An Artificial Neural Network Model for Predicting Mechanical Strength of Bamboo-wood Composite Based on Layups Configuration

Zihua Su, Zhilin Jiang, Yi Liang, Bingzhen Wang, and Jianping Sun *

The transportation application of the bamboo–wood composite container flooring (BWCCF) has increased considerably. However, materials would be destroyed in the process of common mechanical evaluation, resulting in a waste of resources. Therefore, this paper aims to design artificial neural network (ANN) models to predict mechanical strength of BWCCF. The modulus of rupture (MOR) and the modulus of elasticity (MOE) of BWCCF were predicted by ANN models based on layups configuration, including directions, densities, and thicknesses of 21-layer BWCCF in each layer. According to results, the mean absolute percentage errors (MAPE) and the correlation coefficient (R) were determined as 16.93% and 0.619 in prediction of MOR, and 10.10% and 0.709 in prediction of MOE, respectively. The results indicated that ANN can be applied to predict mechanical properties of BWCCF.

DOI: 10.15376/biores.17.2.3265-3277

Keywords: Artificial neural network; Layups configuration; Bamboo-wood composite; Mechanical strength

*Contact information: Materials, School of Resources, Environment and Materials, Guangxi University, Nanning 530004, China; *Corresponding author: jpsun@gxu.edu.cn*

INTRODUCTION

Bamboo-wood composite materials, which can be defined as composite plates mainly made of bamboo and wood through processing into the same or different forms of structural units, have excellent physical mechanical properties due to the composite effect of materials (Li *et al.* 2021). Bamboo-wood composites not only can take advantage of the characteristic of bamboo high strength, but also they can give play to the characteristics of high utilization rate of wood veneer (Chen *et al.* 2017). Based on the anisotropic mechanical nature of the materials, the physical and mechanical properties of the final products, manufacturing parameters and costs can be optimized through rationally arranging the layout of layers (Abdelhamid *et al.* 2004). Some theories of wood production are based on the influence of layups configuration with mechanical strength of itself. Examples include the method of classical theory, the Euler beam theory (Abdelhamid *et al*. 2004), the first-order shear theory, mechanics of composite materials, finite element method (Chen *et al.* 2016b), mechanics of elasticity, theory of laminated plates, and related knowledge of composite materials (Li-Haiwei 2011). From the perspective of composite science, significant differences exist between the products made of the same specific elements while using different combination approaches (Chen *et al.* 2016a). According to laminated plate theory, the advantages of each layer can be maximized by placing the materials with high strength and high elastic modulus in the outermost layer and the materials with poor performance in the core layer (Chow *et al.* 2019). For example, a new composite container flooring was formed *via* the design of rational structure and the research of hot-pressing process based on this theory (He 2005). Other layer characteristics also affect mechanical properties. Bamboo-wood composite on the mechanical properties were affected the layer structure of composite made (Lee *et al.* 2012) and the quality of adding different layers of bamboo fibers (Zhai *et al.* 2011). These findings showed that the mechanical properties of composite can be improved by increasing the proportion of bamboo. Similar results were obtained in the study of composite beams (Zhang *et al.* 2020) and wood-bamboo composites construction concrete (He *et al.* 2019). Furthermore, the arrangement direction of the configuration has a great influence on the properties of bamboo-wood composites. The influences of angle 0°, 45°, and 90° on the properties of bamboo-wood composites were studied (Ashaari *et al.* 2016; Verma *et al.* 2017). In sum, the lay-up of bamboo-wood composite has an important influence on their mechanical properties.

