Prediction of Wood Drying Process Based on Artificial Neural Network

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Taking the conventional drying process of *Pinus sylvestris* square wood with pith as the research material, based on the Back Propagation (BP) neural network algorithm, a model was constructed using the real-time online-measurement data. Softening treatment time and temperature, variable treatment time and temperature, initial moisture content of wood, and position of wood core and sapwood were used as model inputs. Wood drying rate and longitudinal cracking degree were used as outputs to indicate wood drying quality. The results showed that with a suitable model structure of 6-9-2 (input layer-hidden layer-output layer), the coefficient of determination R^2 and mean square error of the test samples were 0.96, 0.99, and 0.00605, respectively, indicating that the neural network model has good generalization ability. Compared with the experimental value, the predicted value basically conforms to the change law and size of the experimental value, and the error distribution is approximately 2%. This shows that the BP neural network model can simulate the drying rate and longitudinal cracking degree in the drying process and realize the prediction of the drying process.

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Keywords: Wood drying; Neural network; Drying rate; Longitudinal crack degree

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INTRODUCTION

The concept of an artificial neural network (ANN), which originated from bionic technology, involves a complex mathematical model composed of multiple nodes. An ANN can realize the rich processing requirements of large-scale data nonlinear processing, multi-thread logic recursion, self-detection, and self-learning ability. Especially in cases of some multi-condition nonlinear problems, ANN can provide better solutions. Unlike traditional regression analysis, neural networks do not need to define a linear or non-linear equation when analyzing data. Neural networks can automatically find patterns, as well as to learn and analyze them based on the details of the input data set. This makes the neural network show excellent performance on large-scale data sets, complex patterns, and non-linear data (Fabijańska 2021). Therefore, it is widely used in biology, chemistry, environment, materials, medicine, and other research fields.

Among various neural network structures, the Back Propagation (BP) neural network structure is a multilayer feedforward neural network trained according to the error back propagation algorithm. Through learning, analyzing, and modeling the input data of the neural network, it can achieve the simulation and analysis results of the drying process. The BP neural network was introduced into the conventional drying of wood to solve the complex non-linear problem in the drying process, and good application results have been obtained in many applications. Avramidis and Iliadis (2005) used ANN technology to conduct research on the thermal conductivity of wood. Related work has been done for dielectric loss factor (Avramidis 2005), wood density (Iliadis *et al.* 2013), and wood heat flux under non-isothermal diffusion conditions (Cai and Chen 2005; Avramidis and Wu 2007). The results show that ANN has strong simulation and prediction ability in the field of wood drying, and it can simulate the required results. Ceylan (2008) built an artificial neural network model using drying temperature, relative humidity, and drying time as input variables, and successfully predicted the moisture content of wood in the drying process. Wu and Avramidis (2006) established a neural network model with back-propagation algorithm and predicted the drying rate of wood. Fu (2020) established a prediction model to predict the elastic strain of birch discs during the drying process. In addition, neural networks are widely used in other areas of wood science, such as the identification of wood defects (Gao *et al.* 2022), tree species, and insect diseases (Huang *et al.* 2022). The above studies demonstrated the feasibility of neural networks for wood drying.

Before conventional drying, the method of improving the drying quality through pretreatment is a common way to improve the drying quality in the initial stage of drying of large-section pine pith-containing square timber. The application of the setting technology (including wood softening, setting and balancing treatment) to the drying of the *Pinus sylvestris* can help to restrain the drying surface cracks and improve the drying speed. Because the application of setting technology in the drying of *Pinus sylvestris* is still in its initial stage, the ANN technology can be used to explore a reasonable drying process ratio with fewer experiments, and subsequent routine drying is of great significance. In this experiment, the BP artificial neural network was used. The steaming treatment time and temperature, set time, set temperature, initial moisture content of wood, and position of wood core and sapwood were used as model inputs, and the drying rate and longitudinal crack of wood were simulated. The relevant research results can provide a theoretical basis for the optimization of the drying process of *Pinus sylvestris* square timber.

