Wood Modification at High Temperature and Pressurized Steam: a Relational Model of Mechanical Properties Based on a Neural Network

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Thermally modified wood has high dimensional stability and biological durability.But if the process parameters of thermal modification are not appropriate, then there will be a decline in the physical properties of wood.A neural network algorithm was employed in this study to establish the relationship between the process parameters of high-temperature and high-pressure thermal modification and the mechanical properties of the wood. Three important parameters: temperature, relative humidity, and treatment time, were considered as the inputs to the neural network. Back propagation (BP) neural network and radial basis function (RBF) neural network models for prediction were built and compared. The comparison showed that the RBF neural network model had advantages in network structure, convergence speed, and generalization capacity. On this basis, the inverse model, reflecting the relationship between the process parameters and the mechanical properties of wood, was established. Given the desired mechanical properties of the wood, the thermal modification process parameters could be inversely optimized and predicted. The results indicated that the model has good learning ability and generalization capacity. This is of great importance for the theoretical and applicational studies of the thermal modification of wood.

Keywords: Wood modification; High temperature and Pressurized steam; BP neural network; RBF neural network; Relational model

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INTRODUCTION

Along with the continued reduction ofglobal forest resources and the growing need for timber, the reasonable application of the wood resources from artificial forests has become intensively studied. Artificial forestshave fast growth and high yields; however, the timber produced by artificial forests deforms and cracks easily, resulting in low added economic value. The exploration of a rational thermal modification process for fast-growing hardwood is of great significance to expanding the application scopes of low-quality wood and increasing its high value-added applications (Cheng and Liu 2007). There are many methods of wood modification. Among them, thermal modification at high temperaturesprovides dimensional stability and biological durability. At the same time, it is also environmentally friendly. Thermal modification is a short-term pyrolytic treatment of wood at 150 to 260 °C in the presence of heating media such as steam, inert gas, or vegetable oil. Wood modified at high temperature and pressure has greatly improved dimensional stability, biological durability, and color. As these properties are improved, corresponding changes in the wood's chemical and biological structure can also occur. If the process parameters of thermal modification are not appropriate, the physical properties of the wood are damaged. Different processing temperature and RH have influence on the mechanical properties of the material, for example, Compared with the unmodified wood, the compressive strength parallel to the grain of the modified wood increased on the whole. Thermal modification of material has been found to decrease the bending strength significantly compared with material (Cheng *et al.* 2008); also, the bending modulus of elasticity generally fell slightly upon thermal modification. The hardness after heat treatment can exhibit a downward trend after rising first (Qi *et al.* 2005).This has, to a great extent, restricted the application scope of thermally modified wood(Shi 2011). Thus, the building of a model that predicts the relationships between the process parameters of thermal modification and the mechanical properties is highly important. The model can contribute to the reasonable application of wood, reduce the number of experiments, and optimize the process.

The influence of the process parameters of thermal modification on the mechanical properties of wood is non-linear and complicated. Thus, it is difficult to build a model that is both satisfactory and realistic. Artificial neural network (ANN) algorithms can approximate any complex non-linear relationship. Possessing self-learning functions and the ability to rapidly seek optimal solutions, artificial neural networks are commonly used for process optimization in material processing. For example, Sun *et al.* (2011) carried out process optimization of the modification of poplar veneers based on a neural network model. Tang *et al.* (2011) employed a neural network model to predict the relationship between the mechanical properties of wheat straw composite material and the process parameters. Zhang (2005) proposed a method for a wood drying process based on a neural network. Jiang *et al.* (2005) established a neural network model for the Chinese fir microstructure and its material characteristic. However, this modeling technique has only rarely been used in the process optimization of the thermal modification of wood.

In the present study, a neural network model was built to study the relationship between the process parameters of wood modification at high temperature and pressure, and the mechanical properties of the wood. The inputs included the temperature, treatment time, and relative humidity of thermal modification. The BP and RBF models were established for the prediction of the final wood properties and the prediction results of two models were compared. This study was aimed at using artificial neural network models to simulate and predict the influences of process parameters on the mechanical properties of thermally modified wood. On this basis, the relationship between the process parameters of thermal modification and the mechanical properties of the modified wood can be established. Thus, a scientific basis is laid for the exploration of the optimal process parameters and reasonable application of thermally modified wood.

THEORETICAL BASIS OF NEURAL NETWORK MODELING

Brief Introduction of Neural Network

An artificial neural network is a data treatment model whose construction is inspired by biological neural networks. Artificial neural networks have become a mature type of algorithm applied in every sector of production. Artificial neural networks exhibit powerful pattern recognition and data fitting capacity (Bhuvaneswari and Sabarathinam

2013). There are a variety of neural networks that have been found to be useful for resolving different problems, and their excellent non-linear approximation performance makes them outstanding tools in many applications (Hagan and Demuth. 2002).

BP Neural Network

BP neural networks are the core of feedforward neural networks and the essence of the entire artificial neural networks, which are widely used in classification, recognition, approximation, regression, and compression. The BP neural network is a multi-layer perceptron consisting of several hidden layers in addition to an input layer and an output layer. Different layers are related to each other through full connections, but there are no connections between the neurons of a particular layer. This multi-layer design enables the mining of more information for more complex tasks from the input by using a BP neural network. The BP neural network generally uses a Sigmoid or linear function as its transfer function. Typically, the Sigmoid function is adopted as the transfer function for the hidden layer and linear function is for the output layer (Tiryaki and Aydın 2014). In BP neural networks, data are transmitted from the input layer and through the hidden layer in a downward manner. When the weight of the network is trained, the connection weights of the network are modified from the output layer towards the upper layers in an upward manner; this is the direction along which the error can be reduced. With continued learning, the final error gradually decreases. However, the BP neural network is a universal approximation network with slow learning speed and cannot meet real-time requirements (Datta and Banerjee 2006).

RBF Neural Network

The RBF neural network has been extensively applied in different fields due to its simple structure, high convergence speed, and its ability to approximate any non-linear function. The RBF network is a feedforward network consisting of 3 layers. The first layer is the input layer, where the number of nodes is equal to the dimensionality of the input data. The second layer is the hidden layer, where the number of nodes depends on the complexity of the problem.The third layer is the output layer, where the number of nodes is equal to the dimensionality of the output data. The RBF network is different from the multi-layer perception in that each layer fulfills different functions. The hidden layer is non-linear and uses RBF as the basis function. In this way, the vector space of the input is converted into the space of the hidden layer such that the linearly inseparable problem becomes linearly separable, and the output layer is linear.

EXPERIMENTAL

Materials and Methods

Sawn *Larix gmelinii*timber with thickness 22 mm was chosen for the experiments. The processing temperature was 120 to 210°C, the pressure was 0.1 to 0.9 MPa, and the processing time was 0.5 to 3h in saturated or superheated steam. The processed timber was placed in a controlled environment with (65±3)% relative humidity(RH) at(20±2)°C. The mechanical properties were determined after the equilibrium moisture content was reached (compressive strength parallel to grain; bending strength, MOR; modulus of elasticity, MOE; hardness of transverse section; and hardness of longitudinal section).