Non-destructive testing of materials enables the physical and mechanical properties to be obtained without permanently or noticeably altering the materials (Abdelhamid *et al.* 2004). Its emphasis depends on whether the material is isotropic or anisotropic (Esteban *et al.* 2009), but mechanical properties are usually based on mathematical models formed from tests carried out on structural members in order to be reliable and statistically robust (Cavalli *et al.* 2016). Recently, interest in artificial neural networks (ANNs) has grown (Agha and Alnahhal 2012). ANNs have been applied successfully to several areas including medicine, engineering, geology, and physics, to design solutions for estimation problems, classification, control, *etc*. (Agha and Alnahhal 2012). ANNs can be used as predictive models because they are capable of modelling complex functions. The ANN can learn and extract knowledge to simulate the functions of human brain, becoming a powerful tool to simulate the complex relationships between variables (Esteban *et al.* 2009). For this purpose, ANNs have been used for predicting the properties of solid wood (Tiryaki and Aydın, 2014), *e.g.*, simulating and predicting the change of wood moisture content (MC) (Chai *et al.* 2018), drying process of wood, calculating wood thermal conductivity and compressive strength (Tiryaki and Aydın 2014), predicting the modulus of rupture (MOR) and elastic of modulus (MOE) of lumber heat treatment (Esteban *et al.* 2009; Tiryaki and Hamzacebi 2014), and calculating heat treatment of wood best bonding strength (Tiryaki *et al.* 2014). Furthermore, the short span of shear force and MOE of plywood were predicted (Fernández *et al.* 2012). It has been possible to raise the utilization efficiency of the wood board and shorten the time of the design process (Jun *et al.* 2003). Wood composites have been studied by ANN, for example, the Buckingham's p-theorem and the MOR and MOE predicted based on a multiple regression of particleboard (Arabi *et al.* 2011), studying the effects of board thickness, moisture content and specific gravity of plywood boards (Fernández *et al.* 2012), forecasting the plywood combined strength (Demirkir *et al.* 2013), and frequencies prediction of laminated timber plates (Sun *et al.* 2020).

Bamboo-wood composites have great requirements in various sectors such as cement templates, container flooring (Jiang *et al.* 2021), concrete formwork, truck platform floor, inner floorboard, and are mostly used as engineering structural parts (Jiang *et al.* 2002). Bamboo-wood composite structure material is subject to external forces, which requires sufficient strength, stiffness, and durability. For instance, bamboo-wood composite used as the bamboo-wood composite container floor (BWCCF) is the main bearing component for container loads. The layups configuration is complex, and the structure is over 20 layers, usually 21, 22, and 23 layers. There has been a need for non-destructive testing of bamboo-wood composite used as the BWCCF. According to the national standards, the vertical and horizontal MOR and MOE is greater than or equal to 85 and 35 MPa and 10000 and 3500 MPa, respectively (GB/T 19536 2015). Therefore, this study used ANN through MATLAB to design the model of BWCCF, which can predict mechanical properties to obtain more economic and safe results without doing comprehensive tests.