EXPERIMENTAL

Materials

A number of specimens with dimensions of 120 mm × 120 mm × 500 mm were processed from Mongolian pine with no defects. The absolute dry weighing method (Cai and Chen 2005) was used to measure the initial moisture content (MC) of the specimens. In this experiment, four similar test materials were taken from each group for each experiment, and the average value of the four groups of test materials was calculated to determine the experimental results of each group. In total, 28 wood samples were taken from seven groups in the experiment.

Methods

Drying process

As the large section sawed timber can easily develop surface cracks, radial cracks, and other defects during the drying process, it is necessary to carry out pretreatment (softening, setting, and balancing) of the square timber of Mongolian pine before drying to reduce the occurrence of drying defects, and then carry out conventional drying treatment. The specific pretreatment process and conventional drying benchmarks are shown in Tables 1 and 2.

Table 1. Treatment Processes of Softening, Setting, and Balancing

Pretreatment Process	Saturated Moist Air Softening Treatment (Dry Bulb Temperature / Time)	Set Processing (Dry Bulb Temperature / Ambient Humidity / Time)
Control Group	Not Processed	Not Processed
Process 1	90 °C / 12 h	120 °C / 30% / 24 h
Process 2	90 °C / 12 h	115 °C / 30% / 24 h
Process 3	95 °C / 12 h	120 °C / 30% / 18 h
Process 4	90 °C / 12 h	120 °C / 30% / 18 h
Process 5	90 °C / 18 h	120 °C / 30% / 24 h
Process 6	90 °C / 24 h	120 °C / 30% / 24 h

Table 2. Conventional Drying Benchmarks

Time (h)	Dry Bulb Temperature (°C)	Wet Bulb Temperature (°C)	Relative Humidity (%)	Equilibrium Moisture Content (%)
0	85	85	100	24.5
6	85	83	96	19.0
12	85	82	92	16.0
18	85	81	88	14.5
24	85	80	84	12.5
30	85	79	80	11.5
36	85	78	77	11.0
42	85	77	74	10.0
48	85	76	71	9.5
54	85	75	68	9.0
60	85	74	65	8.5
66	85	73	62	8.0
72	85	72	59	7.5
78	85	71	56	7.0
84	85	70	54	6.5
90	85	69	51	6.0

Detection of drying rate and longitudinal crack degree

The drying weight method was used to measure the MC at each stage (Fu 2019). The MC of the test piece was divided into 25 equal parts, as shown in Fig. 1. The initial average moisture content of the test material is calculated according to Eq. 1.

$$MC = \frac{\sum_{i=1}^{n=50} G_i - \sum_{i=1}^{n=50} G_{i0}}{\sum_{i=1}^{n=50} G_{i0}} \times 100\% \tag{1}$$

In Eq.1, MC denotes the average MC of 25 specimens, representing the estimated initial MC of the specimens (%); G_i is the initial weight of the i^{th} fastest sample (g) and; G_{io} is the absolute dry weight of the i^{th} fastest sample (g).

1-1	1-2	1-3	1-4	1-5
1-16	1-17	1-18	1-19	1-6
1-15	1-24	1-25	1-20	1-7
1-14	1-23	1-22	1-21	1-8
1-13	1-12	1-11	1-10	1-9

Fig. 1. Schematic diagram of decomposition of moisture content specimen

Because the wood cracking is relatively complex, to quantify and represent it, the longitudinal cracking degree was used. The longitudinal cracking degree of the wood was used to indicate the cracking condition of the wood, which is the ratio of the longest longitudinal crack to the length of the wood. The surface crack length, width, and internal cracking degrees of the wood surface were determined. The cracks with a width less than 2 mm or a length less than 10 mm were ignored. The cracks were less than 3 mm apart from each other and were calculated as a single crack. Then, the one with the highest length was selected to calculate the longitudinal cracking degree was selected as in Eq. 2 (Fu 2017):

$$LS = \frac{L_{max}}{L_0} \times 100\% \tag{2}$$

In the Eq. 2, *LS* is the longitudinal crack degree (longitudinal crack length ratio) (%); L_{max} denotes the maximum cracking (mm); and L_0 is the length of wood (mm).

