Prediction Model for the Mechanical Properties of Compacted Poplar Powder Generated *via* Hot-Pressing

Jin Yan, Jianan Liu,* Liqiang Zhang, Zhili Tan, Haoran Zhang, and Qingding Wu

The influence of the process parameters on the mechanical properties of compact wood powder generated *via* hot-pressing was analyzed through a single-factor experiment. The mechanical properties exhibited a nonlinear trend relative to the process conditions of hot-pressed compact wood powder. The relationship models between the process parameters and the mechanical properties for the compact wood powder were established by applying a multiple regression analysis and neural network methods combined with data from an orthogonal array design. A comparison between experimental and predicted results was made to investigate the accuracy of the established models by applying several data groups among the single-factor experiments. The results showed that the accuracy of the neural network model in terms of predicting the mechanical properties was greater compared with the multiple regression model. This demonstrates that the established neural network model had a better prediction performance, and it can accurately map the relationship between the process conditions and the mechanical properties of the compact wood powder.

Keywords: Wood powder; Hot-pressing technology; Mechanical properties; Neural network; Prediction model

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INTRODUCTION

With the development of the economy, forest products have permeated into all aspects of everyday life. However, during the production and processing of wood products, a large amount of forestry residues will be produced at the same time. Wood is a natural and environmentally friendly material, which consists mainly of cellulose, hemicellulose, lignin, and extractive substances. The effective application of forestry residues not only helps reduce the dependence on wood, but also increases the additional value of forest products. It is of great importance to develop forestry circular economies as well as promoting the sustainable development of forest resources. Alharbi *et al*. (2020) developed value-added, high-strength lignocellulosic biopolymers by the hot-pressing of raw microfibrillated *Phoenix dactylifera* and *Cocos nucifera* fibers and leaves. Alharbi *et al*. (2021) used coconut coir- and regenerated silk-based microparticles as multifunctional natural binders for construction and demolition waste wood or blends to prepare hybrid biomicrocomposites by hot-pressing. Van Dam *et al*. (2004a,b) produced high strength-high density board materials from whole coconut husks by hot pressing without adding chemical binders; they showed that the mechanical properties of these boards were superior to those of commercial medium-density fiberboard and particleboard. Alharbi *et al.* (2020) studied the data on mechanical, thermal, and structural characterization of plant fiber-based biopolymers prepared by hot-pressing raw coconut coir, and milled powders of cotton, waste bagasse, wood, and bamboo. Such data are of benefit to other researchers, with the goal to utilize lignin-based adhesion as a useful adhesive in environmentally friendly materials. Zhang *et al.* (2020) investigated the effects of temperature on color change and the mechanical properties of compact poplar powder formed *via* hot compaction. The results showed that the temperature had a great influence on the static bending strength and the modulus of elasticity of compaction. As the temperature increased, the static bending strength and modulus of elasticity initially increased and then decreased. Unsal and Candan (2008) studied the effects of the pressure on the janka hardness of Scotch pine via hot-pressing. The results showed that the janka hardness of wood increases with the increase of pressure and janka pressure was approximately proportional to the density of the wood.

Compact poplar wood powder was prepared *via* a glue-free hot-pressing technology in the present work. The entire forming process did not include any additives, *e.g.*, glue, and therefore will not release harmful substances. The change in the static mechanical properties of the hot-pressed compact samples were evaluated based on a single-factor experiment and an orthogonal array design. For the hot-pressed board products, the moisture content and the morphological aspects of pieces of lignocellulosic material have an influence on their performance. But binderless board products are more highly dependent on whether or not there is sufficiently high pressure, temperature, and time during pressing (Hubbe *et al.* 2018). To determine the appropriate range of process parameters in an orthogonal array design, the static bending strength and surface hardness were used as evaluation indexes to study the influence of the forming pressure, holding time, and forming temperature on the mechanical properties of the samples *via* a single-factor experiment.

The multiple regression analysis and artificial neural network are usually used to solve the problems in engineering, and science involve exploring the relationships between two or more variables. Regression analysis is a statistical method to explore the relationship between phenomena. In multiple regression analysis, the linear relationship between a dependent variable and several independent variables is expressed with a mathematical equation (Tiryaki *et al*. 2014; Tiryaki and Aydin 2014). Artificial neural network is an information processing system built on the generalization of a mathematical model of biological neurons adapted from the human brain. The information processing of neural network is realized by the interaction through neurons. Each connection is like a synapse in a biological brain, which can transmit signals from one artificial neuron to another (Nguyen *et al*. 2019). Artificial neural network has been successfully applied to several prediction studies in the field of wood science. Tiryaki and Aydin (2014) used an artificial neural network model to predict the compressive strength of heat-treated wood and compared it with a multiple linear regression model. Finally, the results showed that the neural network model has higher predictive performance than the multiple regression model. In order to make better use of forestry residues, reduce the number of experiments, and optimize the process parameters, it is important to establish a relationship model between the process parameters and the mechanical properties of the compacted wood powder samples based on the limited experiments (Fu *et al.* 2017; Cetera *et al.* 2019; Le Guen *et al.* 2019; Nasir *et al.* 2019). In this paper, the multiple regression analysis and neural network methods were applied to establish a relationship model based on the data from an orthogonal array design. This analysis can provide a reference for promoting the application of forestry residues as well as improving the quality of forestry residues.

