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MODELING AND COMPARISON OF BONDING STRENGTH OF IMPREGNATED WOOD MATERIAL BY USING DIFFERENT METHODS: ARTIFICIAL NEURAL NETWORK AND MULTIPLE LINEAR REGRESSION

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ABSTRACT

In this study, the effects of vacuum time, diffusion time and pressing time on the bonding strength of *Larix decidua* wood impregnated with Immersol-Aqua and bonded with Klebit-303 were investigated. The vacuum time, diffusion time, and pressing time were predicted by using the artificial neural network (ANN) model and multiple linear regression (MLR) methods and the results of ANN and MLR methods were compared. The highest bonding strength (7.664 N·mm^{-2}) was achieved when the vacuum time, the diffusion time and the pressing time were 20, 60 and 60 minutes, respectively, while the lowest value (4.62 N·mm^{-2}) was achieved when the vacuum time, the diffusion time and the pressing time were 80, 120 and 20 minutes, respectively. The model results are as follows: The MAPE value for testing phase in the ANN was 7.266 and R^2 value was 0.751 whereas the MAPE value of the MLR was 9.365 and R^2 value was 0.558. The ANN model has been found to have better prediction performance than the MLR model.

KEYWORDS: Artificial neural network, MLR, bonding strength, impregnation.

INTRODUCTION

Although wood have some advantages over other engineering materials, it is degraded by various organisms (bacteria, fungi, insects, termites, marine hazards, etc.). Physical (combustion, abrasion, weather conditions etc.) and chemical factors (strong acids and bases, etc.) also accelerates the degradation of wood materials. To prevent degradation of the wood material, the material must be treated (impregnated) with chemicals, dried well and the surface must be painted or varnished (Bozkurt and Göker 1987, Bozkurt and Erdin 2011, Efe and Bal 2016).

As a result of the impregnation process, the life of the wood material is increasing and the different impregnation materials have been developed and improved (Kartal et al. 2006, Kartal and Kantay 2006). It is also important that the impregnation material is compatible with the adhesive. The type of impregnation material, the amount of retention of impregnation material, and the interaction of impregnation material with surface has an effect on the bonding strength of wood (Vick 1993, Yörür et al. 2010).

Adhesives that play an important role in forest products industry are substance capable of holding materials together by combining the surfaces of materials. Adhesives are widely used in furniture and the construction of building materials and there are many types of adhesives (such as polyurethane, epoxide, polyvinyl acetate etc.) on the market. Adhesives can effectively transfer and distribute stresses, thereby increasing the strength and stiffness of the composite (Vick 1999, Boldis et al. 2016, Gaborik et al. 2016, Svitak and Ruman 2017, Gasparik et al. 2017, Zaborsky et al. 2017).

In this study, the effect of vacuum time, diffusion time and pressing time on the bonding strength of *Larix decidua* wood impregnated with Immersol-Aqua and bonded with Klebit-303 will be investigated. The vacuum time, diffusion time, and pressing time were predicted by using the developed ANN model and MLR methods and the results obtained by ANN and multiple linear regression methods were compared.

The concept of an artificial neural network (ANN)

There is no universally accepted definition of artificial neural networks, and ANN is composed of many interconnected nodes (artificial nerves). An artificial nerve imitates the basic functions of biological nerves. An artificial neural cell basically consists of inputs, weights, aggregation function, activation function, and output. Information received from the environment is transmitted to the nerve by inputs. Each of these inputs is multiplied by the weight value. Then, sum of multiplications multiplied by inputs with each weight in the nerve are aggregated with the threshold value and the result of the summation function is sent to the activation function. After the activation function, it is transmitted to the output (Ahn et al. 2000, Elmas 2011). The process elements form a network in parallel with each other in three layers (input layer, hidden layer and output layer) (Elmas 2007, Öztemel 2012). The input layer is where the input data groups are presented to the network. The number of neurons in this layer is equal to the number of input data and each input neuron has a data. The data in the input layer passes through to the hidden layer without processing. The hidden layer is where the information coming from the input layer is processed. There can be more than one hidden layer for a network. The output layer is where the output set is generated against the set of information given to the network (Elmas 2011, Öztemel 2006). Some aspects should be considered when designing a network in ANN. These are the structure of network, learning algorithm, the number of layers, the number of neurons in layers, the number of connections between neurons, normalization of the data and the selection of performance functions (Öztemel 2012). While artificial neural networks with less hidden layers than the required number of hidden layers are insufficient for the solution of complicated functions, artificial neural networks with many hidden layers are faced with undesirable instabilities (Detienne et al. 2003). Determining the number of neurons in the hidden layer is an important task when designing ANN. There are no mathematical tests on how many neurons are to be found in the hidden layer. If few hidden neuron are used, the pattern in the data may not be learned by the network. The many hidden neurons can cause excessive compliance problem (Detienne et al. 2003, Shu and Quarda 2007).