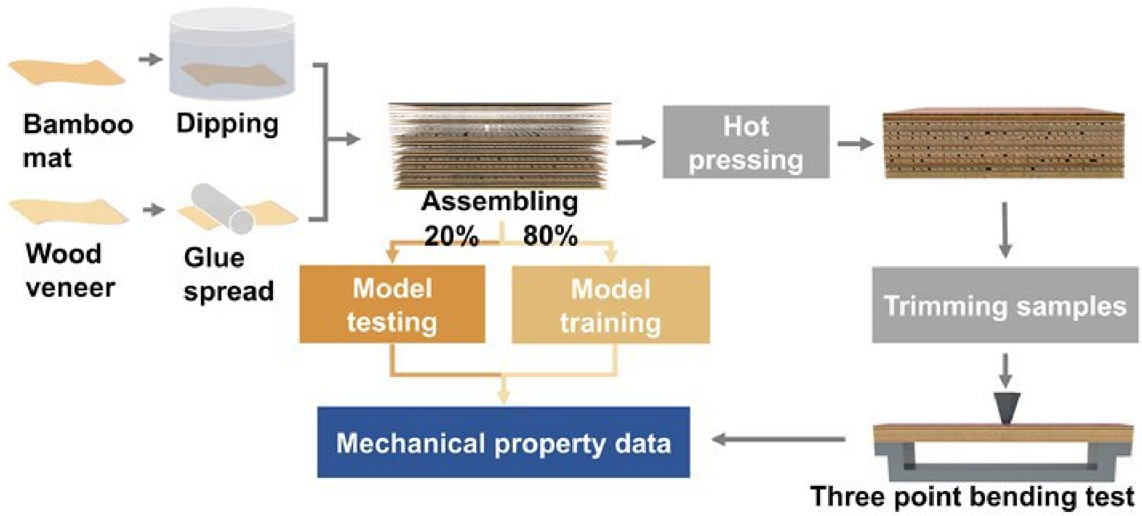

Fig. 1. Flow chart of the experiments

EXPERIMENTAL

Figure 1 shows the flow chart of this experiment. First, the BWCCF was prepared. Next, BWCCF were tested for the MOR and MOE, and the results served as the output of the ANN models. The models were trained, and the generalization performance was verified by the input-output sample sets. Finally, the effective prediction models were obtained.

Materials

Seven commercially produced sheets (Nanning Diwang Village Wood Co.) from China were used, including bamboo curtain, eucalyptus, rubber wood, pine, and other miscellaneous woods, with dimensions of 2400 mm × 1160 mm or 1626 mm × 636 mm. And the thicknesses were 2.2 mm, 2.2 mm, 1.7 mm, 1.2 mm, and 0.5 mm, respectively. The adhesive used was a water-soluble urea formaldehyde (UF) resin (with 48% or 55% solids content produced by Wood Glue Industrial, Guangxi, China).

Prepared Composites

Bamboo curtains were subjected to dipping, the key process for manufacturing bamboo mat, which determines its bonding performance (Huang *et al.* 2019). The bamboo curtains were dipped for three seconds with UF (solid content of 48 ± 2%, pH of 10 ± 1, and viscosity of 45 to 100 mPa.s). In the dipping process, the MC of bamboo curtain needs to be below 10% so that the resins can get into it. All wood veneers were gummed with UF (solid content of 48 ± 2%, pH of 10 ± 1, and viscosity of 50 to 180 mPa.s). The next step was assembly, which is the most important part. The dipped bamboo curtain and coated wood veneer were assembled according to the design plan for lay-up. Finally, the assembled veneers were compressed with hot-pressing at a pressure of 2.5 to 3.0 MPa and 130 ± 5 °C for 45 min. The commonly used size (length × width × thickness) for the BWCCF was either 2400 mm × 1160 mm × 28 mm or 1626 mm × 636 mm × 28 mm.

Blending Properties Test

The mechanical properties, such as MOE and MOR of the BWCCF were determined according to the procedure specified in the plywood standard of container floors (GB/T 19536-2015) and plywood performance standard of international freight container floors (IICL TB 001-2014). According to these standards, the test requires primary specimens with dimensions of 610 mm × 50 mm × 28 mm for the MOR and MOE experiments. The tests were carried out using the computer software SmartText to control the WDW-100E machine (Beijing TIME High Technology Ltd, Beijing, China), and three points bending tests were carried out to calculate the strength. The final mechanical properties are the average value of the six repetitions of the above measurement for further analysis.

ANN Models Prediction Analysis

Two models were built based on layups configuration and mechanical property parameters of BWCCF and were trained by ANN, as shown in Fig. 2. The parameters of blank (direction, thickness, and density) were input to predict the mechanical properties (MOR and MOE) of the bottom plate.