EXPERIMENTAL

Materials

Wooden powder derived from the residue of manufactured poplar (Linyi City, Shandong Province, China) is easily obtained and low in cost. Therefore, the compacted samples in this paper were prepared using poplar powder as a raw material. The residues of manufactured poplar were firstly made into powders with a particle size of less than 83 µm by the F160 small grinder (Zhongxing Weiye Instrument Co., Ltd, Beijing, China) and the 8411 electric vibrating screening machine (Leiyun Testing Instrument Manufacturing Co., Ltd, Shanghai, China). Then, the poplar powder was dried in a DZF-6020AB vacuum drying oven (Zhongxing Weiye Instrument Co., Ltd, Beijing, China) at a temperature of 105 °C. The moisture content of the poplar flour was controlled to be less than 8%.

Methods

Preparation method of poplar powder compacts

The hot-pressing process proposed in this paper is a new technology that combines the theory of glue-free hot-pressing of wood materials and the theory of hot-pressing of metal powders. The hot-pressing process can be divided into four steps: powder filling, preparation *via* heating the raw material, mold-closing, and demolding. A flow chart of the hot-pressing process is shown in Fig. 1.

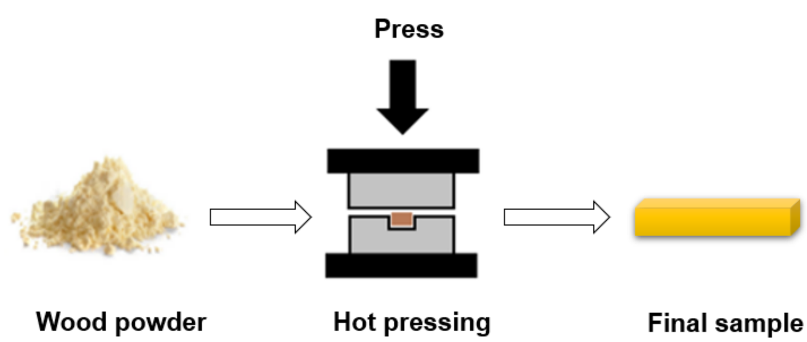

Fig. 1. Flow chart of the hot-pressing process

The main hot-pressing process parameters include the forming pressure, holding time, and forming temperature. Under the effects of forming pressure and temperature, the wood powder can achieve self-adhesive formation after a certain period of time. In this paper, the forming pressure was set to 40, 60, 80, 100, and 120 MPa, respectively. The holding time was set to 10, 30, 50, 70, and 90 min, respectively. The forming temperature was set to 100, 120, 140, 160, and 180 °C, respectively. First, 40 g of poplar wood powder (particle sizes less than 100 mesh) was evenly sprinkled in the HX-100 compression molding machine (Institute of Thermal Processing Engineering, Huazhong University of Science and Technology, Wuhan, China) to undergo hot pressing. The dimension (length × width × thickness) of the blank was 128 mm × 35 mm × 5 mm. The forming temperature was fixed at 140 °C above the glass transition temperature of lignins and the holding time was fixed at 30 min, to allow the wood powder enough sticking time to study the effect of the forming pressure on the mechanical properties of the compacted wood powder. The best forming pressure was described as A0 (MPa). Then, the forming temperature was fixed at 140 °C and the forming pressure was fixed at A0 (MPa) to study the effect of the holding time on the mechanical properties of compact wood powder. The best holding time was described as B0 (min). Finally, the forming pressure was set to A0 (MPa), and holding time was set to B0 (min). The effect of the forming temperature on the mechanical properties of the compact wood powder was investigated to obtain the forming temperature C0 (°C).

Mechanical properties

The static bending strength of the compact samples was measured using a WDW-10 microcomputer-controlled electronic universal testing machine (New Shijin Testing Machine Co., Ltd, Jinan, China). Two support rollers with the diameter of 15 mm and a loading roller with the diameter of 30 mm were used. The span of the two supporting rollers was 80 mm, and the lowering speed of the loading roller was 12 mm/min.

The surface hardness of the compact sample was measured with an HV-5 small load Vickers hardness tester (Dechuan Testing Instrument Co., Ltd, Laizhou, China). A diamond indenter with a load of less than 120 kg and an apex angle of 136° was pressed into the surface of the compact sample. The holding time was set to 12 s. After unloading, the diagonal length of the indentation was measured to calculate the surface hardness of the compact sample using Eq. 1,

$$HV = 0.102 \times \frac{F}{S} = 0.102 \times \frac{2F sin\frac{a}{2}}{d^2} \tag{1}$$

where F is the load (N), S is the area of the indentation (mm^2), a is the opposite surface angle (136°), and d is the average value of diagonal length (mm).