Analysis method of artificial neural network model

The BP neural network model used in this work was developed on the Python integrated development environment PyCharm based on the Python language, using a three-layer feedforward network structure (input layer, hidden layer, and output layer). The factors were not connected and interrelated, which can ensure that each input condition is independent of each other and ensures that the neural network structure can change the input conditions of one layer while other conditions can normally affect the results. The experimental data of wood drying were collected, and then the experimental input layer and output layer were determined, where the input layer is the steaming treatment time, steaming temperature, set time, set temperature, initial moisture content of wood, and the position of wood core and sapwood, and the output layer is wood drying rate and longitudinal cracking degree. The hidden layer was selected as a single multi-hidden layer in this work. Compared with an ordinary single hidden layer, it has a higher generalization ability and prediction accuracy. There are connections with neurons in adjacent layers, there is no connection between neurons in the same layer, and there is no feedback connection between neurons in each layer (Ozsahin and Murat 2018), which also ensures the independence of each variable. The input signal is forwarded from the input layer to the hidden layer. The data are processed by the function transformation in the hidden layer and transmitted from the hidden layer node to the output layer. The data are finally processed in the output layer node to form the output data. Among them, all nodes in the hidden layer use the sigmoid transfer function (Eq. 3), and in the output layer, all nodes use the pureline linear transfer function:

$$f = \frac{1}{1 + e^{-x}} \tag{3}$$

The loss function (Eq. 4) is a parameter that helps to optimize the neural network. Each neural network gives an output, and the loss can be calculated by matching the output with the target value. Through optimizing the parameters of the neural network to minimize the loss, it is a common method for training neural networks. The data are simulated through hidden layers with different numbers of neurons, and the loss function under the number of neurons is counted. At the beginning of training, the loss function decreases greatly with the increase of the number of neurons. When the number of neurons increases and the loss function does not decrease significantly, this number of neurons can be selected as the number of neurons used in this model.

$$Loss = -\frac{1}{outputsize}\sum_{i=1}^{outputsize} x_i \cdot \log \hat{x}_i + (1 - x_i) \tag{4}$$

In Eq. 4, x_i is actual value.

The data obtained from the test were arranged in the order of test piece position, initial moisture content, steaming temperature, steaming time, set temperature, set time, drying rate, and longitudinal cracking degree. A total of four tests were carried out, with four specimens for each test, and five groups of data were collected for each specimen. The obtained data were randomly divided into training groups and test groups. Among them, 60 data in the training group accounted for 75% of the total, and 20 in the test group accounts for 25% of the total.

When training and validating a neural network, a large amount of data needs to be processed by the neural network. Different data have different numerical sizes and physical meanings. To make each input data have the same processing status, it is necessary to normalize the data. The normalized data can effectively prevent the adjustment of weights from entering the flat region of error. In addition, because the neurons of the BP neural network use the sigmoid transfer function, and the output value is between [0, 1], the output data also needs to be normalized (Chai 2018).

Normalization processing formula (Eq. 5):

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{5}$$

In the Eq. 5, X is the value after normalization of x; $X_{\max}$ denotes the maximum value of x; and $X_{\min}$ is the minimum value of x.

The performance of the neural network is generally analyzed by means of the mean square error. A smaller mean square error between the test value and the predicted value results in a better forecast performance. At the same time, the coefficient of determination R^2 is also used as an evaluation index for the performance of the neural network. The learning efficiency of this experiment was set to 0.01 and the mean square error was calculated using Eq. 6 as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2 \tag{6}$$

In Eq. 6, n is the number of groups; x_i is actual value; and y_i denotes the predicted value of the neural network.