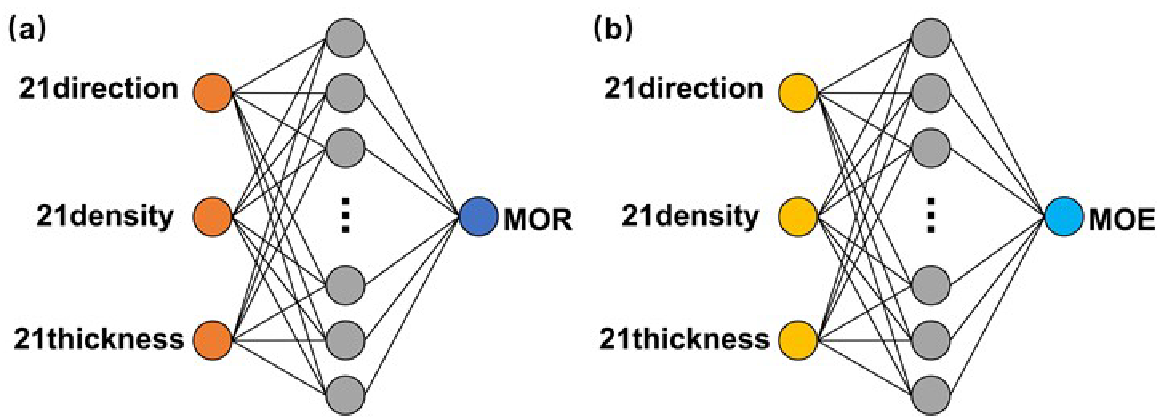

Fig. 2. The ANN architecture used as the prediction model for (a) MOR and (b) MOE

The concept of ANN is inspired by the biological system of the brain, which comprises many neuro connected through synapses that process information (Watanabe *et al.* 2012). In this study, the proposed ANN models were designed by software developed using the MATLAB Neural Network Toolbox. The training was carried out by making attempts to establish different ANNs with different network configurations and learning parameters (Tiryaki and Aydın 2014). In this study, the 51 groups of data were divided randomly into two parts during model construction: 41 groups of training set (80% of the total), 10 groups of test data (20%). The input layer data were the 63 blank parameters (21 directions, 21 densities and 21 thicknesses, the average of raw material veneer) of the

BWCCF. respectively. The data of the output layer were the mechanical properties (the MOR and MOE). In the first model, the 63 blanks parameters were considered as input variables and the MOR used as output, and the 63-10-1 neurons configuration was employed. In the other model, the MOE was used as output, and the 63-11-1 neurons configuration was designed. There is no scientific and explicit method for determining the number of nodes; the number of nodes in the hidden layer could be determined through experience and multiple training (Tiryaki and Hamzacebi 2014). The input signal is propagated forward to the hidden node. After passing the transfer function, the output information of the hidden node is propagated to the output node, and the output result is given after processing. The prediction performance of each model was evaluated and compared for each case using statistical and graphical comparisons (Demirkir *et al.* 2013). The mean absolute (MAPE) values were considered as the most important performance criteria (Tiryaki and Aydın 2014). The average absolute error (MAE) describes the dispersion of data samples, and the root mean square error (RMSE) indicates the deviation between the predicted value and the real value. The correlation coefficient (R) is used to describe the degree of linear correlation between predicted and actual values, which can reflect the positive or negative correlation between them. The determination coefficient (R^2) indicates the correctness of model fitting. The higher values of R and R^2 present the greater similarities between the measured and predicted values. MAPE, MAE, and RMSE values are calculated using Eqs. 1 through 3 (Ozsahin and Aydin 2013; Tiryaki and Aydın 2014; Tiryaki *et al.* 2014),

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{|t_i - td_i|}{t_i}\right) \times 100\% \quad (1)$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|t_i - td_i| \quad (2)$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(t_i - td_i)^2} \quad (3)$$

where t_i is the measured (experimental) values, td_i is the predicted values, n is the total number of data and $\bar{t}$ is the average of predicted values.