RESULTS AND DISCUSSION

The Effect of the Process Parameters on the Mechanical Properties of Compacted Wood Powder

The effect of the forming pressure

Figure 2 shows the poplar wood powder compacts by hot-pressing at different forming pressure. Figure 3 shows the effect of the forming pressure on the mechanical properties of the compacted poplar wood powder. It can be seen that the static bending strength initially increased and then decreased as the forming pressure increased in the hot-pressing process. The static bending strength of the compacted wood powder reached a maximum value at a forming pressure of 60 MPa. The static bending strength gradually decreased when the forming pressure exceeded 60 MPa. This may be due to the degradation of cellulose, which causes a decrease in the static bending strength (Wentzel *et al.* 2019). It can be seen from Fig. 3 that the surface hardness of the compacted wood powder continuously increased as the forming pressure was increased. The surface hardness of the compacted wood powder reached a maximum value at a forming pressure of 120 MPa. Compared with a forming pressure of 40 MPa, the surface hardness increased by approximately 27%. A possible reason for this is that the higher forming pressure causes excess loss of moisture or minor decomposition, which allows for more particles to be packed together. According to the analysis of the static bending strength and surface hardness, the comprehensive mechanical properties of the compacted wood powder were better at 60 MPa. Therefore, the forming pressure and temperature were respectively fixed at 60 MPa and 140 ℃ to study the effect of the holding time on the mechanical properties of the compacted wood powder samples *via* a single-factor experiment.

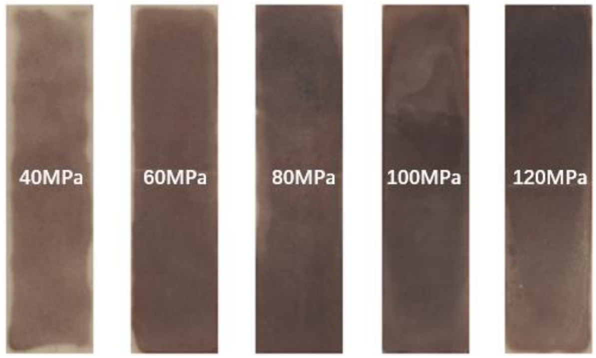

Fig. 2. The poplar powder compacts at different forming pressures

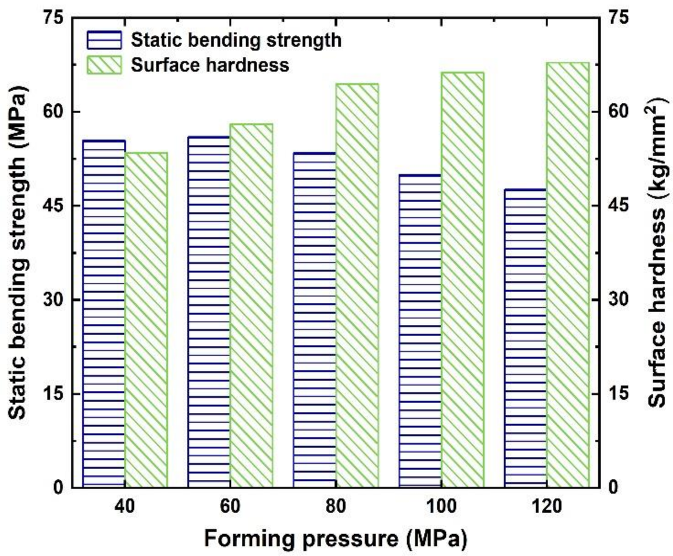

Fig. 3. The effect of the forming pressure on the mechanical properties of compacted wood powder

The effect of the holding time

Figure 4 shows the poplar wood powder compacts by hot-pressing at different holding time. Figure 5 shows the effect of the holding time on the mechanical properties of compacted poplar wood powder. It can be seen that the static bending strength of the compacted wood powder initially increased and then decreased as the holding time increased. The static bending strength increased with the extension of the holding time, as long as the holding time was less than 50 min. Compared with the compacted wood powder samples at a holding time of 10 min, the static bending strength at 50 min increased by 13%. The static bending strength began to decrease when the holding time exceeded 50 min. This may be due to the degradation of hemicelluloses caused by the long holding time, resulting in the embrittlement of the compacted wood powder sample (Bouazara *et al*. 2006). It can be seen from Fig. 5 that the surface hardness of the compact continuously increased as the holding time increased. Compared with a holding time of 10 min, the surface hardness of the compacted wood powder at a holding time of 90 min increased by 26%. This may be due to the increase of lignin content with the increase of holding time (Čabalová *et al*. 2018). It is generally believed that lignin fills the intercellular layer and cell wall framework, thereby increasing the hardness of the cell wall. Based on the above analysis, the forming pressure and holding time will be respectively fixed at 60 MPa and 50 min to study the effect of the temperature on the mechanical properties of the compacted wood powder *via* a single-factor experiment.