Mechanical property determinations were carried out according to the Method of Testing in Compressive Strength Parallel to Grain of Wood (GB/T1935-2009; Jiang *et al.*2009), the Method of Testing in Bending Strength of Wood (GB/T1936.1-2009; Luo *et al.*2009a), the Method for Determination of the Modulus of Elasticity in Static Bending of Wood (GB/T1936.2-2009; Luo *et al.*2009b), and with the Method of Testing in Hardness of Wood (GB/T1941-2009; Wang *et al.*2009). The arithmetic mean of 3 parallel experiments was calculated for each determination and reported as the final result.

Results and Analysis

The mechanical properties of the wood were detected, and the results are shown in Table 1.

Table 1. Process Parameters of Thermal Modification and Mechanical Properties of *Larix gmelinii*

Experiment Temperature (°C)	Time (h)	RH (%)	Average of Sample Data				
			Compressive Strength Parallelto Grain (MPa)	MOR (MPa)	MOE (GPa)	Hardness of Transverse Section (MPa)	Hardness of Longitudinal Section (MPa)
Untreated wood			33.8	68.6	9.135	12.04	13.61
120	0.5	0	39.2	67.4	9.093	14.12	15.56
120	0.5	40	39.1	65.3	9.038	13.02	14.69
120	0.5	60	38.0	69.7	9.1	14.67	15.08
120	0.5	100	36.7	67.2	8.845	14.65	15.45
120	1	0	38.4	67.8	8.649	13.98	14.36
120	1	40	37.6	66.4	8.752	12.98	15.59
120	1	60	38.6	67.8	9.245	13.78	15.32
120	1	100	38.1	63.1	7.895	14.55	14.23
120	2	0	39.5	66.9	9.074	13.33	14.23
120	2	40	38.6	68.2	8.945	12.55	14.58
120	2	60	36.5	65.2	8.854	13.25	14.89
120	2	100	41.9	63.2	8.933	13.36	14.56
120	3	0	37.5	66.5	8.9	13.56	14.78
120	3	40	39.8	67.6	8.963	13.45	14.45
120	3	60	37.6	66.6	8.745	13.01	14.69
120	3	100	38.9	64.2	8.745	12.45	14.78
140	0.5	0	36.7	66.7	8.978	14.69	15.56
140	0.5	40	36.9	67.5	8.845	13.06	15.02
140	0.5	60	35.8	66.8	9.155	14.02	14.23
140	0.5	100	38.4	65.3	8.877	15.02	15.01
140	1	0	37.4	66.5	9.179	14.16	15.68
140	1	40	36	64.5	9.137	13.05	15.01
140	1	60	37.2	67.2	9.024	13.49	15.17
140	1	100	37.5	63.1	8.823	13.45	15.48
140	2	0	37.9	66.3	8.823	13.54	14.69
140	2	40	38.5	65.7	8.852	14.69	14.58
140	2	60	37.6	67.1	8.799	13.99	14.74
140	2	100	35.5	62.7	8.9	14.28	15.63
140	3	0	36.9	65.4	8.811	14.39	14.23
140	3	40	38.9	64.6	8.934	13.23	14.56
140	3	60	38.2	65.5	8.654	14.23	13.65
140	3	100	39.2	62.1	8.798	13.56	14.02

160	0.5	0	36.9	66.3	8.788	14.89	14.99
160	0.5	40	39.1	66.9	9.011	14.87	14.36
160	0.5	60	37.1	66.3	8.745	14.58	14.78
160	0.5	100	38.9	65.8	8.712	14.69	15.69
160	1	0	39.1	62.4	8.679	13.42	14.56
160	1	40	39.7	61.4	8.645	14.09	15.3
160	1	60	37.8	62.2	8.798	14.69	15.9
160	1	100	38.7	62.8	8.679	13.58	15.63
160	2	0	35.9	62.2	8.727	14.63	13.92
160	2	40	35.8	62.1	8.557	14.02	14.17
160	2	60	36.6	63.1	8.687	15.17	14.28
160	2	100	38.2	60.9	8.611	14.65	15.09
160	3	0	37.2	61.9	8.611	13.65	14.36
160	3	40	39.1	61.5	8.534	13.47	14.56
160	3	60	39.5	60.8	8.601	13.58	13.89
160	3	100	37.3	60.5	8.552	13.69	14.36
180	0.5	0	38.9	65.9	8.601	15.21	14.03
180	0.5	40	39.1	65.3	8.689	15.98	14.56
180	0.5	60	37.6	66.1	8.645	16.01	13.97
180	0.5	100	36.1	65.7	8.599	14.32	14.33
180	1	0	38.2	65.4	8.623	15.09	13.79
180	1	40	39.4	64.9	8.645	14.98	14.25
180	1	60	37.6	66.3	8.579	15.45	14.08
180	1	100	38.1	64.8	8.545	14.33	13.64
180	2	0	39.5	65.1	8.574	14.65	13.69
180	2	40	38.7	65.8	8.6	14.13	13.59
180	2	60	38.2	64.5	8.532	13.99	14.49
180	2	100	37.1	64.2	8.544	15.1	13.54
180	3	0	38.1	64.1	8.6	14.21	14.06
180	3	40	37.5	64.2	8.541	13.99	14.21
180	3	60	37.8	64.8	8.456	14.58	13.98
180	3	100	38.5	63.8	8.499	14.99	13.69
200	0.5	0	36.5	62.1	8.483	12	13.6
200	0.5	40	35.4	60.6	8.475	11.96	12.99
200	0.5	60	35.1	59.9	8.399	11.45	13.21
200	1	0	34.5	61.9	8.422	11.69	12.98
200	1	40	35.8	60.8	8.489	11.46	12.64
200	1	60	34.1	61.2	8.321	11.54	12.35
200	2	0	34.6	61.2	8.369	11.99	13.02
200	2	40	35.4	60.8	8.354	11.15	12.69
200	2	60	34.5	60.5	8.211	10.65	12.49
200	3	0	34.1	60.9	8.249	10.68	12.73
200	3	40	34.2	59.8	8.231	11.05	12.57
200	3	60	33.8	58.2	8.011	10.22	12.37
210	0.5	0	34.1	50.1	7.856	10.23	10.98
210	0.5	40	33.2	50.8	7.789	10.59	9.98
210	0.5	60	32.1	49.9	7.865	10.55	10.23
210	1	0	33.9	50.6	7.765	10.21	10.65
210	1	40	32.9	49.8	7.712	9.98	10.21
210	1	60	32.8	48.9	7.498	10.01	10.65
210	2	0	32.9	49.1	7.689	9.98	9.64
210	2	40	32.5	49.5	7.712	9.65	9.35
210	2	60	31.8	49.6	7.623	10.03	9.67
210	3	0	31.5	47.8	7.5	9.21	8.91
210	3	40	30.5	46.5	7.412	9.1	8.21
210	3	60	30.8	45.1	7.321	9.03	8.99

The influence of the thermal modification process parameters on the compressive strength parallel to the grain was considered. Compared with unmodified wood, the compressive strength parallel to the grain in the modified wood increased overall. Temperature had a more significant influence than the treatment time. As the temperature and relative humidity continued to rise, the rate of increase decreased;200 °C was the dividing line after which the compressive strength parallel to the grain decreased slightly, which is consistent with the results drawn by Ding *et al.* (2011)

The influence of the thermal modification process parameters on the bending strength was as follows: the bending strength of the thermally modified wood decreased significantly compared to that of the unmodified wood. Below 200°C, such variation was milder, but there was an abrupt change as the temperature exceeded 200°C. The influence of temperature was greater than that of the treatment time (Ding 2010).