MATERIALS AND METHODS

Wood material

Larix decidua wood which is widely used in the forest industry sector was used as wooden material.

Adhesive

Klebit-303 is a single and double-component adhesive and it can be applied hot and cold. Its density is 1.22 ± 0.01 $g \cdot cm^{-3}$, pH value is 7 and viscosity is 13.000 ± 2.000 mPas at 20°C and 65% relative moisture content. It should be applied to the bonding surface with a calculation of 120-200 $g \cdot mm^{-2}$. Holding time is 6-10 minutes (Altınok et al. 2000).

Impregnation material

Imersol-Aqua was used in the impregnation process and it was supplied from HEMEL (Hemel Hiscon Timber Product Ltd). It is in the form of odorless, non-flammable, environmentally clear. Also, it is soluble in water and does not create corrosion on the metal surfaces. The pH and density values of Imersol-Aqua are 7 and 1.03 $g \cdot cm^{-3}$, respectively. It contains Cypermethrin, Ethylene diamine, Disodium tetraborate decahydrate, 3-iodo-2-propynyl butylcarbamate, Propiconazole, Tebucconazole. Typical application temperatures are 15-25°C and the relative humidity range is 40-65%. Before preservative treatments, wood material should be completely clean and the relative humidity should be below 20%. Impregnation time for soft-textured wood such as pine is at least 6 minutes. The impregnated wood should be allowed to dry for at least 24 hours (Hickson's Timber Impregnation Co. 2017).

Preparation of experimental samples

The test samples were cut to dimensions of 150 x 20 x 10 mm according to TS 2470 (1976) standards (Fig. 1).

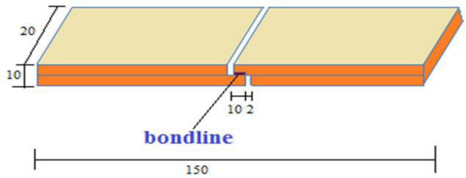


Fig. 1: The test sample (sizes given in mm).

The total numbers of test samples were 510. Then, the test samples cut from *Larix decidua* wood were kept at 20 ± 2°C and at 65 ± 5% relative moisture content until they reach constant weights. The samples reaching equilibrium moisture content were then impregnated and the impregnated samples were kept at 103 ± 2°C until fully dry. 150 $g \cdot cm^{-3}$ of adhesive was applied to one of the surfaces of the fully dried samples. The samples whose surfaces were covered with each other were pressed in different pressing times at 6 $kg \cdot cm^{-2}$ pressing pressure.

Impregnation method

Impregnation process of the samples was carried out according to ASTM D 1413-76 (1976) standards. In the impregnation process, the pre-vacuum equivalent to 60 cm of Hg was applied at different times (20, 40, 60, 80 minutes). Then, the samples were dipped in the Imersol-Aqua solution at atmospheric pressure for different times (30, 60, 90, 120 minutes). After impregnation process, the impregnated samples were kept at the temperature of 103 ± 2°C until fully dry. The % retention ratios (R%) were calculated by the following Eq. 1, with the necessary measurements (weight and volume) of the fully dried samples and given in Tab. 1.

$$R = (M_{oes} / M_{oe\ddot{o}}) \times 100 \qquad (\%) \qquad (1)$$

where: M_{oes} - the weight of the fully dried sample after impregnation (g),
$M_{oe\ddot{o}}$ - the weight of the fully dried sample before impregnation (g).

Determination of full dry density

Full dry samples were used to determine the full dry density values of wood materials. TS 2472 (1976) principles were taken as basis. Accordingly, air dried samples were oven dried up to 103 ± 2°C until they reach constant weights. Then, the samples were cooled in desiccators with $CaCl_2$. Afterwards, the cooled samples were weighed in an analytic balance of 0.01 g sensitivity and the dimensions of the samples were measured in a digital caliper of 0.01 mm sensitivity. The volumes of the samples were determined by the stereometric method. Once the weights and volumes of the full dry samples have been determined, the full dry density (d_0) was calculated according to the following Eq. 2 and the results were given in Tab. 1.

$$d_0 = M_0 / V_0 \qquad (g \cdot cm^{-3}) \qquad (2)$$

where: M0 - the weight of the sample in full dry,
V0 - the volume of the sample in full dry.

