THE USE OF AN ARTIFICIAL NEURAL NETWORK FOR MODELING THE MOISTURE ABSORPTION AND THICKNESS SWELLING OF ORIENTED STRAND BOARD

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In this study, an artificial neural network (ANN) approach was employed for modeling the moisture absorption (MA) and thickness swelling (TS) properties of oriented strand board (OSB) in various applications. A series of ANN models were developed for the analysis and prediction of correlations between processing parameters and MA and TS of OSB. An ANN model was found for modeling the effects of OSB treatment variables on the MA and TS. The required data for training and testing of the model were obtained from the experimental results of Salay (2010). In designing this model, the MA and TS of the OSB were determined using OSB treatment variables, including board layup type, resin type, application rate of resin, and wax content. When experimental data and results obtained from the ANN were compared by regression analysis using Matlab, it was determined that both groups of data (test and train) were consistent. It was demonstrated that the well-trained feed forward and back propagation multilayer ANN model is a powerful and sufficient tool for the prediction of MA and TS; therefore, by using ANN outputs, satisfactory results can be estimated, rather than measured and hence time and cost are reduced in all the required experimental activities.

Keywords: Artificial neural networks; Oriented strand board; Moisture absorption; Thickness swelling; Modeling

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INTRODUCTION

Wood-based composites, such as OSB and plywood have been slowly replacing solid wood in many structural applications. OSB is utilized internationally in a wide array of applications, including commercial and industrial buildings, residential construction, packaging, furniture, and more. OSB has taken a major market share over the last two decades and is still driven by strong demand (APA 2005).

One of the most important factors negatively affecting the use of OSB is its moisture absorption properties. Under long-term cyclic humidity exposure conditions, wood-based composites lose their strength; therefore, to prevent moisture absorption and thickness swelling in OSB, its manufacturing variables must be modified (Wu 1999; Wu and Piao 1999; Moya et al. 2009).

Artificial neural networks (ANNs) are suitable for modeling various manufacturing functions due to their ability to learn complex non-linear and multivariable relationships between process parameters.

Modeling with Artificial Neural Networks

The concept of artificial neural networks was inspired by biological neural networks that consist of many nerve cells called neurons that process information in the brain. Its architecture essentially mimics the biological system of the brain.

The brain has many excellent characteristics such as parallel processing of information, a learning function, self-organization capabilities, and so forth. ANNs are information processing systems that are constructed through the imitation of the thinking and working abilities of the human brain (Oztemel 2006).

ANNs are capable of processing information in a parallel distributed manner, learning complex cause and effect relationships between input and output data, dealing with nonlinear problems, generalizing from known tasks or examples to unknown tasks. ANNs are good for tasks involving incomplete data sets, fuzzy or incomplete information, and for highly complex and ill-defined problems for which humans would usually decide on an intuitional basis. Moreover, they can be faster, cheaper, and more adaptable than traditional methods (Ceylan 2008). ANNs technology brings completely different concepts to computing. Neural computing is a non-algorithmic method of computing that is able to take full advantage of massive parallel computer architectures. ANNs learn an application; they are trained through examples rather than programmed by software (Ince 2004). In general, an ANN is made up of a large number of simple processing elements known as nodes or neurons, which are organized in layers. Each neuron is connected to other neurons by communica-tion links (connections), each of which has an associated numerical value known as a ‘‘weight’’. These weights determine the nature and strength of the influence between the interconnected neurons. Information is stored in the inter-neuron connections. A node has many inputs, but only one output.

The task of an artificial neuron j is simple and consists of receiving input signals (x_i) weighted by connection weights (w_{ij}) from neighboring neurons. The sum of these weighted signals provides the neuron's total or net input (net_j). Then, the activation threshold of neuron j represented by a positive or negative θ_j value is added to the net input, and through applying a mathematical function (f(.)) (generally non-linear and known as an activation or transfer function) to net input, output value y_j is computed and sent to other neurons. This process is summarized in Eq. 1 and Eq. 2 and illustrated in Fig. 1 (Palmer et al. 2006).

$$net_j = \sum_{i=1}^{n} x_i w_{ij} - \theta_j \tag{1}$$

$$y_j = f(net_j) \tag{2}$$

The basic structure of an ANN model usually consists of three distinctive layers: the input layer, where the data are introduced to the ANN, the hidden layer or layers, where the data are processed, and the output layer, where the results of the ANN are produced. The most popular and widespread artificial neural network architecture, called Multi-Layer Perceptron (MLP), is illustrated in Fig. 2. In this type of architecture, data are always transmitted from the input layer to the output layer (Haykin 1994).