The influence of the process parameters of thermal modification on the modulus of elasticity was as follows: compared with that of unmodified wood, the modulus of elasticity of the modified wood generally decreased to a small extent. Moreover, the influence of temperature was greater than that of the treatment time. The relative humidity had a less significant effect. The rate of decrease increased at temperatures above 200°C.

The influence of thermal modification process parameters on hardness was as follows: with increasing treatment temperature and prolonged treatment time, the hardness of the modified wood first increased and then decreased compared to that of unmodified wood. The relative humidity had a smaller influence. The hardness dropped considerably at temperatures above 200°C.

The above results indicate that thermal modification had an influence on the main performance indicators of wood, including the compressive strength parallel to the grain, bending strength, modulus of elasticity, and hardness (though the degree of the change in hardness was insignificant). The influence of high-pressure steam on the mechanical properties of wood was greater than that of normal-pressure steam, but not significantly. The influence of temperature on thermal modification was more significant than that of treatment time. As long as appropriate thermal modification process parameters are chosen, the decrease in mechanical properties will not influence the use of thermally modified wood (Tiryaki and Hamzaçebil 2014).

RESULTS AND DISCUSSION

Samples for Model Construction

The goal of model construction was to study*Larix gmelinii* thermal modification process at high temperature and pressure as affected by three important parameters(time, temperature, and relative humidity) and to determine their relationships between the five important mechanical properties of wood(compressive strength parallel to grain, bending strength, modulus of elasticity, hardness of the transverse section, and hardness of the longitudinal section).To verify the original data, the neural network model was used for the sample data under the condition of each in 3 groups(a total of 264 sets of data); then, 100 groups were randomly chosen as the training data and 30 groups were chosen as testing data.

Parameter Selection for Model Construction

Several factors influence the thermal modification of wood at high temperature and pressure, including temperature, time, pressure, humidity, the protective medium of thermal modification, and the wood species. Among these factors, humidity has a certain connection with pressure. Higher humidity facilitatessteam of greater pressure. A large number of experiments showed that thermal modification temperature had the greatest influence on the material. Treatment effectssimilar to those obtained under high temperatureswere barely achieved by prolonging the treatment time alone at low temperature. In the present study, the input parameters of model were the 3 parameters with the greatest influences: time, temperature, and relative humidity. The outputs were the five indicators of the mechanical properties of the wood. The general framework of the model, showing the relationships between the process parameters and the mechanical properties, is shown in Fig. 1.

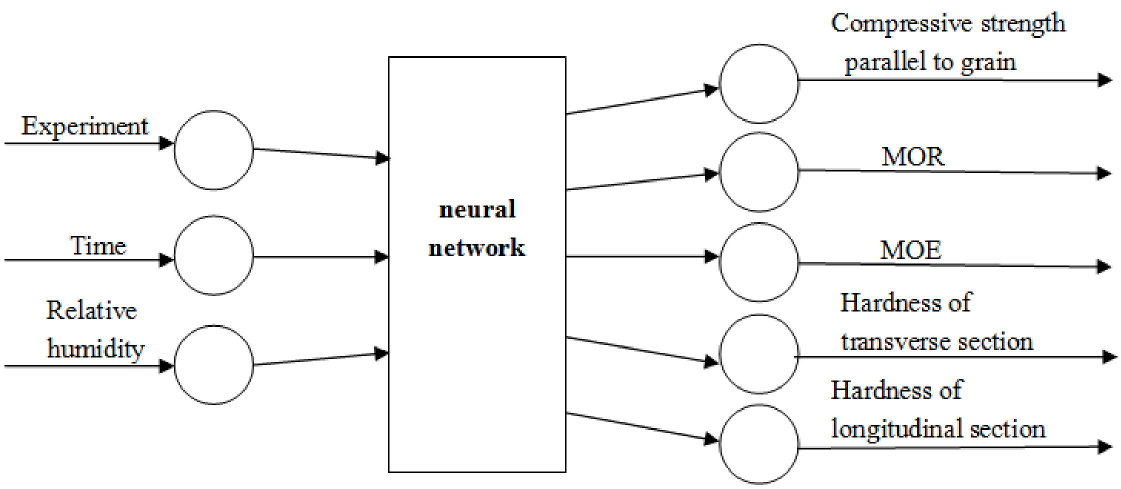

Fig. 1. The relational model between the process parameters of thermal modification and the mechanical properties of the wood

Construction of Neural Network Model and Checking

Construction of BP neural network model and checking

MATLAB software was employed for the construction and checking of the neural network model. Due to the differences in units, the data used for modeling were pretreated before modeling. Normalization was carried out for all training and testing data. It should be kept in mind that anti-normalization was necessary after model construction (Sola and Sevilla1997). Based on the experimental data collected, the BP neural network was configured with three input layer nodesand five output layer nodes. The number of hidden layers was adjusted based on the experimental situation. After repeated experiments, the optimal number of hidden layer nodes was set to 12. The tansig function was adopted as the function of the hidden and the output layers, and the trainlm function was adopted as the training function. The maximum number of iterations was 10000, and the training precision was 0.00001. If there was difficulty in convergence during training, the precision was adjusted to 0.0001. The initial learning rate was set to 0.1. The neural network was constructed using the newff()command in the toolkit. Then, the training of the network began. The results of the training are given below:

TRAINLM, Epoch 0/10000, MSE 0.55001/1e-005, Gradient 41.2702/1e-010

TRAINLM, Epoch 50/10000, MSE 0.000288959/1e-005, Gradient 0.0260177/1e-010
TRAINLM, Epoch 81/10000, MSE 9.69248e-006/1e-005, Gradient 0.0551585/1e-010
TRAINLM, Performance goal met.

The computation of the neural network ended after 81 iterations, when the preset precision was reached. The experiments indicated that the model had a fast convergence speed. The training procedures are shown in Fig. 2.