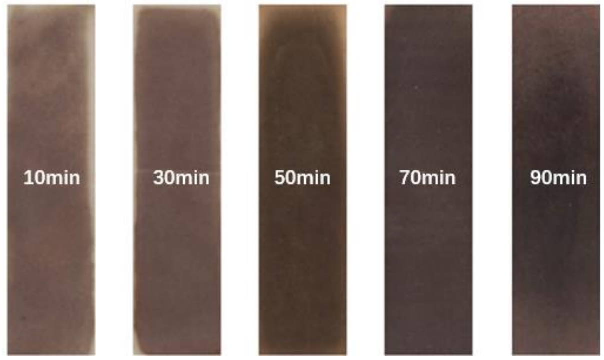

Fig. 4. The poplar powder compacts at different holding times

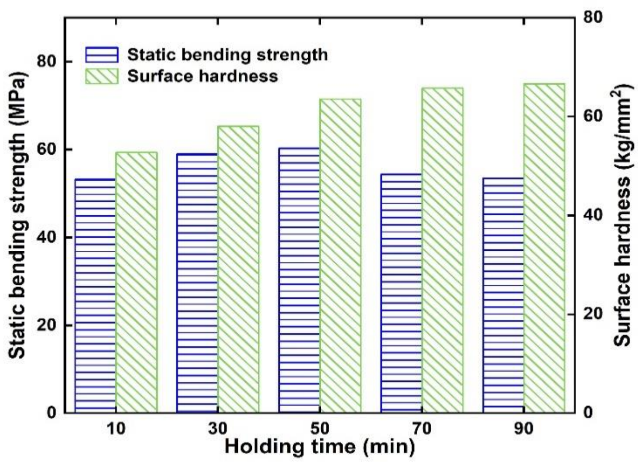

Fig. 5. The effect of the holding time on the mechanical properties of compacted wood powder

The effect of the forming temperature

Figure 6 shows the poplar wood powders compacted by hot-pressing at different forming temperature. Figure 7 shows the effect of the forming temperature on the mechanical properties of compacted poplar wood powder. The static bending strength of the compacted wood powder presented a similar trend compared with the effect of the forming pressure and holding time. The static bending strength reached a maximum value at a forming temperature of 140 °C and increased by 34% compared to a forming temperature of 100 °C. The appropriate increase in temperature can increase the activity of the molecules in the wood flour, which is helpful in terms of the connections between the fibers. However, too high of a temperature will easily lead to the carbonization of the fibers, which reduces the strength of the compacted wood powder (Chai *et al.* 2017). The effect may also be due to material losses in the cell wall, hemicellulose degradation and modification of long chain molecules (Albrektas and Navickas 2017; Altgen *et al*. 2018; Herrera-Díaz *et al*. 2018). The surface hardness of the compacted wood powder increased as the temperature increased and reached its maximum value at a temperature of 160 °C.

The surface hardness of the compacted wood powder increased by 17% compared to the compacted wood powder forming temperature of 100 °C. This may be due to the content of lignin will increase as the forming temperature increases and the lignin in the plant tissues at temperatures above 140℃, where it melts and shows thermosetting properties (Van Dam *et al.* 2004a; Long *et al.* 2021).

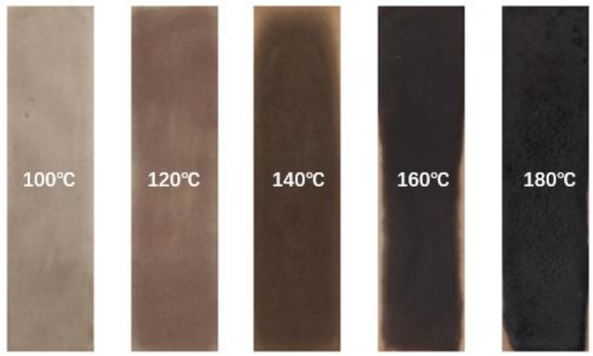

Fig. 6. The poplar powder compacts at different forming temperatures

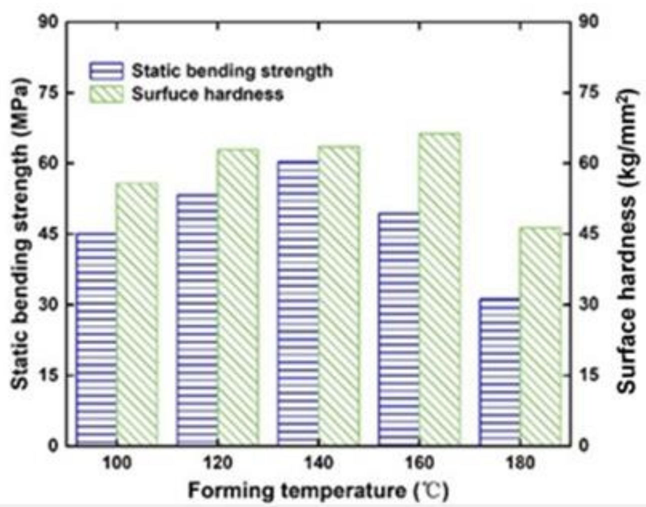

Fig. 7. The effect of the forming temperature on the mechanical properties of compacted wood powder

Modelling the Relationship Between the Process Parameters and the Mechanical Properties of the Compacted Wood Powder

Orthogonal array design

An orthogonal array design of three parameters with five levels was employed to obtain the experimental samples. An orthogonal array is a procedure to systematically organize experimental runs in order to improve processes in the most effective way, *i.e.*, conducting the minimum number of experiments without losing considerable information. According to the results of the single-factor analysis, the forming pressure, the holding time, and the forming temperature were set at 40 to 80 MPa, 10 to 50 min, and 100 to 180 °C, respectively. The results of the orthogonal array design are presented in Table 1.