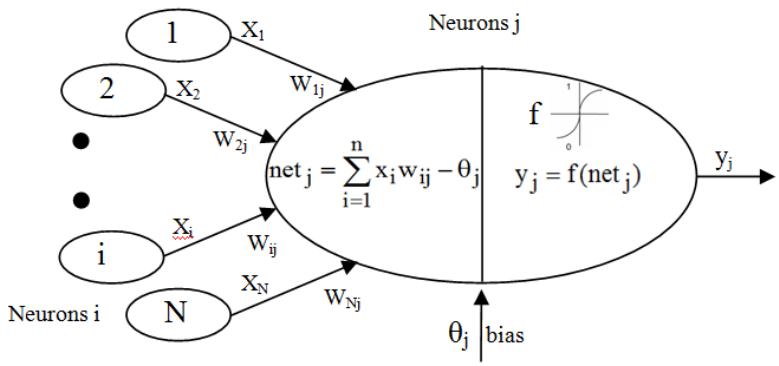

Fig. 1. General functioning of an artificial neuron

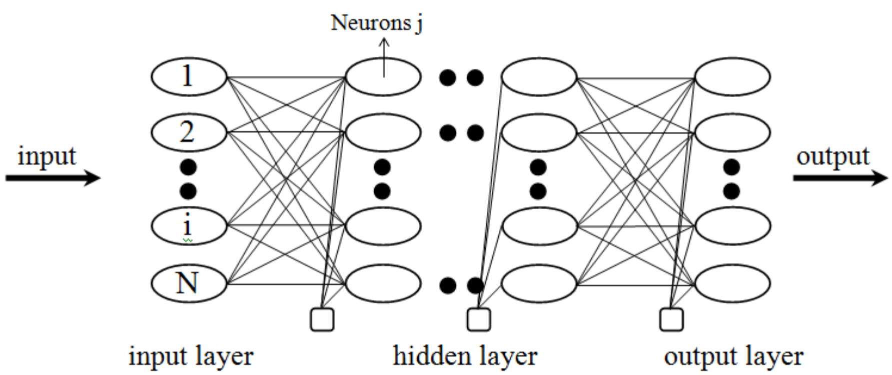

Fig. 2. A schematic description of artificial neural network configuration

Of the various models, the feed forward model of MLP is the most widely and successfully used in applied work and engineering problems, because it is capable of resolving a wide variety of problems, gives efficient results, and is easily provable mathematically (Schmoldt et al. 2000; Ibrahim et al. 2011).

To determine the optimum topology (architecture) and performance of the ANN, several parameters are adjusted, such as the number of neuron layers, the number of neurons in each layer, the transfer functions, the learning rule, learning coefficient ratio, the number of learning cycles, and the initialization of the weights and the biases (Cointe and Rouger 2005). The parameters, which are varied based on the complexity of the problem, are determined by the designer, and the choice of specific parameters is more or less subjective (Avramidis and Wu 2007).

ANNs are trained with known data and then tested with data not used in training. The error measurements between the desired vs. actual output produced by the ANN are performed in both training and testing processes by using various diagnostic methods (instruments). The instruments provide diagnostic information that can be considered as indications of the ANN's good or poor performance. Two well-known, common ANN instruments are the root mean square error (RMSE) and the mean absolute percentage error (MAPE). This process is summarized in Eqs. 3 and 4 (Sagıroglu et al. 2003).

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(t_i - td_i\right)^2} \tag{3}$$

$$\text{MAPE} = \frac{1}{N}\left(\sum_{i=1}^{N}\left[\left|\frac{t_i - td_i}{t_i}\right|\right]\right)\times 100 \tag{4}$$

In Eqs. 3 and 4, t_i is the actual output values, td_i is the neural network predicted values, and N is the number of objects.

A central phase in ANN analysis is 'learning' or 'training'. During this phase, the network learns by adjusting the relationships between its nodes. The input data are presented to the network, which is asked to modify the values of weights and biases so that it finds the desired output by successive iterations. 'Learning' occurs through thousands of iterations, in which the network's ability to predict the output correctly on the basis of the input data constantly improves through continuous adjustments of the relationships until convergence happens. The network compares the calculated output with the desired one and modifies the values of its weights to give minimal error (Grønholdt and Martensen 2005; Cointe and Rouger 2005). The finding of the set of weights that minimize the error between the neural network predicted values and observed values is called the training of the network (Pollard et al. 1992).

Usually, the neural network performance is tested with a testing set that is not part of the training set. The testing set can be seen as the representative cases of the general phenomenon. If the network performs well on the testing set, then it can be expected to perform well on the general case as well. Once the learning is done, the weights and the biases of the network are fixed and a new set of examples that are not in the training sample can be submitted (Cointe and Rouger 2005).

ANNs play an important role in predicting and modeling the linear and non-linear problems in different fields of engineering and have received considerable interest in recent years. Also ANN modeling has been used in the field of wood science; some studies are briefly mentioned as follows:

Khalid et al. (2008) designed an automatic wood recognition system based on artificial neural networks. Esteban et al. (2009) demonstrated that artificial neural networks can be used as an effective tool for identifying similar species with a high percentage of accuracy. Guangsheng and Li (2008) have shown that the artificial neural network is one of the best methods for wood quality forecasting.