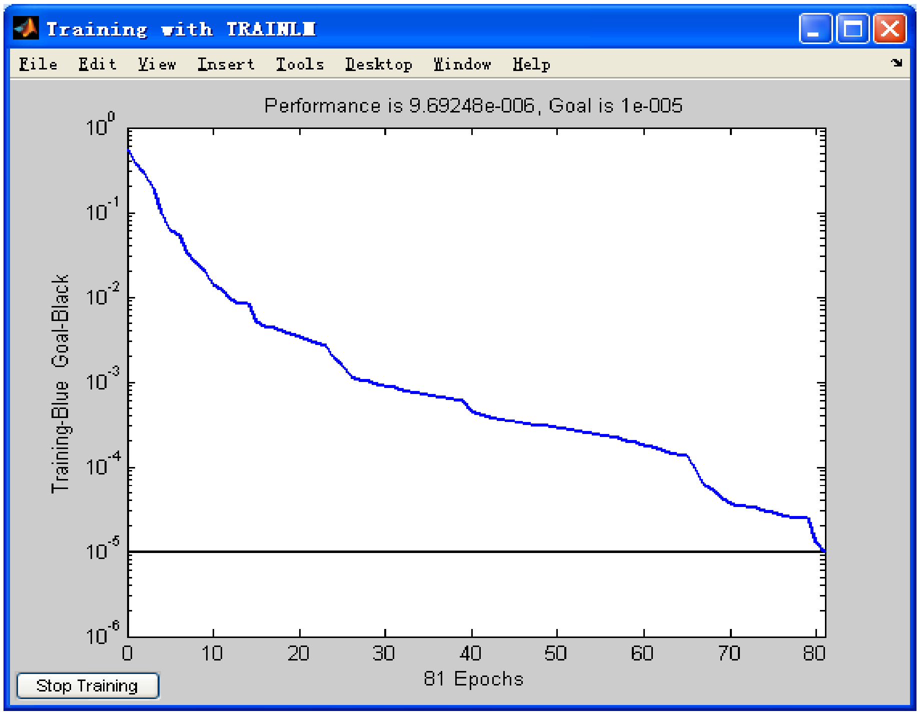

Fig. 2. BP network training results

After training ended, 30 sampling points were randomly selected to validate the efficiency of the network prediction. Table 2 presents the measured values and the predicted values of the mechanical properties after thermal modification in some samples and the corresponding prediction errors. As indicated by Table 2, the BP neural network model established in this study was effective predicting the mechanical properties of the thermally modified wood.

The maximum absolute value relative error was smaller than 9%, and the average relative error was 4.4%. Thus, the basic requirements for the prediction of the relationship between the thermal modification process parameters and the mechanical properties were satisfied.

Figure 3 is a comparison of the measured values of 30 samples and the values predicted by the BP neural network. Except for some large errors in individual samples, the sample values output from most networks were close to the measured values. This indicates that the BP neural network model established in this study effectively reflected the real system and had good generalization ability.

Table 2. Thermal Modification of Wood's Mechanical Properties: Test Values Compared with the BP Neural Network Predicted Values

Experiment Temperature (°C)	Time (h)	RH (%)	Project	Compressive Strength Parallel to Grain (MPa)	MOR (MPa)	MOE (GPa)	Hardness of Transverse Section (MPa)	Hardness of Longitudinal Section (MPa)
			Test Values	35.10	59.90	8.40	11.45	13.21
200	0.5	60	PredictedValues	34.94	58.89	8.38	11.38	12.11
			Error(%)	-0.45	-1.69	-0.27	-0.61	-8.35
			Test Values	34.50	61.90	8.42	11.69	12.98
200	1	0	Predicted Values	35.25	62.16	8.41	11.82	12.97
			Error(%)	2.17	0.42	-0.13	1.08	-0.08
			Test Values	37.80	64.80	8.46	14.58	13.98
180	3	60	Predicted Values	34.75	64.12	8.53	14.00	14.28
			Error(%)	-8.08	-1.05	0.82	-3.97	2.16
			Test Values	35.40	60.60	8.48	11.96	12.99
200	0.5	40	Predicted Values	34.75	59.22	8.42	11.97	13.46
			Error(%)	-1.85	-2.27	-0.61	0.11	3.59
			Test Values	36.50	62.10	8.48	12.00	13.60
200	0.5	0	Predicted Values	37.87	59.86	8.45	12.03	13.06
			Error(%)	3.76	-3.60	-0.35	0.24	-3.95
			Test Values	35.80	60.80	8.49	11.46	12.64
200	1	40	Predicted Values	35.28	61.77	8.44	11.79	13.67
			Error(%)	-1.46	1.60	-0.61	2.90	8.14
			Test Values	38.50	63.80	8.50	14.99	13.69
180	3	100	Predicted Values	35.25	64.16	8.51	14.47	14.13
			Error (%)	-8.44	0.57	0.15	-3.45	3.19
			Test Values	38.20	64.50	8.53	13.99	14.49
180	2	60	Predicted Values	34.75	64.72	8.53	13.52	14.13
			Error (%)	-9.04	0.34	0.00	-3.33	-2.47
			Test Values	39.10	61.50	8.53	13.47	14.56
160	3	40	Predicted Values	37.87	64.68	8.54	14.69	14.55
			Error (%)	-3.14	5.17	0.08	9.07	-0.04
			Test Values	37.50	64.20	8.54	13.99	14.21
180	3	40	Predicted Values	35.28	64.09	8.53	13.72	14.49
			Error (%)	-5.93	-0.16	-0.12	-1.94	1.94