Table 1. The Results of the Orthogonal Array Design

Experiment Number	Forming Temperature (°C)	Forming Pressure (MPa)	Holding Time (min)	Static Bending Strength (MPa)	Surface Hardness (kg/mm^2)
1	100	40	10	34.77	52.70
2	100	50	20	40.46	54.16
3	100	60	30	44.89	55.48
4	100	70	40	50.62	57.80
5	100	80	50	49.46	64.57
6	120	40	20	49.41	54.31
7	120	50	30	57.43	55.72
8	120	60	40	55.30	56.89
9	120	70	50	54.70	58.03
10	120	80	10	45.26	62.03
11	140	40	30	54.84	53.47
12	140	50	40	59.32	54.68
13	140	60	50	63.75	65.55
14	140	70	10	60.68	53.95
15	140	80	20	60.34	60.26
16	160	40	40	57.62	76.84
17	160	50	50	50.07	77.62
18	160	60	10	56.02	55.54
19	160	70	20	59.87	56.45
20	160	80	30	46.38	63.21
21	180	40	50	40.12	54.16
22	180	50	10	39.71	58.10
23	180	60	20	49.24	59.68
24	180	70	30	45.37	60.89
25	180	80	40	37.77	61.34

Multiple regression model

Multiple regression analysis was carried out by using SPSS (Statistical Package for the Social Science). A general multiple regression model can be formulated as Eq. 2.

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n + \varepsilon \tag{2}$$

where Y indicates dependent variable, X_i represents independent variables, β_i represents predicted parameters, and ε is the error term.

Based on the multiple regression analysis method, mathematical models detailing the relationship between the static bending strength (Y_1), the surface hardness (Y_2), the forming temperature (X_1), the forming pressure (X_2), and the holding time (X_3) were established by fitting the orthogonal array design data, as shown in Eqs. 3 and 4,

$$Y_1 = 22.399 - 0.325X_1 - 0.896X_2 + 6.015X_3 + 0.015X_1X_2$$
$$-0.022X_1X_3 - 0.045X_2X_3 \tag{3}$$

$$Y_2 = 46.488 + 0.005X_1 + 0.143X_2 - 0.121X_3 \tag{4}$$

The fitting correlation coefficients of the static bending strength and surface hardness were 0.81 and 0.80, respectively. The closer the correlation coefficient is to 1, the higher the fitting degree of the regression model is. This indicated that the established multiple regression models could not reliably predict the changes in the static bending strength and surface hardness of the compacted wood powder during the hot-pressing process.

Neural network model

In this study, a proposed neural network model was designed using the MATLAB neural network toolbox. The neural network model in this work was trained using the BP algorithm to map the relationship between the forming temperature, forming pressure, and holding time. The neural network architecture adopted in this model consists of three layers: an input layer, a hidden layer, and an output layer. The hidden layer has 13 neurons, whereas the input and output layers have 3 neurons and 2 neurons, respectively. The neurons in the input layer corresponded to the forming temperature, forming pressure, and holding time. The output layer neurons corresponded to the static bending strength and surface hardness. The final neural network model diagram is shown in Fig. 8.

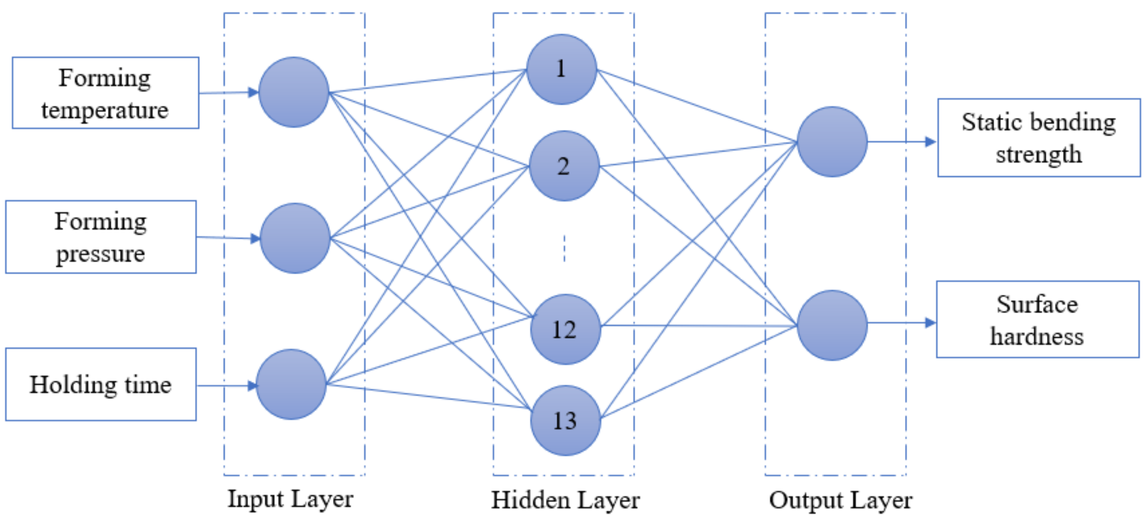

Fig. 8. The neural prediction model for the mechanical properties of compacted poplar powder generated via hot-pressing

In order to speed up the convergence of network training, improve the training effect of the network, and prevent the system from falling into a local minimum, it was necessary to use Eq. 5 to normalize the training sample data. The sigmoid function in the BP algorithm was used as the transfer function in the hidden layer and the output layer. The Trainlm function and the Levenberg-Marquardt algorithm were applied for network training. In the process of training and verification, the optimal number of neurons in the hidden layer was obtained through empirical Eq. 6. The optimal number of hidden layer neurons was determined to be 13 through preliminary experiments. From the orthogonal array designs, 75% of the data was randomly selected to train the BP neural network model. The remaining 15% and 10% of the data were used to verify and predict the model, respectively,

$$y = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{5}$$

where y is the value after normalization, x is the value before normalization, x_{min} is the minimum value in the sample data, and x_{max} is the maximum value in the sample data,

$$p = \sqrt{n + m} + q \tag{6}$$

where p is the hidden layer nodes, n is the input layer nodes, m is the output layer nodes, and q is a constant from 1 to 10.