RESULTS AND DISCUSSION

Determination of the Number of Neurons

The determination of the neurons number has an intuitive impact on the simulation effect of the model. The small number of neurons cannot fully reflect the experimental relationships, which has a great impact on the training of the model, and the excessive number of neurons will lead to overfitting and affect the reality of the experiment. Therefore, a pre-experiment was used to simulate the fitting experiment under each number of neurons.

As shown in Fig. 2, models with different numbers of neurons were used to simulate the input data for one million times, and the representative loss function of 10,000, 500,000, and 1.0 million simulation times are selected to draw the image. It can be seen that the error loss in the neural network before the number of neurons was 7, it decreased with the increase of the number of neurons, and reached the lowest level after the number of neurons was 9. Then, with further increase of the number of neurons, the number of neural network losses under each simulation number remained basically unchanged. Because a large number of neurons will increase the operation time, the result will be unstable or even lead to over-fitting. To simplify the operation, the number of neurons was tentatively selected as 7, 8, 9, and 10 (Fig. 3), and the time error loss was 0.00605.

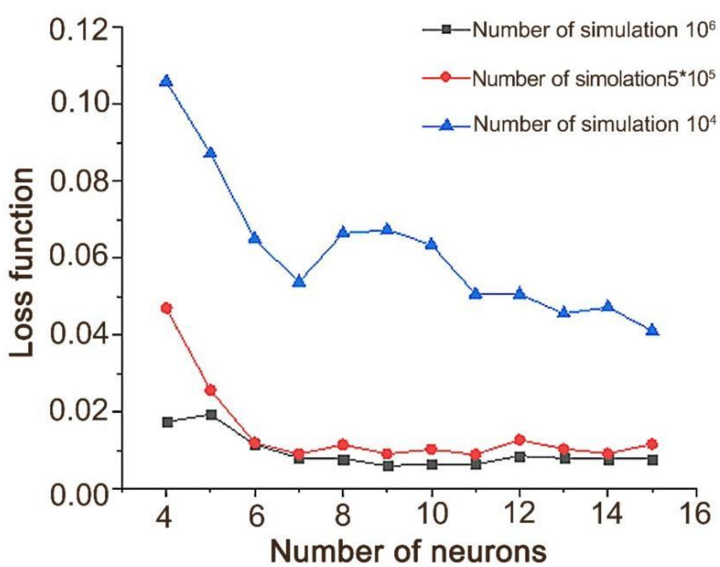

Fig. 2. Loss function with different number of neurons

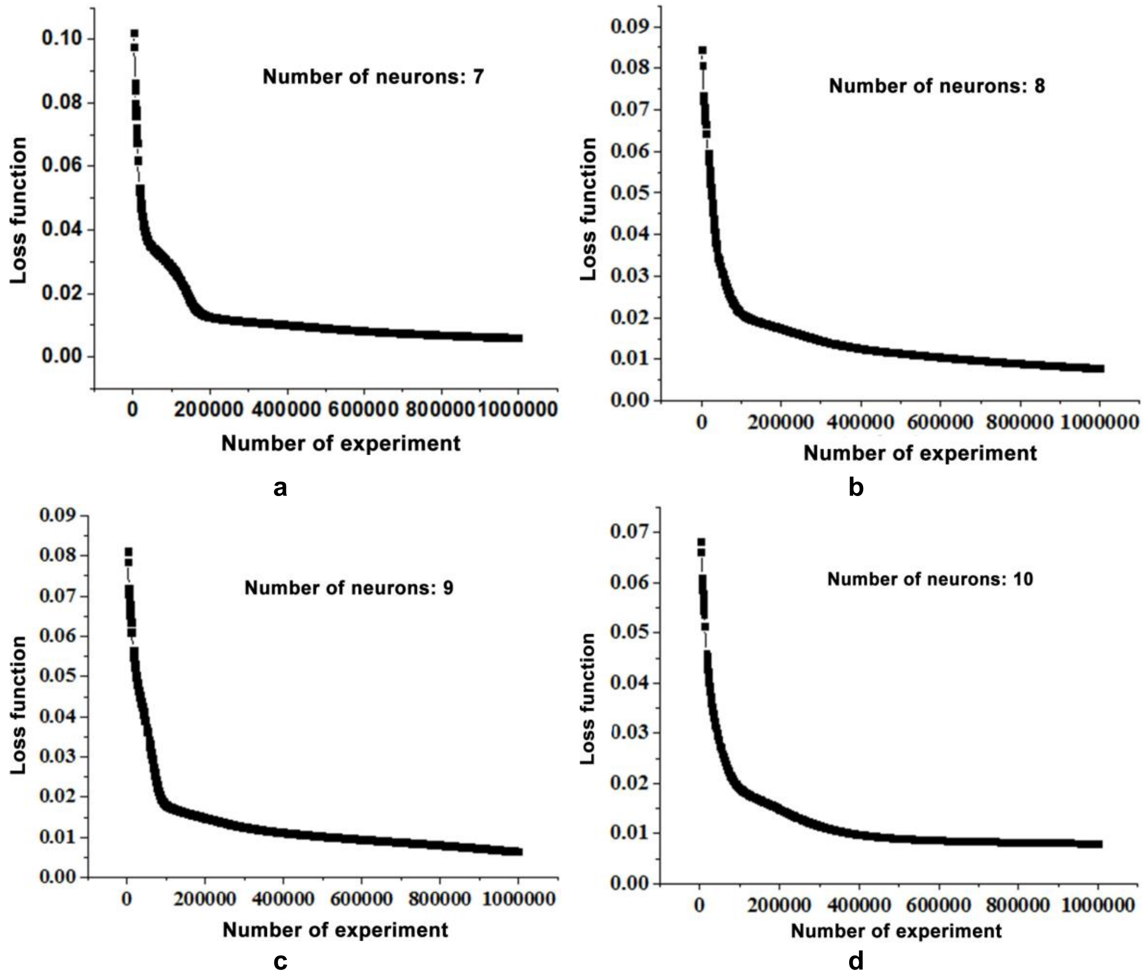

Fig. 3. The number of neurons at 7, 8, 9, and 10 (a through d), and the relationship between the loss function and the number of training

Further comparing the images of the four groups of 7, 8, 9, and 10 where the loss function changes with the number of simulations, it can be observed that the loss function was stable after the number of fittings was 100,000, and there was a clear loss inflection point in the image with the number of neurons at 9. The image inflection points of the number of neurons 7 and 8 were not clear, while the inflection point of the image with the number of neurons of 10 exhibited a gentle curve, which is the performance of the transition fitting phenomenon (Diawanich *et al.* 2009). Thus, the optimum number of neurons was determined to be 9, and the number of neural network fittings was determined to be 100,000 times.

According to the determined number of neurons combined with the input layer and output layer data, the structure diagram of the neural network was obtained as shown in Fig. 4.