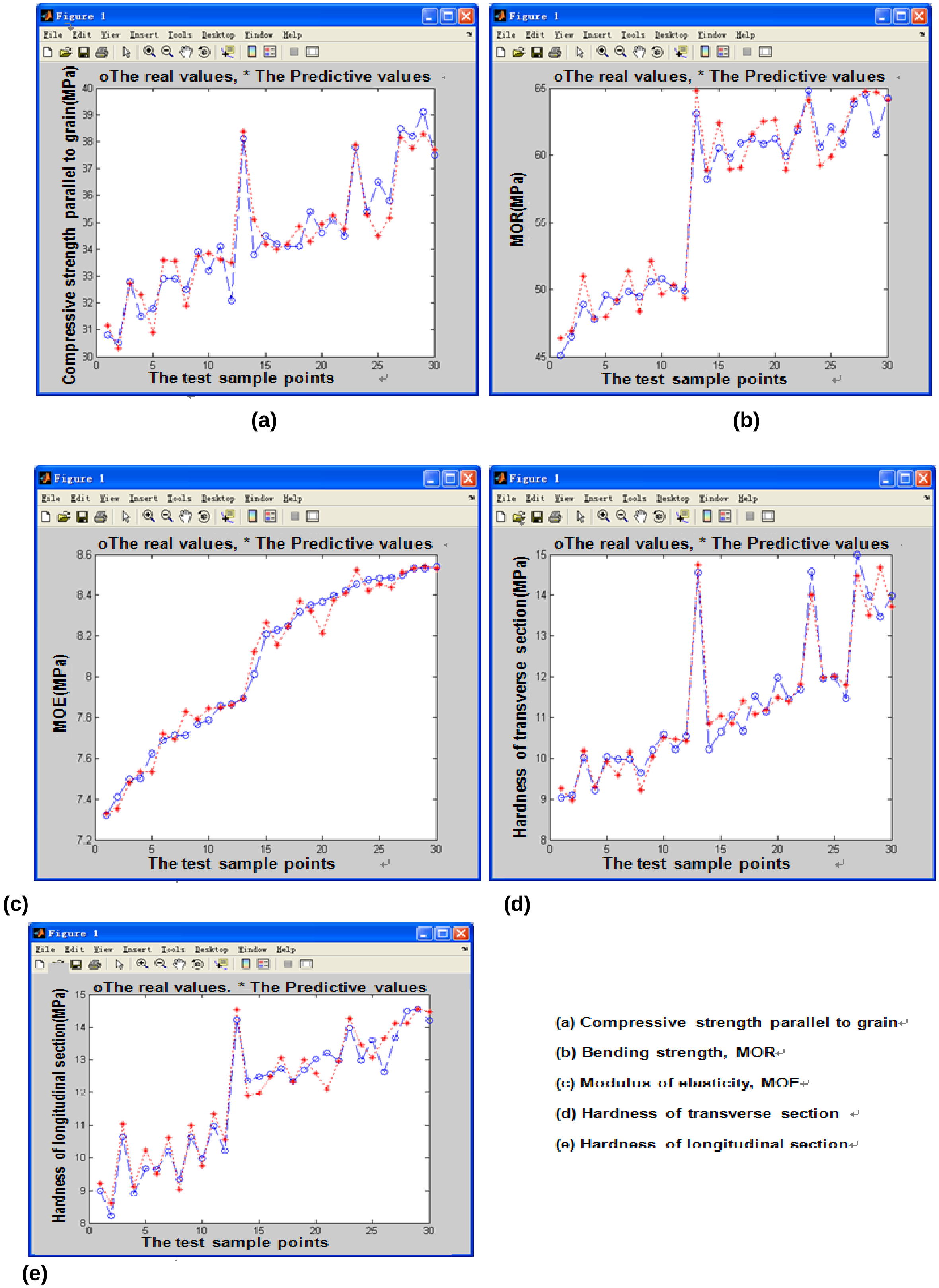

Fig. 3. BP network test sample points of the actual value compared with the predicted value curve

Establishment of RBF neural network and checking

For convenient comparison, the training samples and testing samples used in the RBF network were the same as those used in the BP network. The network parameters were configured as follows: the number of nodes in the input and the output layerswere the same as those in the BP networkat 3 and 5, respectively. The initial number of hidden layers was set to 10 and was adjusted automatically depending on the demands. The precision of network training was set as 0.00001. The function of the RBF network was set as net=newrb (p, t, goal, spread, M, D). Moreover, special attention should be given to the setting of the 'spread' factor. For functions with large variation, if the 'spread' is too large, the result of network approximation could be too rough. For functions with mild variation, too small a spread may lower the smoothness of the approximated function, leading to overlearning and decreasing generalization ability (Fredric 2003). As validated in this study, the spread was finally set as 1.6, at which optimal comprehensive network performance was achieved. As shown in Fig. 4, the computation ended after only 29 iterations, with the preset precision reached.

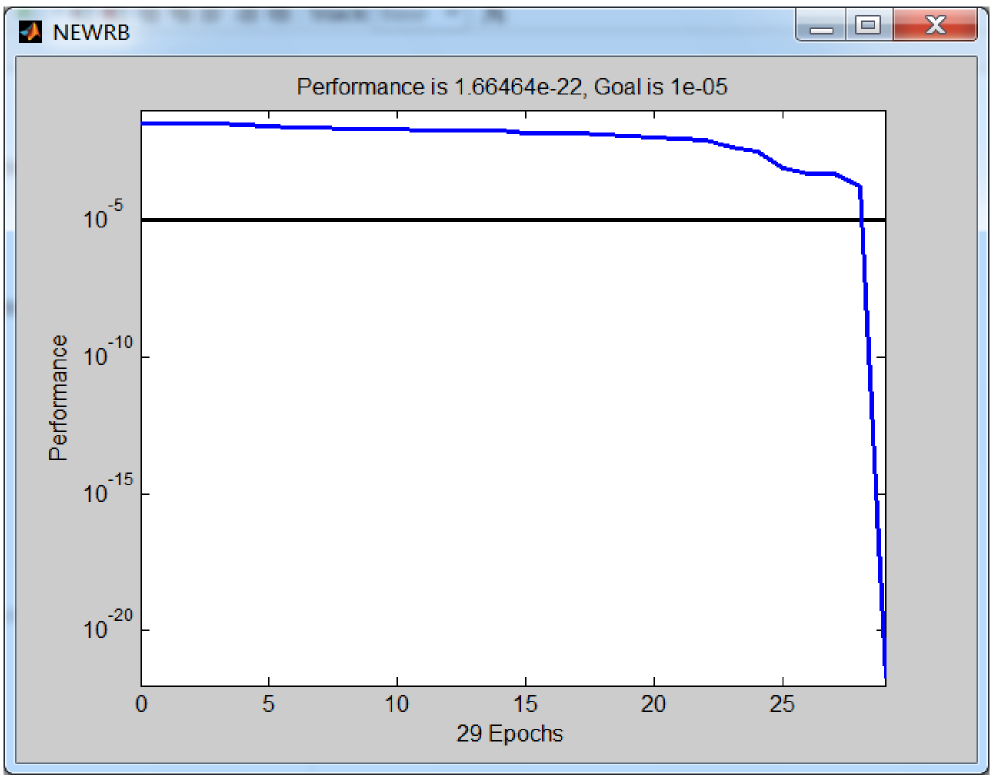

Fig. 4. RBF network training results

The RBF network performance was validated by applying the same 30 sampling points as in the BP network for the predictions. The measured and predicted values of some testing samples, and the corresponding relative errors, are given in Table 3. The maximum absolute value of the relative error between the 30 samples'measured and predicted values was 6.24% and the average relative error was 2.4%. This indicates that the model could effectively fit the predicted data.