The BP neural network prediction results for the mechanical properties of the compacted wood powder are shown in Figs. 9 and 10.

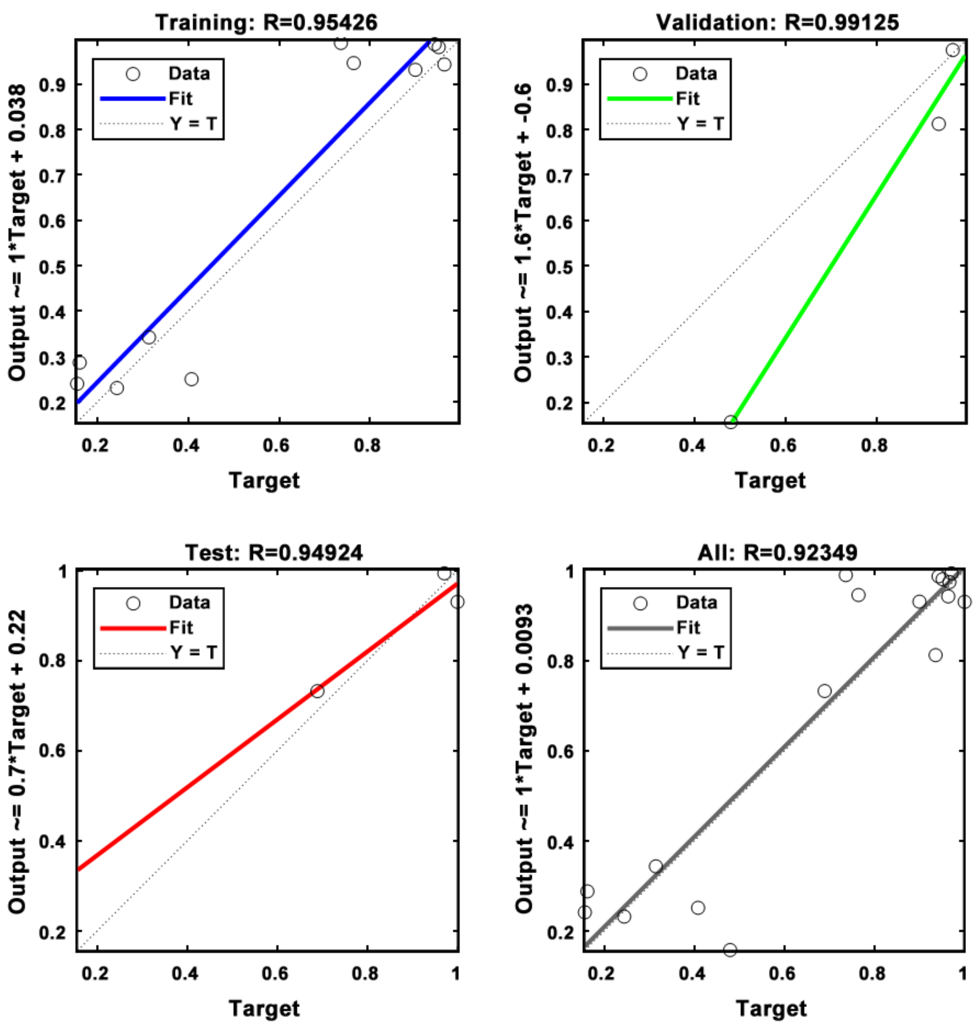

Fig. 9. The relationship between the prediction and the experimental data during training, verification, and test of the static bending strength

Figure 9 shows the fitting results between the output and the experimental value of the static bending strength during the training, verification, and prediction of the neural network model. The correlation coefficient (R) between the predicted and actual value is an important index to test the accuracy of a neural network model (Bouazara *et al*. 2006). The R values during training, verification, and testing of the static bending strength were 0.95, 0.99, and 0.95, respectively. The overall R value was 0.92. Figure 10 presents the fitting results between the output and experimental value of the surface hardness during the training, verification, and prediction of the neural network model. The R values during the training, verification, and testing of the surface hardness were 1.0, 0.78, and 0.93, respectively. The “Data” distribution is discrete and “Y=T” does not coincide with “Fit” in Figs. 9 and 10, which may be caused by the over-fitting of the neural network. This phenomenon may be due to the limited number of samples.