Determination of air-dry density

The moisture content of the samples was determined according to TS 2471 (1976) and the densities of the samples were determined according to TS 2472 (1976). Accordingly, the test samples were oven dried up at 20 ± 2°C and at 65 ± 5% relative moisture content until they reach constant weights. Then, the samples were weighed in an analytic balance of 0.01 g sensitivity and the volumes of the samples were determined by the stereometric method. The air-dry density (d12) was calculated according to the following Eq. 3 and the results were given in Tab. 1.

$$d_{12} = M_{12}/V_{12} \qquad (g \cdot cm^{-3}) \tag{3}$$

where: M_{12} - the weight of the sample in air-dry,
V_{12} - the volume of the sample in air-dry.

Tab. 1: Full and air-dry density and retention values (%).

	Unimpregnated wood		Impregnated wood		R (%)
	d_0	d_{12}	d_0	d_{12}	
$X_{ave.}$	0.6369	0.6444	0.6417	0.6560	0.7794
Sd	0.0809	0.0811	0.0807	0.0849	0.6744

d_0: full dry density value ($g \cdot cm^{-3}$), d_{12}: air-dry density value ($g \cdot cm^{-3}$), $X_{ave.}$: mean value, Sd: standard deviation, R: (%) retention ratio

The full dry and air-dry density values of *Larix decidua* wood were 0.6369 $g \cdot cm^{-3}$ and 0.6444$g \cdot cm^{-3}$, respectively, while the full dry and air-dry density values of wood impregnated by Imersol-aqua were 0.6417 $g \cdot cm^{-3}$ and 0.6560 $g \cdot cm^{-3}$, respectively. Percent retention ratio of Imersol-Aqua was found as 0.7794. In their studies in 1999 and 2006, Örs and colleagues reported that the impregnated samples have higher full dry and air-dry density values than control samples (Örs et al. 1999, Örs et al. 2006).

Determination of bonding strength

The test of bonding strength was carried out by static loading according to BS EN 205 (1991) standard. The loading speed was used as 2 $mm \cdot min^{-1}$. As soon as a break or separation of the sample surface, the loading was stopped. The bonding strength values were calculated by the following Eq. 4.

$$\sigma = F_{max} / A = F_{max} / (b \times l) \tag{4}$$

where: σ - the bonding strength ($N \cdot mm^{-2}$),
F_{max} - the maximum load at the break or separation point (N),
b - the width of glued face (mm),
l - the length of glued face (mm).

Multiple linear regression method

Multiple linear regression is to find that the relationship between two or more variables can be expressed by a linear mathematical function (Altun 2005). In this study, vacuum time, diffusion time and pressing time values were used as independent variables and the bonding strength values were used as dependent variables.

Artificial neural network method

The ntstool application of Matlab program was utilized to develop artificial neural network models. The experimental data were grouped randomly and uniformly in the form of training, validation and test data, and different data sets were used to train the artificial neural network (ANN). 70% of the data were used for training phase, 15% were for validation phase and 15% were for testing phase. The trial and error method which is the most used method in the ANN models has been used to determine the most suitable network architecture and parameters. As a result of the testing, a forward feed and back propagation artificial neural network was chosen as the most suitable network structure. The forward feed and back propagation algorithm consists of two sections. The first of these is the forward feed section and the other is the backward feed section on which changes are made on the linkage weights based on the differences between the forward feed section and the computed and observed information signals in the output unit (Kızılaslan et al. 2014).

The hyperbolic tangent sigmoid function (tansig) is used as the activation (transfer) function between the input layer and the hidden layer. Because hyperbolic tangent function was used, input and output data were normalized in [-1,1] range using functions available in Matlab. Afterwards, the output data generated from the network was transformed into the original again. The choice of the learning algorithm depends on the network structure and Levenberg Marquardt Algorithm (trainlm) which is widely used in network training was used as training algorithm. The Levenberg Marquardt algorithm is derived from steepest descent and Newton's algorithms. The LM algorithm approaches the error surface parabolically in each iteration step and the minimum of parabola is the solution for that step (Bulucu and Kavas 2007, Çavuşlu et al. 2012).

