship between temperature, humidity and light intensity, a large number of samples were needed for calculation in training process, but the actual number of samples obtained is limited, which was unable to fully describe the relationship among greenhouse environmental factors. In order to solve the problem above, the nearest neighbor algorithm was selected to improve the model. The improved algorithm does not need artificial data while training, but only needs to store some high-quality samples for subsequent calculation. The specific calculation process was as follows.

When the training process of neural network was completed, and a new sample was input into the trained model, a distance marked as \(d\) among the stored high-quality samples and the new input would be found according to Euclidean distance formula. The inputs were assumed to be \(X_i = [x_{i1}, x_{i2}, x_{i3}]\) and the high-quality samples were assumed as \(P_j = [p_{j1}, p_{j2}, p_{j3}]\). Where \(x_{i1}\) and \(p_{j1}\) represented indoor temperature, \(x_{i2}\) and \(p_{j2}\) represent humidity while \(x_{i3}\) and \(p_{j3}\) represented light intensity, respectively. The distance between an input sample point and a high-quality sample point could be obtained according to the Euclidean distance formula as follows:

\[
d(X_i, P_j) = \sqrt{(x_{i1} - p_{j1})^2 + (x_{i2} - p_{j2})^2 + (x_{i3} - p_{j3})^2}
\]

(3)

The bigger the distance \(d(X_i, P_j)\) was, the greater the distance between the input sample and the high-quality sample was. Conversely, the smaller this distance was, the higher the similarity was between the input and the high-quality sample. The distance between the input sample and each high-quality sample was obtained according to formula (1). The high-quality sample with minimum distance \(d\) from the input sample would be found and marked as \(P_k = [p_{k1}, p_{k2}, p_{k3}]\). Before the neural network predicted the input sample \(X_i\), the high-quality sample \(P_k\) would be input into the trained neural network first and the output result of \(P_k\) was recorded as \(T_k\). Then the output result of \(X_i\) would be obtained and recorded as \(T_i\). The process of the model improved by nearest neighbor
algorithm was shown in figure 2.

Figure 2. Calculation process of improved model

In addition to the nearest neighbor algorithm, fuzzy clustering, random traversal and other methods could also be used according to the actual needs to select high-quality sample points during the training process\(^{[24]}\).

2.3. Evaluation index

According to the algorithm chosen and the requirements of crops’ growing condition, mean absolute error (MAE), mean relative error (MRE) and maximum absolute error (MaxE) were selected to evaluate the prediction accuracy of the temperature prediction model. The smaller the three indicators above were, the more accurate the predicted results were. The maximum absolute error was the maximum value of all absolute errors (E). The calculation formula of absolute error, mean absolute error and mean relative error were as follows:

\[
E = \left| y_i - \hat{y}_i \right| \tag{4}
\]

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} \left| y_i - \hat{y}_i \right| \tag{5}
\]

\[
MRE = \frac{100\%}{n} \sum_{i=1}^{n} \left( \frac{\left| y_i - \hat{y}_i \right|}{y_i} \right) \tag{6}
\]

In the above formulas, \( y_i \) represented the measured value, \( \hat{y}_i \) represented the predicted value, while \( n \) represented the total amount of samples.

2.4. Experimental design

There were 6160 samples in this model test simulation experiment. Each sample consisted of 3 inputs and 1 output. The inputs were indoor temperature, humidity and light intensity of current time and the output was indoor temperature 20 minutes later. 1230 samples were selected randomly from the total 6160 samples as test set, and the remaining 4930 samples as the training set.

The simulation experiment including two models, the first model was built using traditional BP neural network algorithm and the other one was using algorithm improved by nearest neighbor algorithm. The test results of the two models on the test set were evaluated according to the three evaluation indexes of the mean absolute error (MAE), the mean relative error (MRE) and the
maximum absolute error (MaxE).