RESULTS AND DISCUSSION

Predicting MOR and MOE by ANN

Two BP artificial neural networks were designed in this study. This approach makes use of error gradient descent algorithm to minimize the mean square error between the output value of network and the actual output value (Yu and Xu 2014). While layups direction, thickness, and density were considered as input variables, mechanical properties of the BWCCF were used as output variables in the models. The relationship between the experimental values and predicted values was obtained using the ANN prediction model is shown in Fig. 3. The solid line shows the linear fit between the predicted values and measured values of MOR and MOE. As the R values approaches 1, prediction accuracy increases (Chai *et al.* 2018). According to Fig. 3, the R values for training of MOR and MOE were 0.69 and 0.66, respectively; the R values of testing for MOR and MOE were 0.71 and 0.71, respectively. The results obtained are satisfying compared with those obtained by other authors on applying ANNs for modeling to predict a variety of properties of wood and wood-based products. R values obtained in these studies can be summarized as follow: Fernández *et al.* (2012) predicted MOR and MOE of structural plywood board using an ANN, and the maximum value obtained for the R value was 0.71; Samarasinghe *et al*. (2007) found a R value as 0.62 in modeling to determine the fracture toughness of wood; Watanabe *et al*. (2012) predicted a final MC of individual Sugi samples during air drying, where the R value was 0.80.