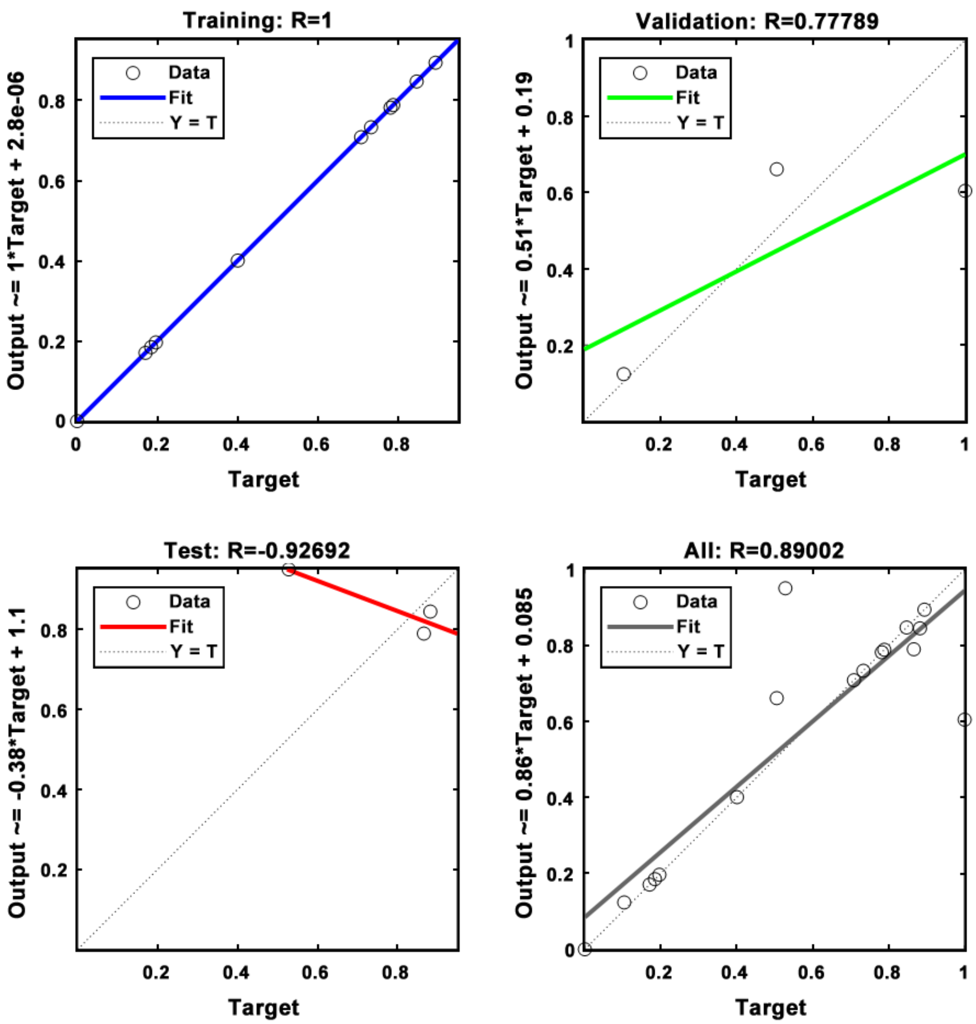

Fig. 10. The relationship between the prediction and the experimental data during training, verification, and test of the surface hardness

Verification of the Predictive Models

Six groups of data among the single-factor experiments (shown in Table 2) were selected to test the prediction accuracy of the multiple regression and neural network model. The predicted values of the two models are shown in Tables 3 and 4, respectively.

Table 2. Verification Data for the Predictive Model

Serial Number	Forming Temperature (°C)	Forming Pressure (MPa)	Holding Time (min)	Static Bending Strength (MPa)	Surface Hardness (Kg/mm^2)
1	140	80	30	53.43	64.48
2	140	100	30	49.95	66.26
3	140	60	10	53.20	52.72
4	140	60	30	59.00	58.05
5	120	60	50	53.29	62.92
6	140	60	50	60.34	63.55

Table 3. Predictive Data of the Multiple Regression Model

Serial Number	Forming Temperature (°C)	Forming Pressure (MPa)	Holding Time (min)	Static Bending Strength (MPa)	Surface Hardness (Kg/mm^2)
1	140	80	30	46.71	54.92
2	140	100	30	42.62	57.78
3	140	60	10	47.05	54.49
4	140	60	30	50.81	52.06
5	120	60	50	66.08	49.54
6	140	60	50	54.56	49.64

Table 4. Predictive Data of the Neural Network Model

Serial Number	Forming Temperature (°C)	Forming Pressure (MPa)	Holding Time (min)	Static Bending Strength (MPa)	Surface Hardness (Kg/mm^2)
1	140	80	30	55.18	58.04
2	140	100	30	54.26	59.60
3	140	60	10	56.47	53.43
4	140	60	30	59.43	65.11
5	120	60	50	48.63	64.92
6	140	60	50	56.63	64.12

The mean absolute percentage error (MAPE) and the root mean square error (RMSE) were used to assess the validity of the multiple regression model and the neural network model. The lower MAPE and RMSE values represent the more accurate prediction results. The MAPE and RMSE were calculated using Eqs. 7 and 8, respectively.

$$MAPE = \left(\frac{1}{N}\sum_{i=1}^{N}\left[\left|\frac{t_i - td_i}{t_i}\right|\right]\right) \times 100 \tag{7}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(t_i - td_i)^2} \tag{8}$$

where t_i is the measured (experimental) values, td_i is the predicted values, and N is the total number of data. The MAPE and RMSE values used to evaluate the performance of the multiple regression model and the neural network model in this study are given in Table 5. In decision-making, MAPE values were considered as the most important performance criterion (Tiryaki and Aydin 2014). According to this, the MAPE values were determined as 6.629% and 13.9176% in the prediction of the static bending strength and the surface hardness with multiple regression model, respectively. Additionally, the MAPE values were obtained as 0.1980% and 1.0893% in the prediction of the static bending strength and the surface hardness with neural network model, respectively. As can be seen, the neural network model exhibited higher prediction performance than the multiple regression model.