Some studies have been performed by artificial neural network modeling for prediction of some mechanical properties of wood (Samarasinghe et al. 2007; Mansfield et al. 2007) and, for detection and classification of wood defects (Nordmark 2002 and Kurdthongmee 2008).

There also have been some studies in the field of wood-based composite materials. Artificial neural networks were used to predict the mechanical properties of particleboard (Fernández et al. 2008; Cook and Chiu 1997), to optimize the process parameters in a particleboard manufacturing process (Cook et al. 2000), and to detect of structural damage in medium density fiberboard panels (Long and Rice 2008). Esteban et al. (2010) presented artificial neural networks as a predictive method to determine moisture resistance of particle and fiber boards.

Some studies have been conducted on the use of artificial neural networks for classification and inspection of wood veneer (Drake and Packianather 1998; Packianather and Drake 2005; Castellani and Rowlands 2008; Packianather 1997; Packianather and Drake 2000).

Artificial neural networks were used in the drying process of wood and the analysis of moisture in wood (Wang and Liu 2003; Wu and Avramidis 2006; Ceylan 2008; Zhang et al. 2006; Avramidis and Iliadis 2005; Avramidis and Wu 2007),

The potential of using neural network in the determinate of hexose and pentose amounts in wood analysis (Yasar 2005), in the prediction of wood dielectric loss factor (Avramidis et al. 2006), and in the modeling of product recovery for trees (Zhang et al. 2006) has been investigated in some studies.

Even in view of the work just cited, the use of artificial neural networks (ANNs) to make predictions on the moisture absorption (MA) and thickness swelling (TS) characteristics of wood-based composites is a new concept.

The goal of this study was to use ANNs as an alternative way of modeling and determining how MA and TS characteristics of OSB are affected in different treatment variables. In the study, a feed forward and back propagation multilayer ANN model was developed and used.

EXPERIMENTAL

Material

The development of ANN models significantly depends on the experimental results. In the present work, relative humidity, board layup type, resin type, application rate of resin, and wax content were considered as the prime processing variables.

This study incorporated data obtained from earlier experimental works (Salay 2010). The materials and method of the experimental works are briefly mentioned as follows: Based on the data obtained from Salay's studies, it was reported that target density and thickness for all southern pine oriented strand boards were 623kg/m^3 and 12.7 mm., respectively. The pressing cycle was the same for all boards. Platen pressure ranged from 6000 to 7000 kPa depending on board type and resin content. The press temperature was measured as 180°C. Forty different board treatments were used. Experimental variables are listed in Table 1 according to Salay (2010).

Table 1. Treatment Variables for the Oriented Strand Board (Salay 2010)

Board Layup	Resin Base Rate (% solids)	Resin Content			Wax %
		% of base	PF % solids	pMDI % solids	
Single-layer Three-layer	Phenol formaldehyde (PF) (base=4.5%) Isocyanete (pMDI) (base=2.0%)	65 83 100 117 134	2.92 3.74 4.50 5.27 6.03	1.30 1.66 2.00 2.34 2.68	0.5% 1.0%
40 treatment combinations (2 x 2 x 5 x2)					

From each test board (457 mm^2), 50 mm^2 samples were sawn and used for testing. Samples were oven dried at 100.3°C for twenty-four hours, then moved to a desiccator over $CaCl_2$ to cool. Weight and thickness measurements were taken in an environmental chamber at 20°C and both 80% and 90% relative humidity, separately, until equilibrium was achieved (Salay 2010).

In this study, the least square means of all treatments for MA and TS at 80% and 90% relative humidity were used for ANN modeling.

Method

The proposed ANN model was designed by software developed using the MATLAB Neural Network Toolbox. The data obtained from experimental works (Salay 2010) were organized. Among these data, 60 (75% of total data) samples were selected for ANN training process, while the remaining 20 (25% of total data) samples were used to verify the generalization capability of ANN. The training and the test data grouped were randomly utilized to train the artificial neural network by constituting different data sets. The data sets used in the prediction model are shown in Tables 2 and 3.

The application of ANN

The ANN models, which have different network structures and parameters were constituted, and ANNs training processes were performed with MATLAB package software to determine weight and bias values and to minimize the mean square error. In order to determine the performance of networks, the models were tested using a set of data (namely test data) containing input–output pairs which were not utilized for training processes. Thus the most sensitive (appropriate) ANN result was targeted.

The obtained predicted values as a result of the testing process were compared with the real (measured) values. The model providing the best prediction values with respect to the root mean-square error (RMSE) ratio, calculated with Eq. 3, and the mean absolute percentage error (MAPE) ratio, calculated with Eq. 4, was chosen as the prediction model.

In Tables 2 and 3, the values calculated by utilizing this prediction model for the training and test data, real values, percentage error ratio, and the RMSE and MAPE values are indicated.

In this study, the ANN structure (architecture) chosen as the prediction model includes the input layer consisting of five input nodes: namely, relative humidity (%), board layup type, resin type, wax content (%), and application rate of resin (%). The output layer consisted of two output nodes: namely, moisture absorption (MA) and thickness swelling (TS). Two hidden layers were in the structure as well with 10 neurons in the first hidden layer and 10 neurons in the second hidden layer. The ANN architecture is shown in Fig. 3. The numbers of hidden layers and neurons in the hidden layers was determined by trying various networks.