3. Results and analysis

3.1. Analysis of test results

The results of model test were shown in Figure 3 and Figure 4. The horizontal axis of coordinates in the two figures above represented the number of sample points, while the vertical axis represented indoor temperature values. It could be inferred from Figure 3 and Figure 4 that the model based on traditional BP neural network got a large difference between its predicted value and measured value. The MAE, MRE and MaxE were 5.62℃, 24.21% and 17.13℃, respectively. While the MAE, MRE and MaxE of the predicted value of the model improved by nearest neighbor algorithm were 2.42℃, 4.62℃ and 13.69%, respectively. Comparing the results of the two models, according to the comparison of the test results, the prediction value of the improved model was much closer to the measured value. However, it also could be seen from figure 3 and figure 4 that the improved model was not performing well while predicting samples with a low indoor temperature.

Figure 3. Comparison between predicted values of the model based on traditional BP neural network and measured value

Figure 4. Comparison between predicted value of the model improved by nearest neighbor algorithm and measured value
After analyzing the experimental data, it was found that when the indoor temperature in the input sample was lower than 20 °C and the light intensity was very low (recorded as < 1 lux for convenience), the prediction results of the traditional BP neural network model were better than those of the improved model based on the nearest neighbor algorithm. Table 1 showed the result comparison between the two models when facing different input samples. It could be inferred from table 1 that although the improved model was more accurate while dealing with all the input samples, when the indoor temperature of the input samples were lower than 20 °C and the light intensity were less than 1 lux, the prediction effect of the improved model was not as good as the previous model and the MAE, MRE and MaxE of the improved model were increased by 2.5 °C, 15.16% and 1.53 °C, respectively. While dealing with other kind of input samples, the improved model was the better one with a huge reduce compared with the previous model on MAE, MRE and MaxE by 8.45 °C, 34.21% and 13.69 °C, respectively.

| Input samples | Evaluating indicators | Traditional BP model | Model improved by KNN algorithm |
|---------------|-----------------------|----------------------|---------------------------------|
| Samples which K<20℃ and I<1 lux | MAE (°C) | 1.10 | 3.60 |
| | MRE | 7.46% | 22.62% |
| | MaxE (°C) | 3.09 | 4.62 |
| Other samples | MAE (°C) | 9.79 | 1.34 |
| | MRE | 39.66% | 5.45% |
| | MaxE (°C) | 17.13 | 3.44 |
| All samples | MAE (°C) | 5.62 | 2.42 |
| | MRE | 24.21% | 13.69% |
| | MaxE (°C) | 17.13 | 4.62 |

3.2. Model improvement based on test results

According to the test results above, after consulting the administrator of the greenhouse and consulting the relevant document[25], it was found that the samples were collected through the seedling stage, flowering stage and fruiting stage of tomato and the day temperature of tomato in seedling stage, flowering stage and fruiting stage was 20-25 °C, 20-30 °C and 24-26 °C, while the night temperature was 10-15 °C, 15-20 °C and 12-17 °C, respectively. The greenhouse selected in this paper was also controlled according to this temperature range. Most of the greenhouses including the experimental greenhouses, chose to close the rolling curtain and other institutions at night for heat preservation, and open the rolling curtain and other institutions in daytime for temperature increase. And the light intensity in the greenhouse could be regarded as 0 lux when the rolling curtain and other devices were closed. Therefore, it could be approximately assumed that the samples with indoor temperature lower than 20 °C and light intensity less than 1 lux were collected during the nights.