As learning rule, momentum gradient descent with momentum back propagation algorithm (traingdm) was used. The following mean square error (MSE) Eq. 5 was used as a performance function.

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

where: N - the number of observations,
t_i - the measured (actual) value,
td_i - the predicted value of the model.

Evaluation of data

Statistical analyzes were performed by using the SPSS 19.0 software. A variance analysis was used to determine effect of vacuum time, diffusion time and pressing time on the bonding strength of wood. When the interaction was statistically significant ($p < 0.05$), Duncan test was used for binary comparisons between groups and homogeneous groups were formed. The bonding strength values in different vacuum time, diffusion time and pressing time were found by using multiple linear regression (MLR). The optimal artificial neural network (ANN) model is also determined by using Matlab package program. The ANN model and the MLR methods were compared. The following accuracy criteria were used to compare the methods (Tiryaki and Aydın 2014):

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - yd_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{6}$$

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

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - yd_i)^2} \tag{8}$$

$$\mathrm{MAE} = \sum_{i=1}^{N}\left|\frac{yd_i - y_i}{N}\right| \tag{9}$$

where: R^2 - correlation coefficient,
MAPE - the mean absolute percentage error,
MSE - the root mean square error,
MAE - the mean absolute error,
y_i - the measured value, yd_i - the predicted value and
N is the number of observations.

RESULTS AND DISCUSSION

Results of experimental

A variance analysis (ANOVA) was applied to investigate the effects of vacuum time, diffusion time and pressing time on bonding strength of the samples. While the effect of vacuum time ($F=6.656$, sig=0.000, $p<0.001$) and pressing time ($F=9.199$, sig=0.000, $p<0.001$) variables on bonding strength was statistically significant, diffusion time ($F=1.607$, sig=0.186, $p>0.05$) was not significant. Although the diffusion time was not statistically significant, as the diffusion time increased, the bonding strength of the samples was reduced. According to diffusion time, the highest bonding strength value was in 30 min whereas the lowest value was in 120 min. It was determined that the bonding strength of the wood reduced, as the exposure time of wood in the impregnated (Imersol-Aqua) solution increased.

If the test results are significant, Duncan test, one of the multiple-comparison (post-hoc) techniques for determining the difference between the groups, has been applied. The results are shown as different homogenous groups in Tab. 2.

Tab. 2: The average of the experimental data and Duncan test results ($p \leq 0.05$).

Vacuum time	Bonding strength ($N \cdot mm^{-2}$)	Diffusion time	Bonding strength ($N \cdot mm^{-2}$)	Pressing time	Bonding strength ($N \cdot mm^{-2}$)
Non vacuum	9.17 (1.60) c	Non diffusion	9.17 (1.60) b	20 minute	5.66 (1.37) a
20 minute	5.90 (1.60) ab	30 minute	6.11 (1.49) a	40 minute	6.06 (1.97) ab
40 minute	6.53 (1.52) b	60 minute	5.96 (1.43) a	60 minute	6.51 (1.76) b
60 minute	5.81 (1.82) ab	90 minute	5.92 (1.79) a		
80 minute	5.30 (0.96) a	120 minute	5.57 (1.51) a		

Note: the numbers that are not in parentheses indicate the average of the groups; standard deviations are shown in parenthesis; capital letters represent homogeneity groups (according to the Duncan's multiply range test at $p<0.05$).

According to the Duncan test results, as the vacuum time increased, the bonding strength reduced, except for 40 minutes. At 40 minutes, there is an increase in the bonding strength. This increase may be due to the anatomical structure and permeability of the wood, the viscosity, the value of pH, the molecular weight, the manner application and the amount of solid context of adhesive, the penetration of the impregnation material, the amount of retention of impregnation material and the impregnation method and time. As the pressing time increased, the bonding strength of the test samples increased. The highest bonding strength (6.51 N·mm^{-2}) was in 60 minutes and the lowest strength (5.66 N·mm^{-2}) was in 20 minutes. Because, there is no strong bond structure between wood and adhesive at the short pressing time. The pressing time for the bonding of the solid must be long (Marra 1992). Ahmad and Osman (2011) were said that as the pressing time increases, the bonding strength increases. Also, when Tab. 2 was examined, it was observed that the impregnation process reduced the bonding strength of the wood. Previous studies have shown that impregnation process reduced the bonding strength of wood materials (Örs et al. 2004, Özçifçi and Okçu 2007, Kesik et al. 2016).