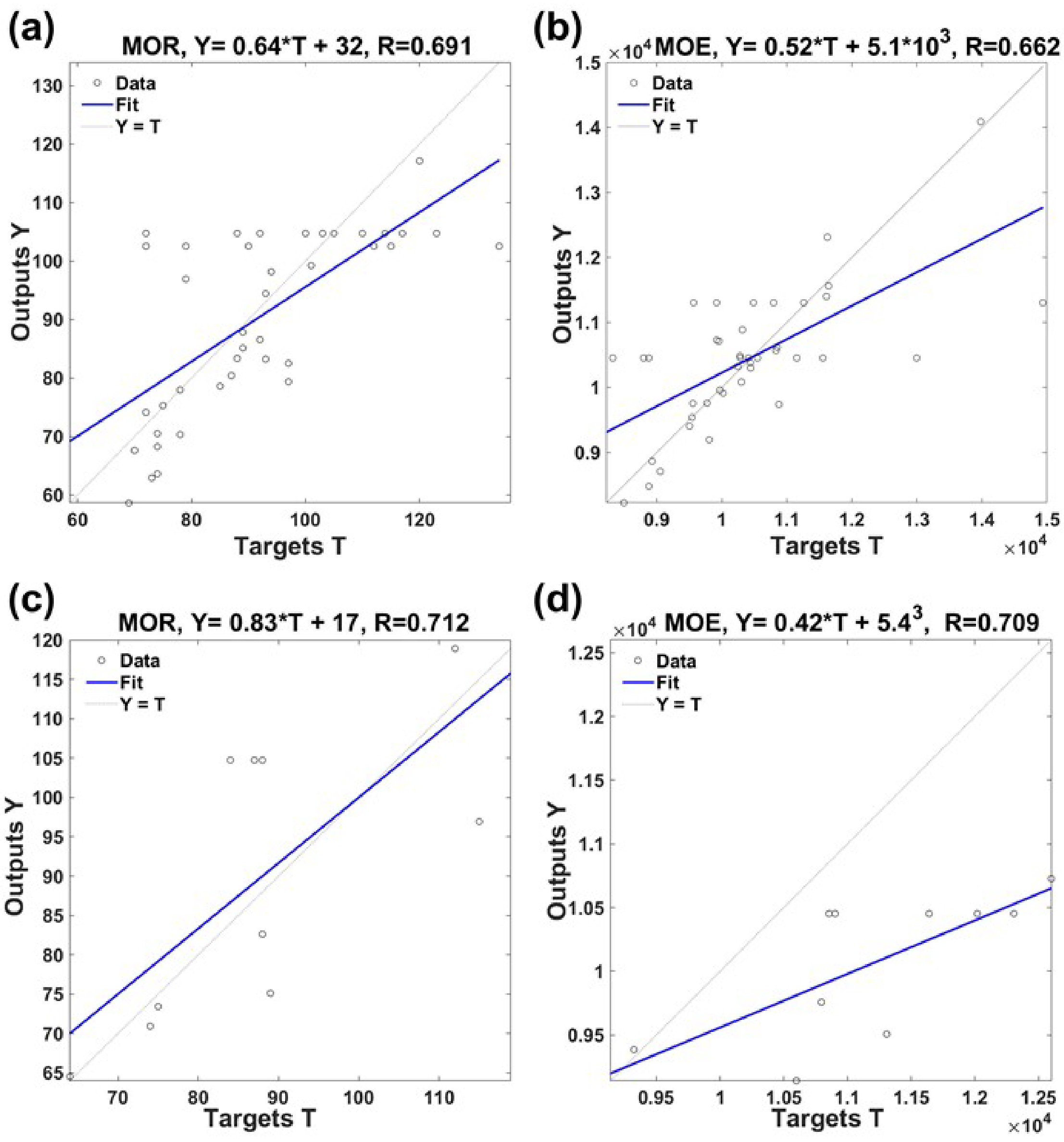

Fig. 3. Relationship between actual and predicted values of ANN training and testing models for (a, c) grain MOR and (b, d) grain MOE

The verification percentage error of ANN model obtained and the distribution of model error are shown in Fig. 4 and Table 1. As shown in Table 1, the prediction values obtained by ANN were determined with not high percentage errors. The prediction error of MOE was less than MOR, which is consistent with the results of R values in Fig. 3. Overall, the prediction accuracy of each measurement point is moderate and can meet the demand for stratified mechanical property prediction. These levels of errors are satisfactory for predicting MOR and MOE values.

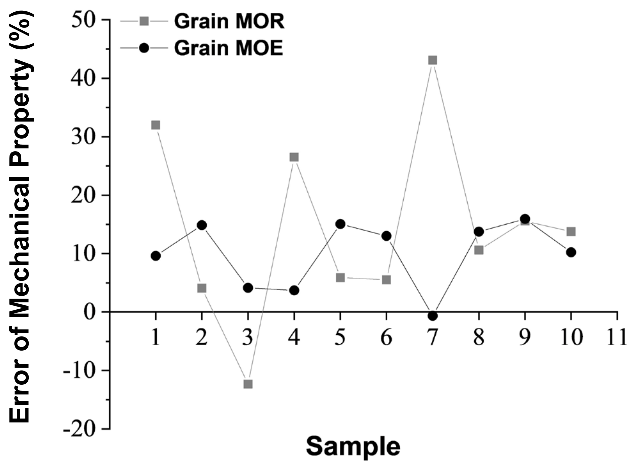

Fig. 4. The error of validation

Table 1. The Percentage Error of Validation

Mechanical property	1	2	3	4	5	6	7	8	9	10
Grain MOR (%)	31.97	4.09	12.31	26.50	5.92	5.51	43.10	10.60	15.56	13.76
Grain MOE (%)	9.61	14.87	4.14	3.72	15.07	13.03	-0.65	13.75	15.92	10.22

MAPE, MAE, and RMSE values were utilized to evaluate the performance of the neural networks, as shown in Table 2. MAPE values of the MOR and MOE training set were 10.5% and 5.98%, while in validation set the corresponding values were 16.9% and 10.1% respectively. The ANN approach has a sufficient accuracy level in the prediction of MOR and MOE values. Furthermore, the predicted optimum bonding strength of heat-treated woods training and testing MAPE were 1.49% and 3.06%, respectively (Tiryaki *et al.* 2014). Ozsahin and Aydin (2013) predicted the optimum veneer drying temperature, and the MAPE of training and testing were 1.08% and 2.29%, respectively. In this study, the thickness and density of veneer were difference in the process of prepared composites. Moreover, the detection of mechanical properties was affected by the cracks of BWCCF. The training and testing MAE of MOR were 381 and 15.9, and MOE were 630 and 1170. The training and testing RMSE of MOR were 13.5 and 19.4, MOE were 1006 and 1328, respectively. By other studies, scientists have calculated values of RMSE and MAE obtained of the various wood products. For example, predicting compression strength of heat-treated woods learning, the RMSE of training and testing were 0.432 and 1.082, respectively, and the MAE of training and testing were 0.336 and 0.960 (Tiryaki and Aydın 2014). In addition, by predicting the MOR and MOE of the heat-treated material, the MAE for training and testing of the MOR were 0.654 and 0.922, respectively, and the MAE for training and testing of the MOE were 91.0 and 170, respectively (Tiryaki and Hamzacebi 2014). The values of the MOR and MOE were 60 to 100 MPa and 7000 to 12000 MPa, respectively. In the present study, the results were slightly larger. The discrete nature of the data was the cause of insufficient model training sample and influences the result directly. These levels of errors were satisfactory when using ANN models for predicting MOE and MOR.