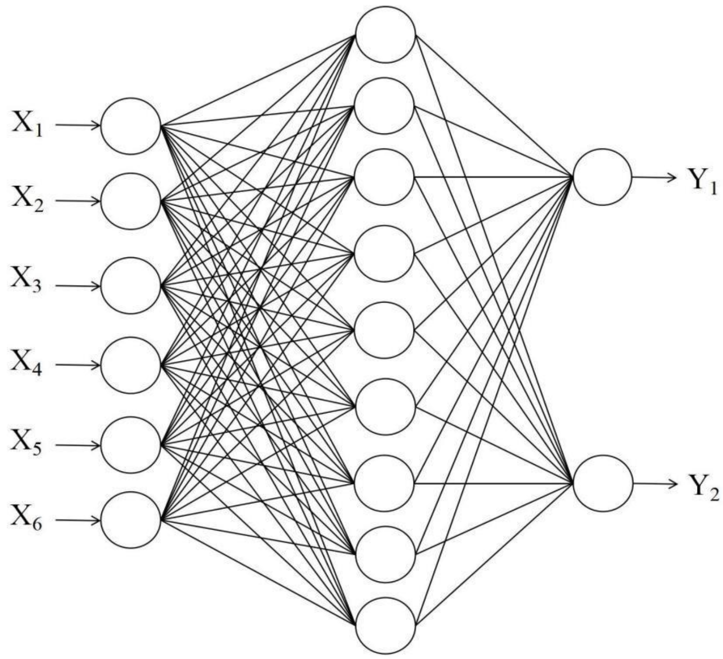

Fig. 4. Neural network structure diagram (X_1 is the position of the specimen, X_2 is the moisture content, X_3 is the steaming temperature, X_4 is the steaming time, X_5 is the set temperature, X_6 is the set time, Y_1 is the drying rate, and Y_2 is the longitudinal cracking degree. The number of neurons in the input layer, hidden layer, and output layer is 5, 9, and 2 respectively)

Regression Fitting Analysis

With the position of the specimen (X_1), moisture content (X_2), steaming temperature (X_3), steaming time (X_4), set temperature (X_5), set time (X_6) as independent variables, and the drying rate (Y_1) and longitudinal cracking degree (Y_3) as dependent variables, multiple regression fitting analysis was conducted using Origin. The results were as follows:

$$Y_1=6.19042\times10^{-5}X_1+0.06915X_2-0.00338X_3-6.39869\times10^{-4}X_4+0.05734X_5-0.00139X_6-5.54984,\ R^2=0.94266\ \text{(Drying rate)} \quad (7)$$

$$Y_2=0.45158X_1+6.0305X_2-0.24371X_3-0.04526X_4-0.48296X_5-0.35659X_6+86.23459,\ R^2=0.04007\ \text{(Longitudinal cracking degree)} \quad (8)$$

The simulation coefficient of determination for drying rate was 0.94, and the simulation coefficient of determination for longitudinal cracking degree was 0.04. The experimental value of drying rate was in good agreement with the predicted value, which can simulate most situations. The experimental value of longitudinal cracking degree was in poor agreement with the predicted value, so it is impossible to predict the result. To sum up, it is feasible for regression fitting analysis to predict only specimen drying rate, but it is impossible to predict complex longitudinal cracking degree and other information. Therefore, regression fitting analysis was not able to predict the actual drying process.

Model Performance Analysis

When the data was input into the network built for learning, the experimental value with the predicted value of the neural network model was compared and a regression fitting to obtain the BP neural network training regression diagram was performed as shown in Figs. 5 and 6. The linear equations (Eqs. 9 and 10) obtained are given below:

$$Y_1 = 0.9964X + 0.00025 \quad \text{(Drying rate)} \tag{9}$$

$$Y_2 = 0.9959X + 0.00061 \quad \text{(Longitudinal cracking degree)} \tag{10}$$

The simulation coefficient of determination for drying rate was 0.96; the simulation coefficient of determination for longitudinal cracking degree was 0.99, indicating that the experimental value was in good agreement with the predicted value, and the BP neural network had good performance and will be able to simulate most situations.

Figures 7 and 8 show the comparison between the predicted value of the neural network and the experimental value. Approximately 75% of the samples were randomly selected for learning and the remaining 25% of the samples were predicted. The blue line in the figure is the experimental value, the red line is the predicted value. The absolute error range of the simulation results and the experimental values was within 2%, and the drying rate and longitudinal cracking degree can be predicted to a certain extent for the conventional drying quality of wood after softening and setting treatments. As indicated from the two sets of graphs, the BP neural network can be used to predict the drying rate and the degree of longitudinal cracking.