In the solution of the problem, Feed Forward and Back Propagation multilayer ANN was chosen to calculate errors and adjust the weights of the neurons.

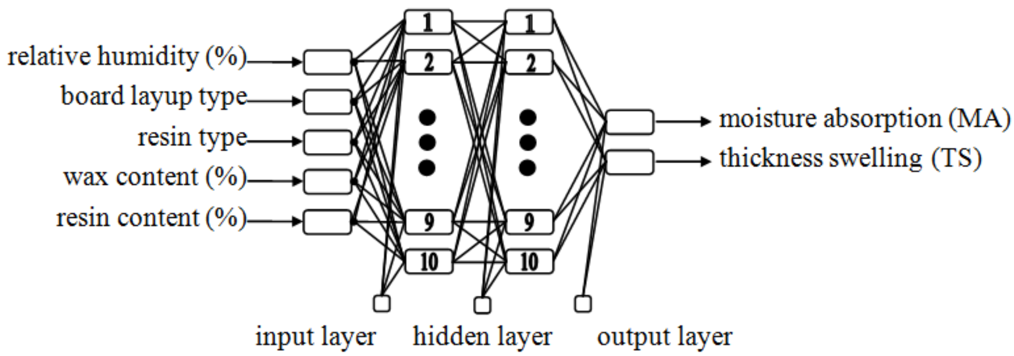

Fig. 3. The MLP network architecture used for the training and modeling of MA and TS.

In the present work, hyperbolic tangent sigmoid and linear transfer functions were preferred as the activation function of the nodes in the hidden layers and output layer, respectively; traingdm (gradient descent with momentum backpropagation algorithm), Levenberg Marquardt algorithm, and the mean square error (MSE) were used as the network training function, the activation function, and the performance function, respectively. The mean square error (MSE) was calculated using Eq. 5,

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(t_i - td_i\right)^2 \tag{5}$$

Where, t_i is the actual output (targeted values), td_i is the neural network output (predicted values), and N is the total number of training patterns.

The data in the training and test sets must be normalized in order to increase the efficiency of the neural network. Inputs and outputs were min-max normalized within the range of -1-1 for ANN modeling by the operation given in Eq. 6 in Matlab. In this equation, X_{norm} is the normalized value of a variable X (real value of the variable), and X_{max} and X_{min} are the maximum and minimum values of X, respectively.

$$X_{norm} = 2 \times \frac{X - X_{min}}{X_{max} - X_{min}} - 1 \tag{6}$$

It was assumed that the 0.001 targeted mean square error value would be sufficient for the training of the artificial neural network.

RESULTS AND DISCUSSION

When MSE of ANN training process reached 0.001, the training was terminated and change of MA and TS were modeled with obtained network parameters.

The amount of error variation depending on iteration of the selected artificial neural network is shown in Fig. 4; and the number of epoch, at which training of the model was stopped, is 933.

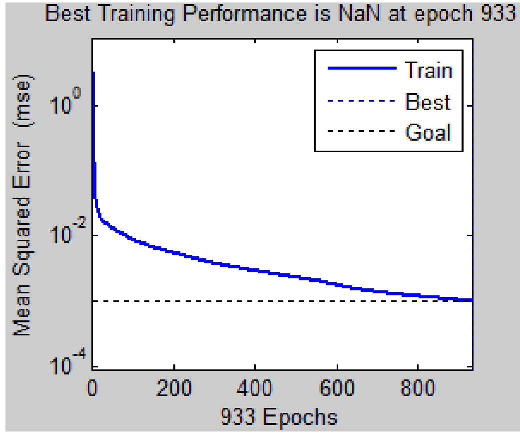

Fig. 4. The graphic of error variation depending on iteration of the ANN

The MAPE and RMSE values, the predicted values, and % error for MA and TS are given in Tables 2 and 3. The ANN prediction was very close to the actual data.