Results of models

The ANN model consisting of 1 input layer, 1 hidden layer and 1 output layer, which are selected for modeling of the bonding strength and which give the closest results to the measured values was in Fig. 2. In the model, the vacuum time, diffusion time and pressing time constitute the input variables whereas the bonding strength constitutes the output variable. The number of neurons in the hidden layer was 5. In the ANN model, the best performance (MSE) value was found to be 0.122 in the 16th period.

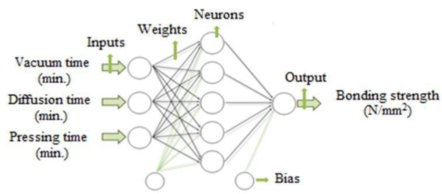


Fig. 2: ANN architecture chosen as the model of prediction.

The measured values, the predicted values and percent absolute errors of the prediction as artificial neural network (ANN) and multiple linear regression (MLR) were given in Tab. 3.

Tab. 3: The measured (actual) and predicted bonding strength values and their absolute percentage errors.

Vacuum time (min)	Diffusion time (min)	Pressing time (min)	Measured	ANN		MLR	
				Predicted	Absolute error (%)	Predicted	Absolute error (%)
20	30	20	5.376	5.436	1.124	6.684	24.33
20	60	20	5.294	5.224	1.331	6.354	20.023
20	90	20	5.218	**5.141**	**1.47**	6.024	15.447
20	120	20	5.112	5.11	0.045	5.694	11.385
20	30	40	6.19	***6.771***	***9.38***	7.124	15.089
20	60	40	5.994	***6.435***	***7.352***	6.794	13.347
20	90	40	6.002	***5.859***	***2.38***	6.464	7.697
20	120	40	5.504	5.52	0.295	6.134	11.446
20	30	60	6.27	6.903	10.088	7.564	20.638
20	60	60	7.664	6.814	11.085	7.234	5.611
20	90	60	5.996	6.833	13.961	6.904	15.143
20	120	60	6.184	6.361	2.857	6.574	6.307
40	30	20	6.566	6.469	1.477	6.264	4.599
40	60	20	6.506	6.399	1.64	5.934	8.792
40	90	20	6.484	**6.337**	**2.265**	5.604	13.572
40	120	20	6.43	**6.189**	**3.741**	5.274	17.978
40	30	40	7.626	6.913	9.351	6.704	12.09
40	60	40	6.86	6.435	6.201	6.374	7.085

40	90	40	6.72	***6.432***	***4.285***	6.044	10.06
40	120	40	6.502	6.427	1.161	5.714	12.119
40	30	60	6.57	***7.099***	***8.052***	7.144	8.737
40	60	60	5.4	***6.856***	***26.965***	6.814	26.185
40	90	60	6.8	6.804	0.062	6.484	4.647
40	120	60	5.84	6.435	10.186	6.154	5.377
60	30	20	5.244	5.249	0.096	5.844	11.442
60	60	20	5.12	**5.081**	**0.766**	5.514	7.695
60	90	20	5.528	**5.039**	**8.845**	5.184	6.223
60	120	20	5.13	**5.021**	**2.129**	4.854	5.38
60	30	40	5.988	6.039	0.849	6.284	4.943
60	60	40	5.888	**5.526**	**6.152**	5.954	1.121
60	90	40	5.462	5.28	3.331	5.624	2.966
60	120	40	4.868	5.135	5.489	5.294	8.751
60	30	60	6.958	**7.399**	**6.331**	6.724	3.363
60	60	60	6.854	**7.1**	**3.593**	6.394	6.711
60	90	60	6.37	6.368	0.036	6.064	4.804
60	120	60	6.272	**5.8**	**7.532**	5.734	8.578
80	30	20	5.12	***5.142***	***0.431***	5.424	5.937
80	60	20	5.08	5.01	1.381	5.094	0.276
80	90	20	5.676	5.009	11.753	4.764	16.068
80	120	20	4.62	5.009	8.418	4.434	4.026
80	30	40	5.264	5.242	0.427	5.864	11.398
80	60	40	5.104	5.012	1.795	5.534	8.425
80	90	40	4.946	***5.009***	***1.275***	5.204	5.216
80	120	40	4.634	5.009	8.091	4.874	5.179
80	30	60	6.104	6.185	1.328	6.304	3.277
80	60	60	5.716	5.698	0.321	5.974	4.514
80	90	60	5.616	***5.477***	***2.482***	5.644	0.499
80	120	60	5.538	5.475	1.142	5.314	4.045
0	0	20	7.53	7.549	0.248	7.434	1.275
0	0	40	9.454	***8.503***	***10.06***	7.874	16.713
0	0	60	10.536	10.501	0.331	8.314	21.09

Note: bold values: validation data, bold italic values: test data, other values: training data.