As the results showed that the model based on traditional BP neural network was the better one dealing with samples collected at night while the improved model was good at dealing with other samples, a mixed model was proposed in this chapter. The mixed model would directly use traditional BP neural network while predicting the samples collected at night and chose the improved algorithm when dealing with other samples. The calculation process of the mixed model was shown in figure 5.
3.3. Analysis of test results of mixed model

Figure 6 showed the test results of the mixed model. It could be seen from figure 6 that this mixed model had much better performance when predicting samples collected at night than the improved model. According to table 2, compared with traditional BP model, the MAE, MRE and MaxE of the mixed model was reduced by 4.73 °C, 19.55% and 14.90 °C, respectively. While comparing with the model improved by nearest neighbor algorithm, the MAE, MRE and MaxE of the mixed model was reduced by 1.53 °C, 9.03% and 2.39 °C, respectively. The evaluation indexes of the mixed model were all pretty accurate and that meant this mixed model was capable of providing accurate prediction of greenhouse indoor temperature.
Table 2 Comparison of evaluating indicators between three models

| Evaluating indicator | Traditional BP model | Model improved by nearest neighbor algorithm | Mixed model |
|----------------------|----------------------|---------------------------------------------|-------------|
| MAE (℃)              | 5.62                 | 2.42                                        | 0.89        |
| MRE                  | 24.21%               | 13.69%                                      | 4.66%       |
| MaxE (℃)             | 17.13                | 4.62                                        | 2.23        |

4. Conclusion

At present, there was an unavoidable hysteretic nature in the temperature regulation of solar greenhouse, which would delay the temperature regulation and may cause the crops grow in unsuitable temperature. In order to solve this problem, a model based on traditional BP neural network algorithm which improved by nearest neighbor algorithm was proposed in this paper. The model took greenhouse indoor temperature, humidity and light intensity at current time as input and took greenhouse indoor temperature after 20 minutes as output. The improved model was improved again according to the test results, and eventually came out with a mixed model. The MAE, MRE and MaxE of this mixed model were 0.89 ℃, 4.66% and 2.23 ℃, respectively.

In this paper, the nearest neighbor algorithm was used to improve the traditional BP neural network algorithm. The improved algorithm retained the advantages of BP neural network algorithm, such as simple structure, small amount of computation, strong adaptive ability and so on, and solved the problem that BP neural network algorithm needed a large number of training samples to some extent. The model using the improved algorithm had a simple network structure and did not need to set complex parameters in training process. Even when the number of training samples was relatively small, there was no need to make data manually, but only to retain some high-quality samples for subsequent steps. However, the accuracy of the improved model when predicting the samples collected at night was lower than that of the original model. In this case, a mixed model was proposed by using the traditional BP neural network algorithm to predict the samples collected at night and the improved algorithm to predict other samples. By combining the advantages of the two models, a mixed model which was able to accurately predict the indoor temperature of solar greenhouse was finally obtained.

The final model proposed in this paper was capable of predicting the indoor temperature after 20 minutes based indoor temperature, humidity and light intensity of current time. The output of this model could provide crucial information for greenhouse operators. The operator could make decisions according to the temperature after 20 minutes predicted by the model in this study, and judge whether it was necessary to turn on the temperature regulating mechanism for temperature regulation in advance. This could shorten the length of time when the crops were in unsuitable growth temperature and thus reduce the adverse effect of hysteretic nature in temperature regulation on crop planting. The model proposed in this study did well in simulation experiments, while since it had not been working in a real solar greenhouse environment, the performance of this model in dealing with the complex real greenhouse environment was unknown. In practical application, there might be many interference factors, and the model might need some adjustments according to the actual greenhouse environment. Therefore, combining this solar greenhouse temperature prediction model with actual project would be the future research direction.

References

[1] Hao F L, Shen M W, He Y, et al.. (2014) Three Dimensional Steady Simulation of Microclimate Pattern inside Single Plastic Greenhouse Using Computational Fluid Dynamics. Transactions of the Chinese Society for Agricultural Machinery, 45(09):297-304.

[2] Wang L. (2013) Regulation and control of environmental impact factors of greenhouse vegetable planting. Agricultural Development & Equipments, (12):116-117.
[3] Wang J, Yang D. (2018) Research progress on control methods of greenhouse environment. Journal of Chinese Agricultural Mechanization, 39(08):49-53.

[4] Liu S Y. (2008) Study of Intelligence Greenhouse Control System Based on Adaptive Prediction Fuzzy Controller. Qinhuaingdao: Yanshan University, Master Dissertation.