Table 2. Training Data Set and MA and TS Prediction Model Results

No	Relative Humidity (%)	Board Layup	Resin Type	Wax (%)	Resin Content (%)	Moisture Absorption			Thickness Swelling		
						Measured	Predicted	Error (%)	Measured	Predicted	Error (%)
1	80	single layer	PF	0.5	117	11.40	11.42	-0.18	5.70	5.61	1.52
2	80	single layer	PF	1	117	9.30	9.34	-0.41	4.80	4.87	-1.40
3	80	single layer	PF	0.5	134	9.90	9.96	-0.65	5.10	4.99	2.13
4	80	three layer	pMDI	0.5	83	11.40	11.37	0.23	7.00	7.01	-0.16
5	90	three layer	pMDI	1	83	15.50	15.47	0.17	10.50	10.54	-0.43
6	90	three layer	PF	1	100	15.10	15.17	-0.47	10.60	10.71	-1.02
7	90	single layer	pMDI	1	83	14.30	14.65	-2.46	12.70	12.96	-2.02
8	80	single layer	PF	1	83	9.50	9.48	0.26	5.70	5.55	2.60
9	90	single layer	pMDI	1	100	14.70	14.45	1.71	10.80	10.36	4.07
10	80	three layer	PF	0.5	83	9.00	9.01	-0.14	4.70	4.85	-3.12
11	80	three layer	PF	1	134	9.90	9.85	0.46	5.60	5.39	3.75
12	90	three layer	pMDI	1	134	13.90	13.84	0.42	8.20	8.35	-1.85
13	80	three layer	pMDI	0.5	117	11.00	11.11	-1.01	5.90	5.52	6.45
14	80	three layer	pMDI	1	83	11.10	10.87	2.11	5.20	5.56	-6.92
15	90	three layer	pMDI	0.5	83	14.40	14.51	-0.77	11.40	11.30	0.88
16	80	single layer	PF	1	100	7.60	7.50	1.34	3.30	3.72	-12.72
17	80	single layer	PF	0.5	100	9.90	9.86	0.39	4.30	4.44	-3.24
18	80	three layer	PF	1	100	10.10	10.07	0.33	6.00	5.80	3.33
19	80	single layer	pMDI	1	65	8.00	8.07	-0.90	5.00	4.82	3.64
20	80	single layer	pMDI	1	100	10.60	10.51	0.88	6.90	7.25	-5.05
21	80	single layer	PF	0.5	65	10.50	10.49	0.11	5.20	5.19	0.28
22	90	single layer	PF	0.5	65	14.30	14.41	-0.75	12.70	12.66	0.30
23	80	three layer	PF	0.5	100	10.70	10.23	4.43	6.70	5.97	10.91
24	80	three layer	pMDI	1	65	10.30	10.48	-1.76	5.50	5.16	6.15
25	80	three layer	pMDI	0.5	65	9.80	9.81	-0.06	5.50	5.56	-1.15
26	90	single layer	PF	0.5	100	14.90	14.71	1.31	11.90	11.87	0.24
27	90	single layer	pMDI	1	65	15.20	15.05	1.01	16.40	16.31	0.56
28	90	three layer	pMDI	0.5	134	15.60	15.63	-0.18	8.70	8.73	-0.30

29	90	single layer	PF	0.5	117	15.10	15.29	-1.25	11.40	11.46	-0.55
30	90	single layer	PF	0.5	134	15.70	15.59	0.69	12.70	12.66	0.28
31	90	single layer	PF	1	134	14.60	14.42	1.25	9.00	9.33	-3.69
32	90	three layer	PF	1	117	15.40	15.31	0.55	11.30	11.19	1.02
33	80	single layer	PF	1	65	8.90	8.97	-0.77	5.20	5.04	3.01
34	80	single layer	PF	1	134	7.80	7.80	0.05	3.50	3.60	-2.76
35	90	three layer	PF	0.5	83	15.30	15.36	-0.38	13.90	13.89	0.04
36	90	three layer	pMDI	0.5	65	15.50	15.43	0.48	11.70	11.77	-0.56
37	90	single layer	PF	1	65	15.40	15.40	-0.02	14.00	13.96	0.30
38	90	three layer	PF	0.5	134	16.10	16.06	0.24	12.00	11.98	0.17
39	90	three layer	PF	1	65	16.20	16.20	-0.01	15.10	15.15	-0.30
40	90	three layer	pMDI	0.5	117	16.00	15.95	0.34	10.50	10.43	0.64
41	90	three layer	PF	0.5	117	16.10	16.17	-0.45	13.70	13.67	0.21
42	90	three layer	pMDI	1	100	14.50	14.66	-1.08	9.40	9.33	0.70
43	80	three layer	pMDI	1	100	10.10	10.26	-1.56	5.10	5.00	1.97
44	90	single layer	PF	1	117	13.10	13.25	-1.14	9.20	8.90	3.23
45	80	three layer	pMDI	0.5	134	11.10	10.97	1.14	5.20	5.59	-7.52
46	80	three layer	pMDI	1	134	10.30	10.28	0.17	5.60	5.48	2.18
47	80	single layer	pMDI	1	117	7.90	7.92	-0.25	4.60	4.52	1.77
48	90	three layer	PF	0.5	100	15.70	15.58	0.74	13.10	13.14	-0.31
49	90	single layer	pMDI	0.5	100	14.30	14.32	-0.14	12.30	12.26	0.33
50	80	three layer	PF	0.5	117	9.80	10.26	-4.69	5.50	6.17	-12.18
51	80	three layer	PF	0.5	65	10.40	10.43	-0.26	8.10	8.04	0.68
52	80	three layer	PF	1	83	11.20	11.22	-0.14	6.50	6.50	0.06
53	80	single layer	pMDI	0.5	100	10.60	10.56	0.33	6.50	6.56	-0.95
54	90	single layer	PF	1	83	13.50	13.49	0.11	11.00	11.10	-0.87
55	80	single layer	pMDI	0.5	83	9.70	9.70	0.03	6.10	6.07	0.50
56	90	single layer	pMDI	1	134	13.90	13.98	-0.60	9.70	9.66	0.44
57	90	single layer	pMDI	0.5	83	15.70	15.69	0.03	12.50	12.54	-0.32
58	80	single layer	pMDI	0.5	134	9.20	9.21	-0.16	5.40	5.34	1.15
59	90	single layer	pMDI	0.5	117	15.90	15.87	0.18	13.20	13.31	-0.82
60	80	three layer	PF	1	117	9.80	9.83	-0.32	5.30	5.65	-6.51
	MAPE					0.74			2.37		
	RMSE					0.13			0.22		