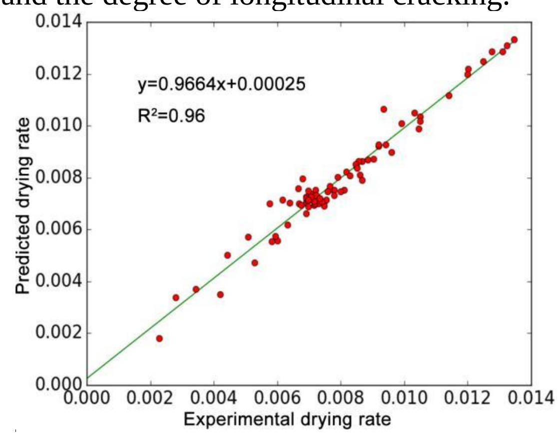

Fig. 5. Training regression curve of drying rate

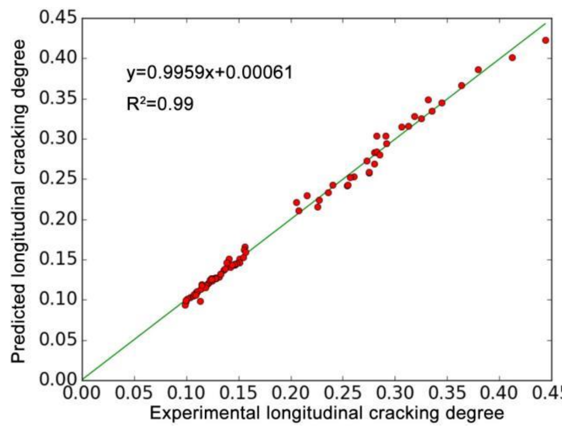

Fig. 6. Training regression curve of longitudinal crack degree

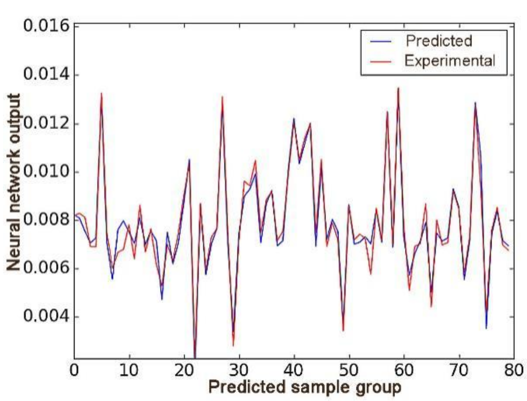

Fig. 7. Comparison of predicted and experimental values of drying rate

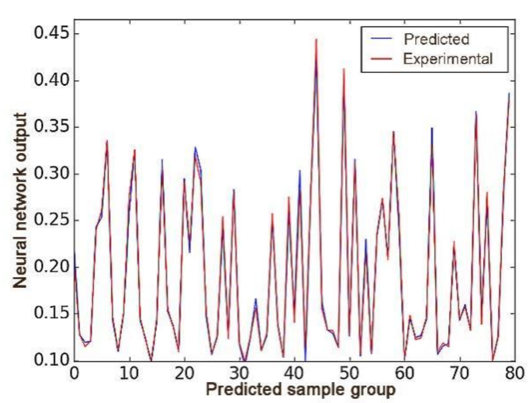

Fig. 8. Comparison of predicted and experimental values of longitudinal cracking degree

CONCLUSIONS

In this paper, the BP neural network was used to simulate and predict the drying rate and longitudinal cracking degree of wood. The steaming treatment time, steaming temperature, set time, set temperature, initial moisture content of wood, and position of wood core and sapwood were the input quantities of the model; the drying rate and the longitudinal cracking degree were the output. There were 60 test data in the training group, accounting for 75% of the total data, and 20 data in the test group, accounting for 25% of the total data.

1. The results show that when the number of neurons in the hidden layer was 9, the neural network training error was the smallest, which was 0.00605; at this time, the determination coefficient R^2 of the neural network training set was 0.96 (drying rate prediction) and 0.99 (longitudinal crack prediction).
2. The experimental test value was in good agreement with the predicted value, which demonstrated that the constructed BP neural network achieved good stability. The absolute error range between the simulation results and the experimental values was within 2%.
3. In general, the neural network model has a good predictive ability for drying rate and longitudinal cracking degree. Therefore, it can be considered that although the properties of wood vary widely and the complex relationship between them has not been fully elucidated, the network model provides a reliable model and good prediction ability, which is of great significance to the optimization of the drying process of pine wood squares.