Table 3. Thermal Modification of Wood's Mechanical Properties: Test Values Compared with the RBF Neural Network Predicted Values

Experiment Temperature (°C)	Time (h)	RH (%)	Project	Compressive Strength Parallel to Grain (MPa)	MOR (MPa)	MOE (GPa)	Hardness of Transverse Section (MPa)	Hardness of Longitudinal Section (MPa)
			Test Values	35.10	59.90	8.40	11.45	13.21
200	0.5	60	Predicted Values	34.78	59.18	8.37	10.77	12.87
			Error (%)	-0.91	-1.20	-0.33	-5.94	-2.55
			Test Values	34.50	61.90	8.42	11.69	12.98
200	1	0	Predicted Values	35.23	60.89	8.39	11.57	13.16
			Error (%)	2.13	-1.63	-0.34	-0.99	1.41
			Test Values	37.80	64.80	8.46	14.58	13.98
180	3	60	Predicted Values	37.80	64.76	8.47	14.18	14.31
			Error(%)	-0.01	-0.06	0.20	-2.71	2.33
			Test Values	35.40	60.60	8.48	11.96	12.99
200	0.5	40	Predicted Values	35.32	60.57	8.47	11.53	13.10
			Error(%)	-0.22	-0.04	-0.02	-3.57	0.86
			Test Values	36.50	62.10	8.48	12.00	13.60
200	0.5	0	Predicted Values	36.41	61.52	8.47	11.59	13.39
			Error (%)	-0.25	-0.94	-0.21	-3.43	-1.54
			Test Values	35.80	60.80	8.49	11.46	12.64
200	1	40	Predicted Values	35.16	60.54	8.39	11.53	13.01
			Error (%)	-1.79	-0.42	-1.19	0.61	2.91
			Test Values	38.50	63.80	8.50	14.99	13.69
180	3	100	Predicted Values	38.41	64.46	8.53	15.46	13.88
			Error (%)	-0.23	1.03	0.31	3.14	1.42
			Test Values	38.20	64.50	8.53	13.99	14.49
180	2	60	Predicted Values	38.29	64.42	8.55	14.19	14.14
			Error (%)	0.25	-0.13	0.19	1.41	-2.39
			Test Values	39.10	61.50	8.53	13.47	14.56
160	3	40	Predicted Values	39.09	62.12	8.59	13.44	14.40
			Error (%)	-0.02	1.00	0.68	-0.24	-1.11
			Test Values	37.50	64.20	8.54	13.99	14.21
180	3	40	Predicted Values	37.46	64.31	8.54	14.10	14.15
			Error (%)	-0.10	0.17	-0.04	0.78	-0.41

Figure 5 shows the comparison of the measured values *versus* the predicted values of 30 testing samples. The model realistically reflected the real values of the testing samples. Thus, the RBF neural network can be applied in the prediction of the mechanical properties of thermally modified wood with high precision.

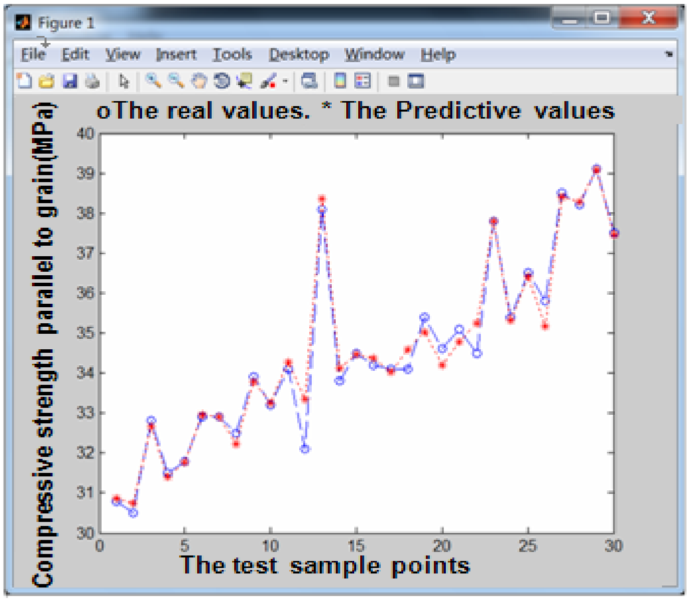
Figure 1
File Edit View Insert Tools Desktop Window Help
oThe real values. * The Predictive values
Compressive strength parallel to grain(MPa)
The test sample points

(a)

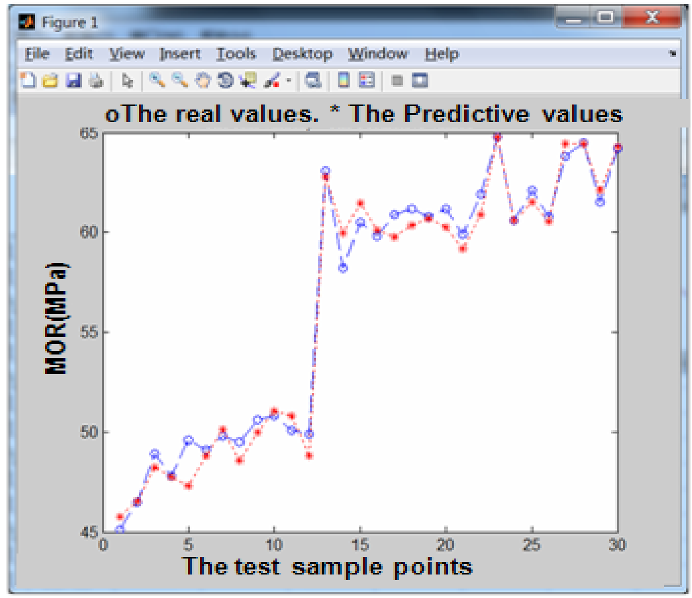
Figure 1
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oThe real values. * The Predictive values
MOR(MPa)
The test sample points

(b)

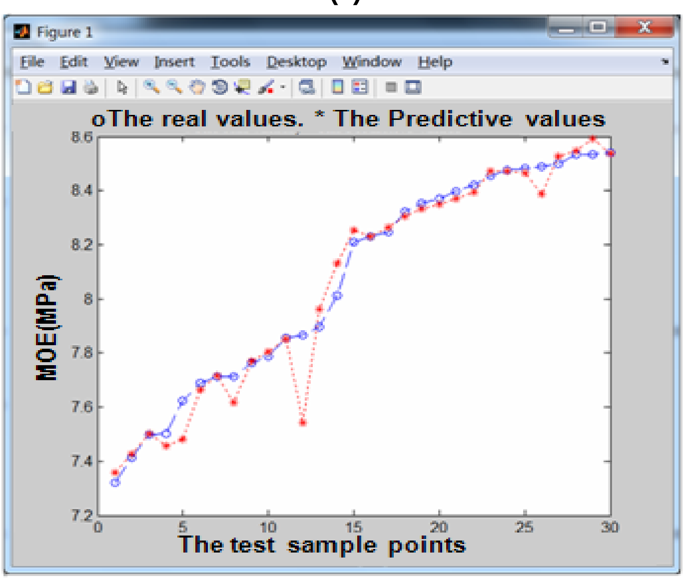


Figure 1
File Edit View Insert Tools Desktop Window Help
oThe real values. * The Predictive values
MOE(MPa)
The test sample points

(c)

