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COMPARISION OF THE MULTIPLE REGRESSION, ANN, AND ANFIS MODELS FOR PREDICTION OF MOE VALUE OF OSB PANELS

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ABSTRACT

This research investigates the prediction of modulus of elasticity (MOE) properties, which is the most important properties in many applications, of the oriented strand board (OSB) produced under different conditions (pressing time, pressing pressure, pressing temperature and adhesive ratios) by multiple regression, artificial neural network (ANN) and adaptive Neuro-fuzzy inference system (ANFIS). Software computing techniques are now being used instead of statistical methods. It was found that the constructed ANFIS exhibited a higher performance than multiple regression and ANN for predicting MOE.Software computing techniques are very useful for precision industrial applications and, also determining which method gives the highest accurate result.

KEYWORDS: OSB, multiple regression, ANN, ANFIS, mechanical properties.

INTRODUCTION

The timber resource has declined during the past several decades. Available timber source is now the smaller in diameter and lower in quality. One response to the decreasing supplies of high-qualitywood is an increase in demand for reconstituted wood products in which previously used smaller species or mill residues was processed into high-value wood composite materials (McKeever 1997).

Oriented strand boards are a relatively new kind of wood-based panels that are defined in the European standard. Particle boards are classified depending on the size and orientation of their components (Rebollar et al. 2007). OSB panels are made of compressed strands lined up and arranged in three to five layers that are oriented at right angles to each other. And in some cases, the strands used in core layers are randomly oriented. OSB is generally similar to three-layered symmetric laminate. The outer layers of strands are orientated with the long dimension, and the inner layers are orientated at right angles to the outer layer (Green and Hermandez 1998).

Artificial neural networks resemble the human brain in two respects; the network through a learning process acquires knowledge, and the interconnection strengths known as synaptic weights are used to store the knowledge (Bekat et al. 2012) (Yılmaz and Kaynar 2011). Artificial neural networks are non-linear data-driven self-adaptive approaches, and they can identify and learn correlated patterns between input data sets and corresponding target values, even when the underlying data relationship is unknown. Artificial neural networks have been widely used to model complex and non-linear agricultural data (Xing-Mei et al. 2010).

ANNs were used in many studies in the literatures. Artificial neural networks (ANNs) are computer algorithms whose structure and function are based on models. ANNs are currently being used in a variety of applications with great success in many applications (Vosniakos and Benardos 2007). Artificial neural network modeling has been widely used in the field of wood, in the wood recognition system (Tou et al. 2007, Marzuki et al. 2008), in the modeling of product recovery for trees Zhang et al. (2006), in the classifying of wood veneer defects (Packianather and Drake 2000), in the calculation of wood thermal conductivity (Xu et al. 2007), in the predicting fracture toughness of wood (Samarasinghe et al. 2007), in the prediction of bending strength and stiffness in western hemlock (Shawn et al. 2007), in the analysis of moisture in wood (Stavros and Hongwei 2007), the determination of modulus of rupture and modulus of elasticity on flake board (Yapıcı et al. 2009).

The aim of this study is to determine the empirical relationships for estimation of MOE value of OSB, from different circumstances by using multiple regression, artificial neural network and ANFIS models.

MATERIAL AND METHODS

Production of OSB panel's

Scotch pine wood (*Pinus sylvestris* L.) was used for the production of the oriented strand boards (OSB). The strands' dimension in usage was approximately 80 long, 20 wide and 0.7 mm thick. First, the wood strands were dried to 3 % moisture content before adhesive was sprayed on them for three minutes. Then, adhesive material without wax, a solid content of 47 % liquid phenol- formaldehyde resin, was applied in 3, 6, 9 and 12 percent ratios based on the weight of oven dry wood strands.