Table 2. Collection of ANNs Model Data

Performance Measure		MOR (MPa)	MOE (MPa)
MAPE (%)	Training	10.51	5.98
	Testing	16.93	10.1
MAE	Training	381.3	630
	Testing	15.9	1170
RMSE	Training	13.5	1006
	Testing	19.4	1328
R	Training	0.607	0.662
	Testing	0.619	0.709
R^2	Training	0.368	0.438
	Testing	0.383	0.502

The actual and predicted values of MOR and MOE were compared. As shown in Fig. 5(a), the consistent agreement between the predicted and measured values of mechanical strength in training set shows that the decision method was effective. According to Fig. 5(b), the prediction values were closer to the measured values in validation set. The results indicate a consistent agreement between the outcomes of the ANN modeling and the experimental results.

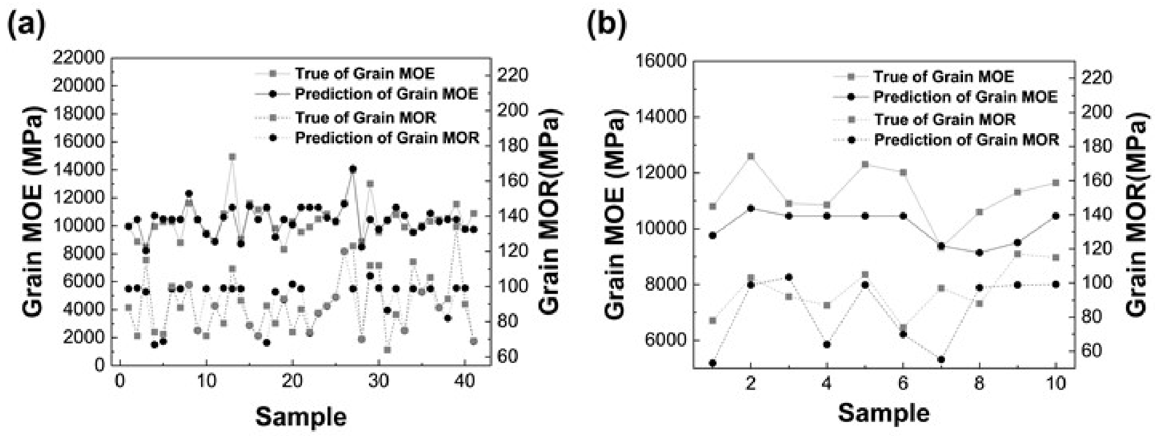

Fig. 5. Comparison of the real and predict values results in (a) training and (b) testing for all data

Relationship between Mechanical Strength and Layups Configuration

The materials of bamboo-wood composite contain both bamboo and wood, and the material properties of bamboo and wood are different. Bamboo is superior to wood in some mechanical properties. Therefore, the proportion and position of bamboo and wood should be considered when making BWCCF. The direction, thickness and density of all raw materials affect the mechanical properties of composite.