The highest and the lowest absolute percentage error values of the ANN were 26.965% and 0.036%, respectively, whereas the highest and the lowest absolute percentage error values of the MLR were 26.185% and 0.276%, respectively. The predicted values of the ANN were found with very low percentage errors. These error values are quite satisfactory values for predicting the bonding strength values. It is possible to say that the predictions made with the ANN are quite good. Because the similarity and closeness between the experimental output values and the predicted output values is high.

The performance criteria values used to assess the performances of the ANN and MLR methods in predicting bonding strength values were given in Tab. 4.

Tab. 4: The performance criteria results.

Models	Datasets	Bonding strength ($N \cdot mm^{-2}$)			
		RMSE	MAE	MAPE (%)	R^2
ANN	Training data	0.226	0.35	3.739	0.9076
	Validation data	0.262	0.308	4.282	0.9041
	Test data	0.630	0.461	7.266	0.7512
MLR	All data	0.726	0.581	9.365	0.558

As seen in Tab. 4, the RMSE values were found as 0.226 for the training phase, 0.262 for validation phase and 0.630 for testing phase of the ANN whereas the RMSE value obtained by MLR was found as 0.726. The MAE values were found as 0.35 for the training, 0.308 for validation and 0.461 for testing of the ANN whereas the MAE value was found as 0.581 for the MLR. The MAPE values were found as 3.739% for the training, 4.282% for validation and 7.266% for testing of the ANN whereas the MAPE value was found as 9.365% for the MLR. MAPE is considered to be better than the other statistics. MAPE refers to prediction errors as percentage and although alone, it makes sense (Akgül 2003). According to Lewis (1982), the MAPE values are categorized as follows: MAPE≤10% means a high accuracy prediction, 10≤MAPE≤20% - a good prediction, 20≤MAPE≤50 – a reasonable prediction, and MAPE≥50 – an inaccurate prediction.

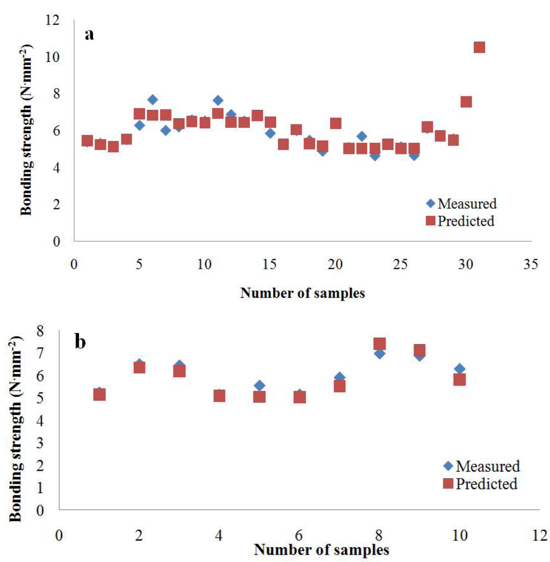
An important criterion used to evaluate the validity of the model is the correlation coefficient (R^2) between the experimental and the prediction results. The R^2 value takes a value between 0 and 1. If this value approaches to 1, the model is very compatible with the data (Özşahin 2012). According to Tab. 4, the R^2 values were found as 0.9076, 0.9041 and 0.7512 in the training, validation and test data sets of the ANN, respectively, and 0.558 in the multiple linear regression (MLR). In other words, the ANN model provides higher prediction results than the MLR model.

When we applied MLR analysis to the data used in the ANN, the following MLR model was obtained.

$$Y = 6.994 - 0.021X_1 - 0.011X_2 + 0.022X_3$$

where: Y - dependent variables (the bonding strength),
X_i - independent variables (X_1: vacuum time, X_2: diffusion time, X_3: pressing time).