[5] Mou S. (2018) Bays Model of Solar Greenhouse Temperature Prediction and Roof Ventilation Regulation. Shenyang: Shenyang Agricultural University, Master Dissertation.

[6] Li X S. (2003) Development of Intelligent Monitoring and Controlling System for Greenhouse Environment. Yangling: Northwest A&F University, Master Dissertation.

[7] Zhang X H, Zhang W, Yang X, et al. (2017) Survey of Research Methods on Agricultural Greenhouse Environment Control. Control Engineering of China, 24(01):8-15.

[8] Su C J. (2018) Model Establishment and Research on Couple Effects of Environmental Factors on Controlling Tomato Growth in Greenhouse. Yangling: Northwest A&F University, Master Dissertation.

[9] Hu J, Li W Q. (2011) Experimental Research on the Relationship Between Temperature and Humidity in Greenhouse in Summer. Journal of Southwest University(Natural Science Edition), 33(11):18-22.

[10] Lu M, Li Y B. (2015) The Summer Glasshouse Temperature Modeling Based on the Intensity of the Sun Light. Journal of Agricultural Mechanization Research, 37(09):59-64.

[11] Jiao L C, Yang S Y, Liu F, et al. (2016) Seventy Years Beyond Neural Networks: Retrospect and Prospect. Chinese Journal of Computers, 39(08):1697-1716.

[12] He F, Ma C W. (2008) Application of BP Neural Network Based on Genetic Algorithm in Predicting the Air Humidity of Sunlight Greenhouse. Chinese Agricultural Science Bulletin, (01):492-495.

[13] Zhu C X, Tong S M, Hu J H, et al. (2012) Application of Nerve Network on Forecasting Temperature in Sunlight Greenhouse. Journal of Agricultural Mechanization Research, 34(07):207-210.

[14] Ferreira P. M., Faria E. A., Ruano A. E. (2002) Neural network models in greenhouse air temperature prediction. Neurocomputing, 43(1):51-75.

[15] Xia X, Li L H. (2017) Application of greenhouse temperature prediction based on PSO-RBF neural network. Computer Engineering and Design, 38(03):744-748.

[16] Xu Y, Ji R H. (2019) Research on temperature prediction of intelligent greenhouse based on complex neural network. Journal of Chinese Agricultural Mechanization, 40(04):174-178.

[17] Wang H J, Shi L R, Zhao H, et al. (2015) Temperature Prediction Model for Sunlight Greenhouse Based on Bayesian Regularization BP Neural Network. Hubei Agricultural Sciences, 54(17):4300-4303.

[18] Wen Y J, Li C, Xue Q Y, et al. (2018) Temperature and Humidity Prediction Models in Solar Greenhouse: Comparative Analysis Based on Stepwise Regression and BP Neural Network. Chinese Agricultural Science Bulletin, 34(16):115-125.

[19] Tan Y H. Adaptive (1994) Control Based on BP Neural Networks. Control Theory & Applications, (01):84-88.

[20] Shen H Y, Wang Z X, Gao C Y, et al. (2008) Determining the number of BP neural network hidden layer units. Journal of Tianjin University of Technology, (05):13-15.

[21] Liu X T. (2010) Study on Data Normalization in BP Neural Network. Mechanical Engineering & Automation, (03):122-123.

[22] Zhu D Q. (2004) The Research Progress and Prospects of Artificial Neural Networks. Journal of Southern Yangtze University, (01):103-110.

[23] Hao H W, Jiang R R. (2007) Training Sample Selection Method for Neural Networks Based on Nearest Neither Rule. Acta Automatica Sinica, (12):1247-1251.

[24] Zhou Y, Zhu A F, Zhou L, et al. (2012) Sample data selection method for neural network classifiers. Journal of Huazhong University of Science and Technology(Natural Science
[25] Wen Y J. (2011) Environment condition requirement of off-season cultivation for tomato. Jilin Vegetable,(03):9-10.