As shown in Table 3, the following conclusions can be drawn: 1) All the bamboo curtain was longitudinal, indicating that the curtain in the process of making the bottom plate is suitable for grain arrangement, which could contribute maximum mechanical properties. This result is in agreement with most of the bamboo-wood composite literature. (Xiao *et al.* 2014; Chen *et al.* 2016a,b). 2) The direction of group 10 was the same as group

11, but one species layer was different. Therefore, the MOR and MOE of group 10 were both lower. This result shows that the mechanical properties of the BWCCF can be improved by adding bamboo veneer, which is in agreement with literature (Chen *et al.* 2016a; Zheng 2016). 3) The groups of 4-9, 11-12, 13-14 had the same layups configuration, but their mechanical parameters were different. The differences can be attributed to the influence of mechanical parameters, such as the thickness, density, and the presence of cracks in BWCCF.

Table 3. Layups Configuration and Mechanical Strength of BWCCF

Groups	Layups configuration	Grain MOR (MPa)	Grain MOE (MPa)
1	│─│¦¦│─│││││─│¦│¦│─││	94	10877
2	│─││¦─¦│¦│¦│¦│¦─¦│─││	120	13983
3	│─││¦─¦│¦│¦│¦│─│¦│─││	92	11624
4	││─│││¦─¦│¦│¦│¦─¦│─││	88	10904
5	││─│││¦─¦│¦│¦│¦─¦│─││	72	8878
6	││─│││¦─¦│¦│¦│¦─¦│─││	88	10409
7	││─│││¦─¦│¦│¦│¦─¦│─││	100	12307
8	││─│││¦─¦│¦│¦│¦─¦│─││	105	11153
9	││─│││¦─¦│¦│¦│¦─¦│─││	84	8798
10	││─││─¦│¦│¦│¦│¦─¦│─││	101	10316
11	││─│¦─¦│¦│¦│¦│¦─¦│─││	115	12600
12	││─│¦─¦│¦│¦│¦│¦─¦│─││	79	9918
13	││─│¦│¦─¦│¦│¦│¦─¦│─││	115	11260
14	││─│¦│¦─¦│¦│¦│¦─¦│─││	134	14939

Notes: Within the table, the symbol │ means along the grain of wood veneer, whereas ─ means the horizontal grain wood veneer and ¦ is arranged grain bamboo curtain.

The optimal layup configuration is represented by group 14 in Table 3. Compared with other types of layups, the optimal layup had the following characteristics: 1) The fifth layer (define layer bottom is the first layer) tended to fracture, and this layer was a longitudinal bamboo curtain which has better mechanical properties than wood. 2) No transverse arrangement of veneer was used on the outermost three layers. Moreover, the thickness of veneer was symmetrically distributed in the center.

CONCLUSIONS

1. This study developed artificial neural network (ANN) models to predict modulus of rupture (MOR) and modulus of elasticity (MOE) values of bamboo-wood container composite flooring (BWCCF) based on layups configuration, including directions, densities, and thicknesses of 21-layer BWCCF in each layer. According to obtained data, the following was concluded. In the established ANN models, the MAPE and R fitting parameters for an ANN model for predicting MOR were 16.9% and 0.619, and that of an ANN model for predicting MOE were 10.1% and 0.709, respectively. Considering the complexity of BWCCF, this demonstrates that the ANNs are

appropriate for modeling the relations between layups configuration and mechanical properties of BWCCF.

2. In order to further realize the nondestructive testing of BWCCF, it is necessary to continuously explore new testing methods to improve the accuracy of the model. Based on the present study, there are several aspects that need to be improved: 1) Increase the number of training samples to reduce the contingency of data and improve the generality of data; 2) Explore a more concise way to represent the structural parameters of the layups. The input parameters for this study were 63, which leads to a complex training process. Therefore, the simpler digital forms are needed to reflect the thickness, density, and direction.

ACKNOWLEDGMENTS

This work was financially supported by the National Natural Science Foundation of China (31660174).

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Article submitted: December 29, 2021; Peer review completed: March 12, 2022; Revised version received and accepted: April 6, 2022; Published: April 25, 2022.
DOI: 10.15376/biores.17.2.3265-3277