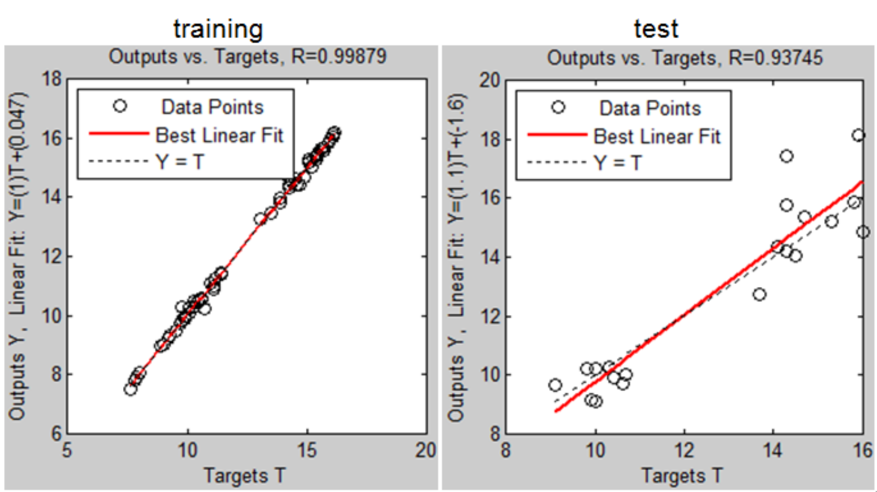

Fig. 5. The relationship between experimental results (values) and ANN predicted values for MA

Figs. 5 and 6 show the relationship between the real values and calculated values obtained using the prediction models. The comparative plot of these values is given in Figs. 7 and 8.

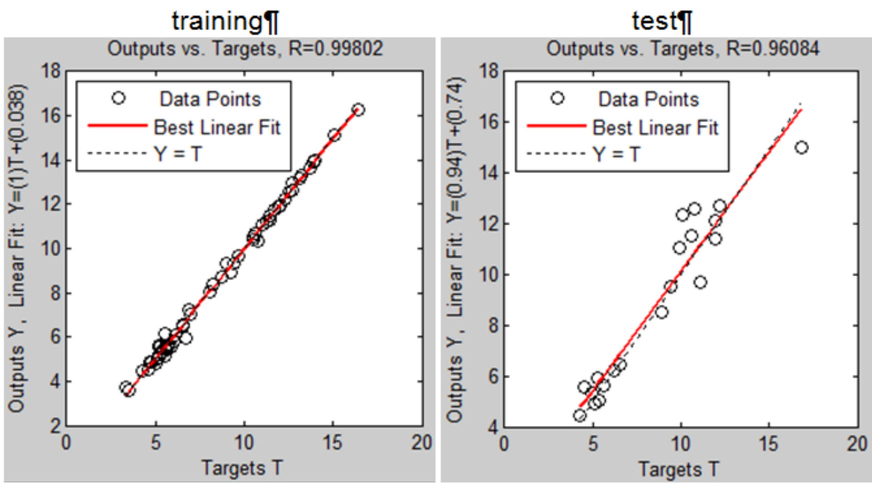

Fig. 6. The relationship between experimental results (values) and ANN predicted values for TS