When the results of the graphical comparisons in Fig. 3 were examined, the predicted outputs in the training, validation and testing phases overlapped with the measured outputs. It is possible to say that models are trained correctly and it shows an acceptable accuracy to predict the bonding strength values.



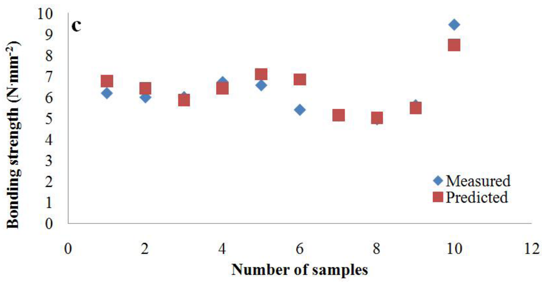


Fig. 3: Comparison of measured values and predicted values: training data set (a), validation data set (b), test data set (c).

Comparison of ANN and multiple linear regression methods

As seen in Fig. 4, it is seen that the predicted values obtained with the ANN are closer to the measured values.

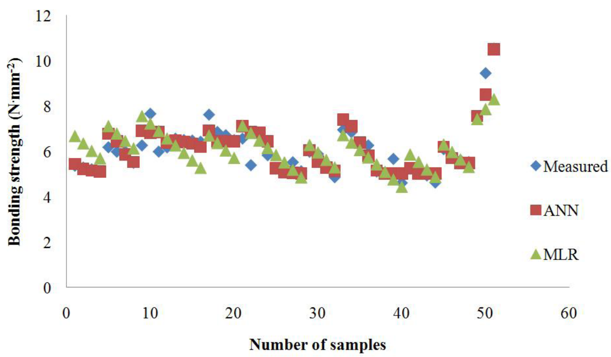


Fig. 4: Comparison of the measured values and the predicted values for the bonding strength.

In other words, according to the MLR results, the ANN results seem to have lower deviation values than measured values. When we compare the results obtained with other study results, we have similar results. Fernandez et al. (2008) predicted the internal bonding value of particleboard by using artificial neural network and multiple linear regression methods and compared these methods. The results of artificial neural network were found to be more successful than the results of multiple linear regression. In the study of using and comparing artificial neural networks and multiple linear regression methods for predicting optimum bonding strengths of heat treated wood, Tiryaki et al. (2014) found that the artificial neural network had more successful results than the multiple linear regression method. In this study, they tried to predict and compare the internal bonding strength of particleboards exposed to outside weather conditions by using artificial neural networks and multiple linear regression methods. As a result, the R^2 and RMSE values of the multiple linear regression (MLR) model were given as 0.87 and 0.07, respectively, and the R^2 and RMSE values of the artificial neural network model were given as 0.93 and 0.05, respectively. In another study conducted by Bardak et al. (2016), the R^2 value was found as 0.977 for the testing phase of the ANN, while the R^2 value of the MLR was 0.524.

CONCLUSIONS

In this study, the bonding strength values of impregnated wood materials were predicted by the ANN and MLR models. The criteria such as MAE, RMSE, MAPE and R^2 were used for assessing the performances of the models. According to the obtained data, the following results were obtained:

- The impregnation process reduces the bonding strength of wood materials. The bonding strength of wood impregnated with Imersol-Aqua was found as 5.88 $N \cdot mm^{-2}$, while the bonding strength of control (not impregnated) wood was found as 9.17 $N \cdot mm^{-2}$.
- Generally, as the vacuum time and the diffusion time increase, the bonding strength of the samples reduces. Also, the bonding strength of the samples increases as the pressing time increases. The highest bonding strength value (7.66 $N \cdot mm^{-2}$) was achieved when the vacuum time was 20, the diffusion time was 60 and the pressing time was 60 minutes. The lowest bonding strength value (4.62 $N \cdot mm^{-2}$) was achieved when the vacuum time was 80, the diffusion time was 120 and the pressing time was 20 minutes.
- In contrast to the MLR model, the outputs of the ANN models and the results of the experimental data are close to each other.
- The MAPE and R^2 values obtained by the ANN were better than those obtained by the MLR. While the MAPE and R^2 values for the test phase of the ANN were 7.266% and 0.751, respectively, the MAPE and R^2 values for the MLR were 9.365% and 0.558, respectively.
- The ANN can be recommended as an alternative method for non-destructive, cost-effective and rapid analysis of quality control of wood materials.

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