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REFERENCES CITED

Avramidis, S., and Iliadis, L. (2005). "Predicting wood thermal conductivity using artificial neural networks," *Wood and Fiber Science* 37(4), 682-690.

Avramidis, S., Iliadis, L., and Mansfield, S. D. (2005). "Wood dielectric loss factor prediction with artificial neural networks," *Wood Science and Technology* 40, 563-574. DOI: 10.1007/s00226-006-0096-3

Avramidis, S., and Wu, H. (2007). "Artificial neural network and mathematical modeling comparative analysis of nonisothermal diffusion of moisture in wood," *Holz als Roh- und Werkstoff* 65(2), 89-93. DOI: 10.1007/s00107-006-0113-0

Cai, Y. C., and Chen, G. Y. (2005). "Discussion on improving measurement accuracy of wood moisture content by oven drying method," *Journal of Beijing Forestry University* (S1), 64-67. DOI: CNKI:SUN:BJLY.0.2005-S1-014

Ceylan, L. (2008). "Determination of drying characteristics of timber by using artificial neural networks and mathematical models," *Drying Technology* 26(12), 1469-1476.

DOI: 10.1080/07373930802412132

Chai, H. J., Chen, X. M., and Cai, Y. C. (2018). "Artificial neural network modeling for predicting wood moisture content in high frequency vacuum drying process," *Forests* 10(1), article 16. DOI: 10.3390/f10010016

Diawanich, P., Matan, N., and Kyokong, B. (2009). "Evolution of internal stress during drying, cooling and conditioning of rubberwood lumber," *European Journal of Wood and Wood Products* 68, 1-12. DOI: 10.1007/s00107-009-0343-z

Fabijańska, A., Danek, M., and Barniak, J. (2021). "Wood species automatic identification from wood core images with a residual convolutional neural network," *Computers and Electronics in Agriculture* 181(1), article 105941. DOI: 10.1016/j.compag.2020.105941

Fu, Z. Y., Avramidis, S., and Zhao, J. Y. (2017). "Artificial neural network modeling for predicting elastic strain of white birch disks during drying," *European Journal of Wood and Wood Products* 75(6), 949-955. DOI: 10.1007/s00107-017-1183-x

Fu, Z. Y., Zhou, F., and Gao, X. (2019). "Assessment of mechanical properties based on the changes of chromatic values in heat treatment wood," *Measurement* 152(1), article 107215. DOI: 10.1016/j.measurement.2019.107215

Fu, Z. Y., Cai, Y. C., Gao, X., and Zhou, F. (2020). "Simulation and prediction of wood drying strain based on artificial neural network model," *Forestry Science* 56(06), 76-82.

Gao, M., Wang, F., Liu, J., Song, P., Chen, J., Yang, H., Mu, H., Qi, D., Chen, M., Wang, Y., and Yue, H. (2022). "Estimation of the convolutional neural network with attention mechanism and transfer learning on wood knot defect classification," *Journal of Applied Physics* (23), 131, article no. 233101. DOI: 10.1063/5.0087060

Huang, J., Lu, X., Chen, L., Sun, H., Wang, S., and Fang, G. (2022). "Accurate identification of pine wood nematode disease with a deep convolution neural network," *Remote Sensing* 14(4), 913. DOI: 10.3390/rs14040913

Iliadis, L., Mansfield, S. D., and Avramidis, S. (2013). "Predicting Douglas-fir wood density by artificial neural networks (ANN) based on progeny testing information," *Holzforschung* 67(7), 771-777. DOI: 10.1515/hf-2012-0132

Ozsahin, S., and Murat, M. (2018). "Prediction of equilibrium moisture content and specific gravity of heat treated wood by artificial neural networks," *European Journal of Wood and Wood Products* 76(2), 563-572. DOI: 10.1007/s00107-017-1219-2

Wu, H. W., and Avramidis, S. (2006). "Prediction of timber kiln drying rates by neural networks," *Drying Technology* 24(12), 1541-1545. DOI: 10.1080/07373930601047584

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