Table 3. Test Data Set and MA and TS Prediction Model Results

No	Relative Humidity (%)	Board Layup	Resin Type	Wax (%)	Resin Content (%)	Moisture Absorption			Thickness Swelling		
						Measured	Predicted	Error (%)	Measured	Predicted	Error (%)
1	90	three layer	pMDI	1	65	15.90	18.15	-14.17	10.10	12.36	-22.37
2	90	three layer	PF	1	134	15.30	15.20	0.65	12.20	12.71	-4.22
3	80	single layer	pMDI	1	83	9.90	9.15	7.54	5.30	5.89	-11.20
4	90	single layer	PF	1	100	13.70	12.73	7.11	9.40	9.50	-1.07
5	80	single layer	pMDI	0.5	117	10.60	9.67	8.75	5.60	5.61	-0.11
6	80	three layer	pMDI	0.5	100	9.80	10.19	-4.00	5.40	5.03	6.85
7	80	three layer	PF	0.5	134	10.30	10.27	0.25	6.20	6.21	-0.23
8	90	three layer	pMDI	1	117	14.50	14.06	3.06	8.90	8.49	4.61
9	90	three layer	pMDI	0.5	100	16.00	14.88	6.98	9.90	11.04	-11.52
10	90	single layer	PF	0.5	83	14.10	14.37	-1.91	10.80	12.58	-16.47
11	90	single layer	pMDI	0.5	134	14.30	15.76	-10.21	11.90	12.12	-1.87
12	80	three layer	pMDI	1	117	10.00	10.19	-1.90	4.90	5.35	-9.16
13	90	three layer	PF	0.5	65	15.80	15.86	-0.38	16.80	15.02	10.58
14	80	single layer	PF	0.5	83	9.10	9.65	-6.05	4.50	5.58	-24.03
15	90	single layer	pMDI	1	117	14.30	14.18	0.82	11.10	9.69	12.67
16	80	three layer	PF	1	65	10.40	9.91	4.69	6.50	6.43	1.12
17	80	single layer	pMDI	1	134	10.00	9.08	9.21	4.30	4.47	-3.87
18	90	single layer	pMDI	0.5	65	14.30	17.46	-22.07	10.60	11.55	-8.94
19	90	three layer	PF	1	83	14.70	15.34	-4.38	11.90	11.41	4.15
20	80	single layer	pMDI	0.5	65	10.70	10.02	6.35	5.10	4.93	3.32
	MAPE					6.02			7.92		
	RMSE					1.08			0.96		