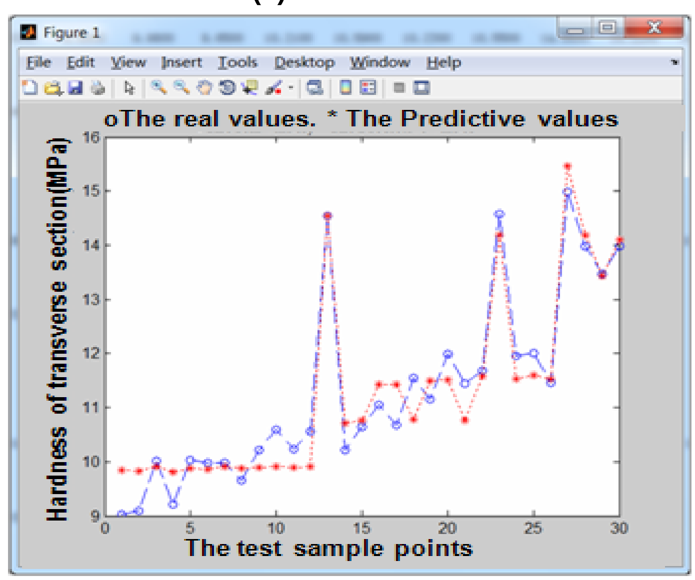
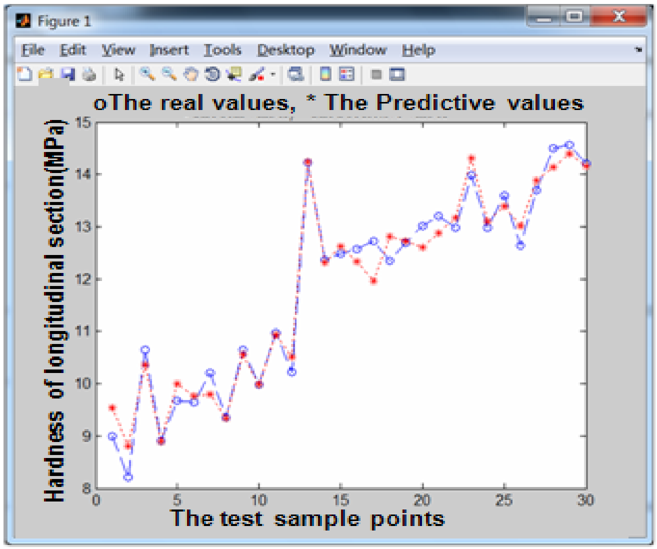


Figure 1
File Edit View Insert Tools Desktop Window Help
oThe real values. * The Predictive values
Hardness of transverse section(MPa)
The test sample points

(d)

(e)



(a) Compressive strength parallel to grain
(b) Bending strength, MOR
(c) Modulus of elasticity, MOE
(d) Hardness of transverse section
(e) Hardness of longitudinal section

Fig. 5. RBF network test sample points the actual value compared with the predicted value curve

Summary of the performance of BP and RBF neural networks

Models were established for the prediction of the mechanical properties of thermally modified wood based on BP and RBF neural networks, respectively, in this study. The maximum relative error between the output of the BP neural network over between testing samples and the measured values was 9.2%, the minimum relative error was 0.12%, and the average relative error was 4.4%. The maximum relative error between the output of the RBF model and the measured values was 6.24%, the minimum relative error was 0.10%, and the average relative error was 2.4%.

The same testing samples and precision were set for each of the two models. The BP network converged after 81 iterations, while the RBF network reached the preset precision after only 29 iterations. The number of nodes in the hidden layer of the RBF neural network could be determined by training. However, the number of nodes in the hidden layer of the BP neural network had to be determined upon initialization. If the number of hidden layers was repeatedly changed until reaching the preset precision, the modeling time would be longer and the difficulty would be higher than that of that RBF neural network.

In summary, the RBF neural network was easier and more convenient to establish than the BP neural network. The former had stronger generalization ability and better prediction performance. With more powerful numerical approximation ability and higher superiority in its comprehensive performance, the RBF neural network can be regarded as preferable(Song and Zhang2001).

Optimization and Analysis of Process Parameters of Wood Thermal Modification in Light of the Influence on Mechanical Properties

Based on the experimental data collected, a relational model of the process parameters of the thermal modification of wood was established. The model was used to predict the mechanical properties of thermally modified wood. Moreover, the model showing the relationship between the mechanical properties of the thermally modified wood and the process parameters was established. Thus, a scientific basis was provided for the optimization of the thermal modification process parameters in light of their influence on the mechanical properties.

The inverse model showing the relationships between the thermal modification process parameters and the mechanical properties of wood was built using the experimental data shown in Table 1. The RBF neural network, with its simple structure and good generalization ability, was selected for further modeling. The input parameters of the network were five main mechanical properties: the compressive strength parallel to grain, bending strength, modulus of elasticity, hardness of transverse section, and hardness of longitudinal section. The output parameters were three important thermal modification parameters: the temperature, time, and relative humidity.

Figure 6 shows the measured and predicted temperature values corresponding to the desired mechanical properties of the thermally modified wood. The maximum absolute value of the relative error was 6.49% and the minimum relative error was 0.34%. The average relative error was 1.35%.

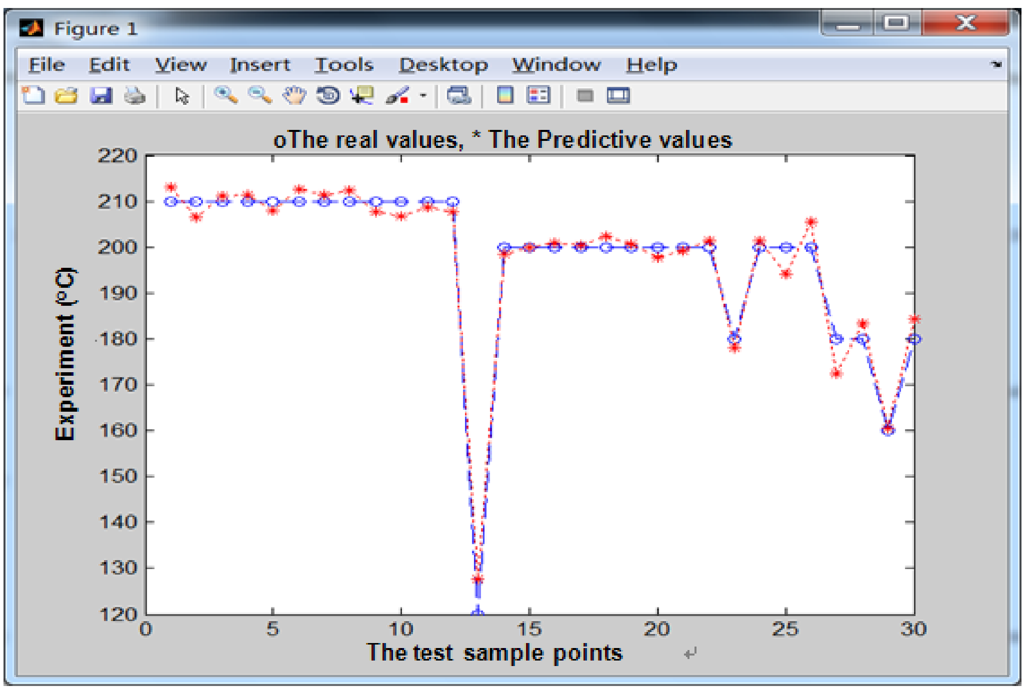


Fig. 6. The comparison of network output and the actual output temperature

Figure 7 shows the measured and predicted values of time corresponding to the desired wood mechanical properties. The maximum relative error between the measured and the predicted values was 9.38%. The minimum relative error was 1.88%, and the average relative error was 3.44%.