Table 5. Evaluation Criteria Used in Predicting Mechanical Properties by the Multiple Regression Model and the Neural Network Model

Model	Mechanical Property	Performance Criteria	
		MAPE	RMSE
Multiple regression model	Static bending strength	6.629	20.0195
	Surface hardness	13.9176	23.9756
Neural network model	Static bending strength	0.1980	8.2460
	Surface hardness	1.0893	11.8533

Figure 11 presents the comparisons between the experimental data and the predicted data obtained *via* two types of prediction models. It can be seen in Fig. 11a that the maximum error rate between the experimental data and the predicted data of the static bending strength values based on the multiple regression model was 24.00% and the minimum error rate was 11.56%. The average error rate was 15.19%. The maximum error rate between the experimental data and the predicted data of the static bending strength based on the neural network model was 8.74% and the minimum error rate was 0.73%. The average error rate was 5.61%.

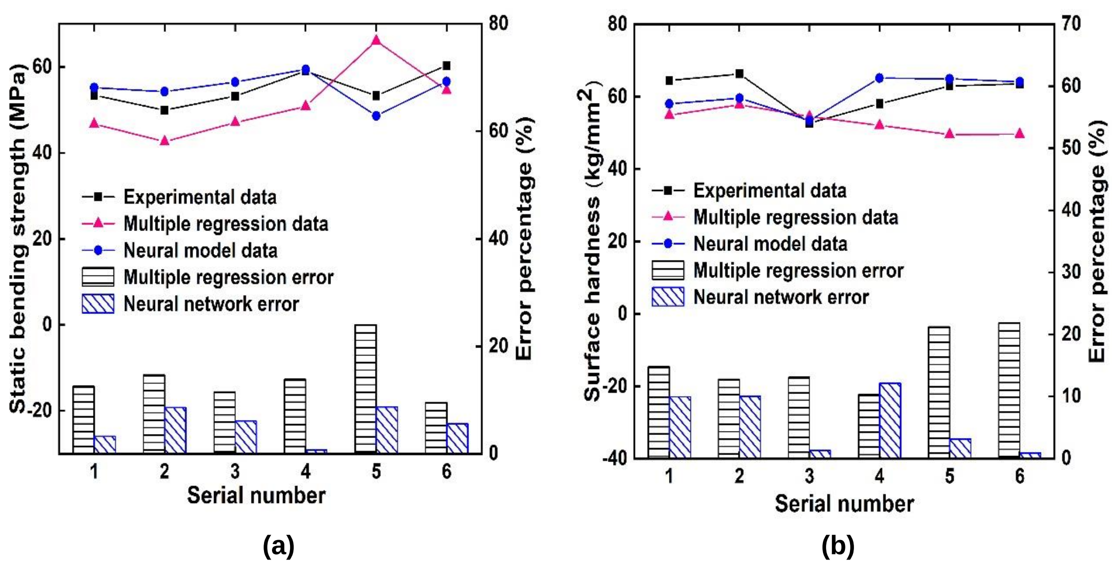

Fig. 11. Comparison between the experimental and predicted data of the mechanical properties: (a) static bending strength; and (b) surface hardness

Figure 11b shows that the maximum error rate between the experimental data and the predicted data of the surface hardness based on the multiple regression model was

21.89% and the minimum error rate was 10.31%. The average error rate was 15.70%. The maximum error rate between the experimental data and the predicted data of the surface hardness based on the neural network model was 12.16% and the minimum error rate was 0.9%. The average error rate was 6.27%. It can be clearly seen that the prediction error rate of the neural network model was smaller compared to the multiple regression model. Through the previous analysis *via* single-factor experiments, it can be seen that the mechanical properties of the compacted wood powder showed a nonlinear trend with the process conditions. This may lead to a non-ideal prediction ability of the multiple regression model. This further indicated that the established neural network model had a better prediction performance and can more accurately map the relationship between the process conditions and the mechanical properties of the compacted wood powder.

CONCLUSIONS

1. The process parameters of the hot-pressing process have a considerable influence on the mechanical properties of compacted wood powder. The mechanical properties showed a nonlinear trend relative to the process conditions during the hot-pressing of wood powder. The static bending strength reached a maximum value at a forming pressure of 60 MPa, a holding time of 10 min, and a forming temperature of 140 °C. The surface hardness reaches a maximum value at a forming pressure of 120 MPa, a holding time of 90 min, and a forming temperature of 160 °C.
2. The relationship models between the process parameters and mechanical properties for the compacted wood powder were established by applying the multiple regression analysis and neural network methods combined with the data from the orthogonal array design. The error rate, MAPE and RMSE of the neural network model in terms of predicting the mechanical properties was smaller compared to the multiple regression model. This indicated that the established neural network model has a better prediction performance, and it can more accurately map the relationship between the process conditions and the mechanical properties of the compacted wood powder.

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