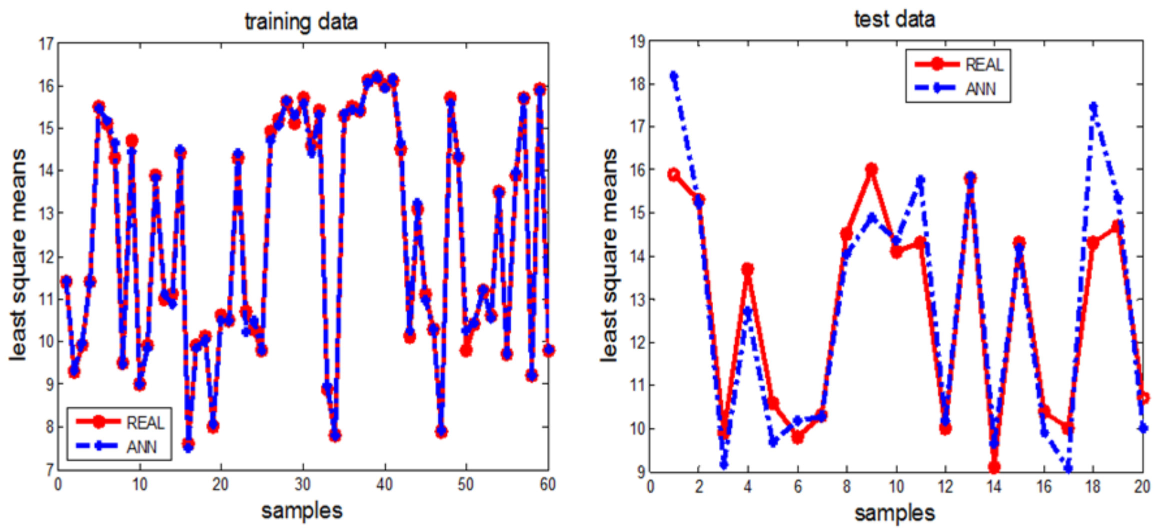

Fig. 7. The comparison of the real and calculated values for MA

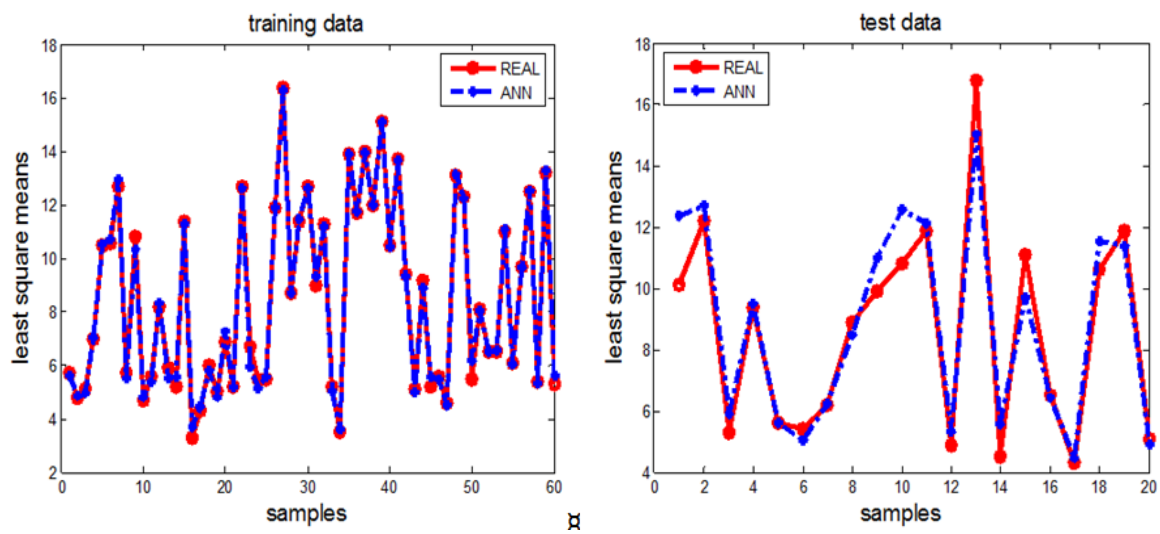

Fig. 8. The comparison of the real and calculated value for TS

In order to assess the validity of the networks and their accuracy, it is often useful to perform regression analysis between the network response and the corresponding target. The regression curves of the output variables for the experiment and ANN data set are shown in Figs. 5 and 6 (training $R_{MA} = 0.99879$ and $R_{TS} = 0.99802$, testing $R_{MA} = 0.93745$ and $R_{TS} = 0.96084$). As the correlation coefficients approach 1, prediction accuracy increases and indicates good agreement between the experimental results and the model predication. The values of R^2_{MA} and R^2_{TS} in the testing set are 0.88 and 0.92, respectively, which indicates that the network obtained explains at least 0.88% and 0.92% of the observed data. This value supports the applicability of using ANNs in the present study.

The mean absolute percentage error (MAPE) results are shown in Tables 2 and 3. The results indicate a consistent agreement between the outcomes of the ANN modeling and the experimental results. This implies that the ANN model can be used to optimize MA and TS properties of OSB.

Comparisons of the results between the outcomes of ANN modeling and experimental values for MA and TS are plotted in Figs. 7 and 8; close examination reveals that the fits were quite reasonable. In most cases, the neural network prediction was very close to the actual value; however, some values were not as close as others. This is attributed to errors caused by the material, the measurements, and process parameters. These errors, however, could be neglected given that the leaning level of the ANN is 95%.

The ANN can be used for optimization. For example, the optimization of the resin content for OSB can be carried out through an analysis of evaluated network response and the MA and TS plots. Relative humidity (%), board layup type, resin type, and wax content (%) are fixed (80%, single layer, phenol formaldehyde (PF), and 0.5%, respectively), the application rate of resin (%) is changed, and MA and TS results are obtained (Fig. 9). As seen from the graphics, intermediate values are not performed on the experiment set but are obtained from the designed system.

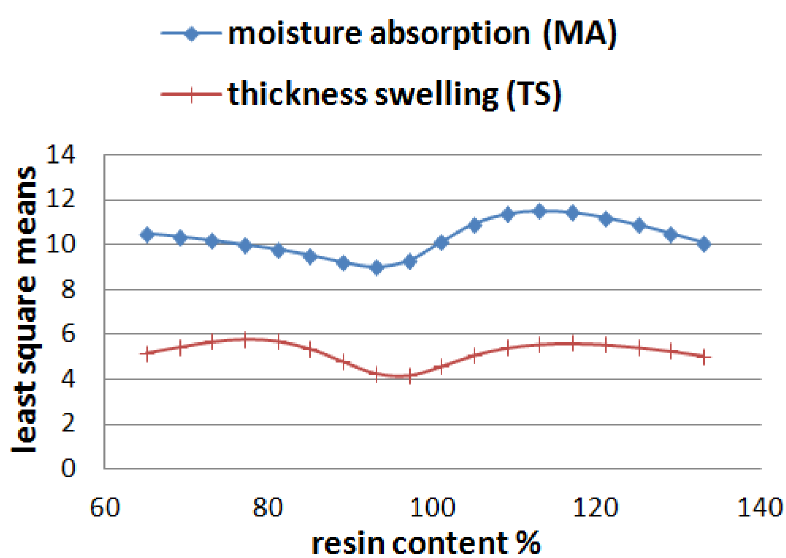

Fig. 9. The change in least square means for MA and TS with increasing resin content

CONCLUSIONS

This paper presents an artificial neural network (ANN) application used for the prediction of moisture absorption (MA) and thickness swelling (TS) of oriented strand board (OSB).

The comparison of ANN and experimental results for MA and TS are shown in Figs. 7 and 8. The results of graphic comparisons showed similarities between the experimental study and the ANN model and supported the reliability of the model.

Mean absolute percentage error (MAPE) and root-mean squared error (RMSE) were used to evaluate the performance of the proposed ANN in the prediction technique. The mean absolute percentage errors were 0.74% for MA and 2.37% for TS in training, and 6.02% for MA and 7.92% for TS in testing. These levels of error are satisfactory for MA and TS. As seen from the results, the ANN approach has a sufficient accuracy rate for the prediction of MA and TS of OSB.

ANN modeling can be used for the modeling (the optimization) of MA and TS at various OSB treatment variables without the need to develop a mechanism (Fig. 9); therefore, time, material, and costs can be saved.

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