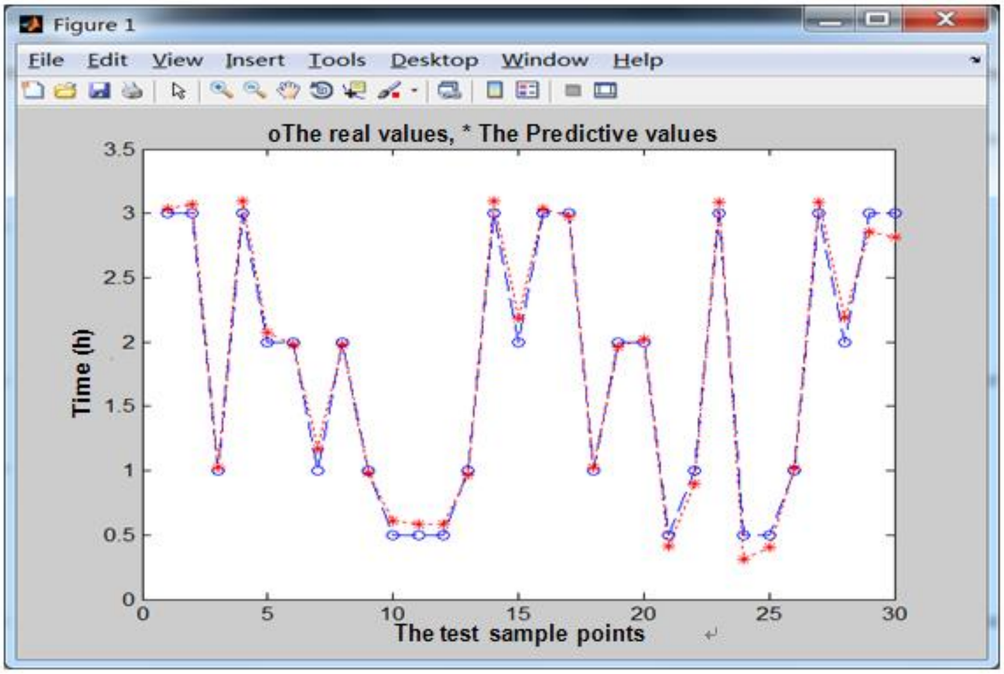


Fig. 7. The comparison of network output and the actual output time

Figure 8 shows the measured and predicted values of relative humidity corresponding to the desired wood mechanical properties. The maximum relative error was 9.08%, the minimum relative error was 0.14%, and the average relative error was 5.68%.

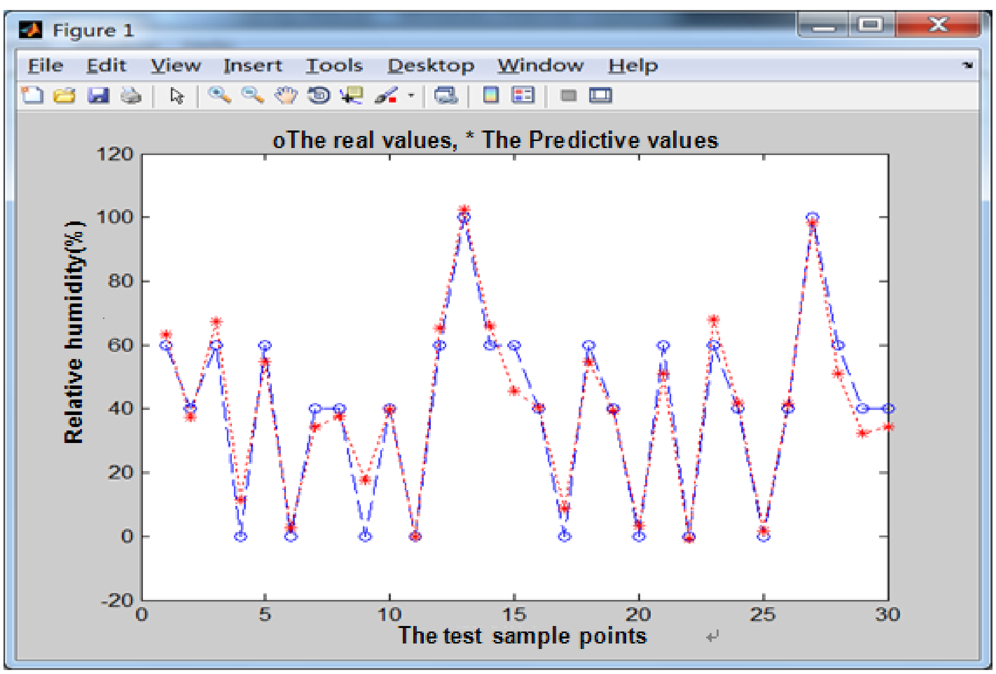


Fig. 8. The comparison of network output and the actual output relative humidity

This model describes the relationships between the mechanical properties of thermally modified wood and the process parameters (Kerh and Yee2000). Using the mechanical properties of the modified wood as the inputs and the process parameters as the outputs, the inverse model can provide the process parameter values corresponding to the desired mechanical properties. The analysis indicates that the process parameters can be inversely optimized according to the target wood properties. In this way, the thermal modification process can be optimized to achieve the desired mechanical properties, which is very important for the reasonable utilization of wood, improvement of the efficiency of thermal modification, and reduction of experiment duration.

CONCLUSIONS

1. *Larix gmelinii* was subjected to high-temperature, high-pressure thermal modification. Variations in the mechanical properties of the wood after thermal modification were explored. The process parameters could be optimized in terms of their influence on the mechanical properties, which providesa scientific basis for the reasonable use of *Larix gmelinii*.
2. An artificial neural network model was employed in this study to discuss the influences of time, temperature, and relative humidity on the mechanical properties of thermally modified wood. The developed network exhibited high precision and good generalization ability.It was a novel attempt to use the artificial neural network model for the thermal modification of wood.
3. A comparison was made between the BP and RBF neural network models. The RBF neural network model had higher comprehensive performance in predicting the relationships between the process parameters and the mechanical properties of the wood.
4. The inverse neural network model established in this study can be used to inversely optimize the process parameters with high precision. If people want to establish relational and inverse models between the process parameters and mechanical properties of other wood species, they would only need to input the relevant data into the developed network.
5. In actual production, the thermal modification process parameters can be optimized according to the desired wood product applications and mechanical property requirements, which allows for more scientific, rational use of wood.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the financial support from the National Natural Science Foundation of China (Grant No. 30871981).

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Article submitted: April 15, 2015; Peer review completed: July 6, 2015; Revised version received: July 7, 2015; Second revised version received: July 13, 2015; Accepted: July 14, 2015; Published: July 27, 2015.
DOI: 10.15376/biores.10.3.5758-5776