The pressing periods and pressing pressure were 3, 6 and 9 minutes under the 30, 40 and 50 kg.cm^{-2} pressing pressure, respectively. The shelling ratio was 50 % for core layer and 50 % for face layer, and density of the boards was aimed at 0.65 $g.cm^{-3}$ density. OSB panels, which were dimensioned as 56 x 56 x 1.2 cm were made for experiments, in the 108 conditions. Hand formed mats were pressed in a hydraulic pressing. These panels were labeled from 1 to 108. All mats were pressed under automatically controlled conditions at 175±3, 185±3, 195±3°C, respectively. After pressing, the boards were conditioned to constant weight at 65±5 % relative humidity and at a temperature of 20±2°C until they reached stable weight (TS 642/ISO 554, 1997). After then, MOE value was determined according to the related standard (TSEN 310, 1999).

Experimental design and data analyses

Zwick/Roell Z050 universal test device with capacity of 5000 kg and measurement capability of 0.01 N in accuracy was used in measurement of MOE values of test samples. In testing, loading mechanism was operated with a velocity of 6 $mm.min^{-1}$. Data for each test were statistically analyzed. The analysis of variance (ANOVA) was used ($\alpha<0.05$) to test for significant difference between factors. When the ANOVA indicated a significant difference among factors, the compared values were evaluated with the Duncan test to identify which groups were significantly different from other groups.

Multiple regression model construction

The general purpose of multiple regressions is to learn more about the relationship between several independent or predictor variables and a dependent or criterion variable. A linear regression model assumes that the relationship between the dependent variable and independent variable (s) is linear. The model takes form $y_i= \beta_1 x_i + \ldots + \beta_p x_{ip} + \varepsilon_I= 1, \ldots, n$, where ´ denotes the transpose, so that $x_i\acute{}\beta$ is the inner product between vectors x_i and β. Some remarks on terminology and general use: y_i is called the dependent variable, x_i are called independent variables. Usually, a constant is included as one of the repressors' (Erper et al. 2011). In this search for the best circumstances to predict, the MOE values were conducted under different manufacturing conditions.

Design of artifical neural network (ANN)

In this study, artificial neural network and ANFIS were applied by using the program MATLAB software (Matlab ® 7.11.0.584 (R2010b)). Determination of weights and biases is called training. We need training data to set for this. The training data set consists of input signals assigned with the corresponding target (desired output). The network training procedure is an iterative process. In each iteration weight's coefficients of nodes are modified using new data from training data set. Modification is calculated by using algorithm described as: E teaching step starts with forcing both input signals and training set. After this stage, we can determine output signal's values for each neuron in each network layer.

In this study, Levenberg-Marquardt (LM) Algorithm was used to train network. The Levenberg-Marquardt (LM) algorithm is originally an intermediate optimization algorithm between the Gauss–Newton (GN) method and Gradient Descent (GD) algorithm (Arfken 1985). It combines the speed of the Newton algorithm with the stability of the GD method.

For LM algorithm, the performance index to be optimized is defined as:

$$e_k = \sum_{K=1}^{K} (d_{KP} - o_{KP})^2 \quad k = 1 \ldots K \tag{1}$$

where : e_k - error vector,
$w = (w_1\ w_2 \ldots w\ N)\ T$ consists of all weights of the network,
d_{KP} - the desired value of the k^{th} output and the p^{th} pattern,

o_{KP} - the actual value of the k^{th} output, p^{th} pattern,
P - number of pattern,
K - the number of the network outputs (Wilamowski et al. 1999).

Jacobien matrix can be computed as:

$$J = \begin{bmatrix} \frac{\partial e_1}{\partial w_1} & \frac{\partial e_1}{\partial w_2} & \cdots & \frac{\partial e_1}{\partial w_N} \\ \frac{\partial e_2}{\partial w_1} & \frac{\partial e_2}{\partial w_2} & \cdots & \frac{\partial e_2}{\partial w_N} \\ \vdots & \vdots & & \vdots \\ \frac{\partial e_K}{\partial w_1} & \frac{\partial e_K}{\partial w_2} & \cdots & \frac{\partial e_K}{\partial w_N} \end{bmatrix} \tag{2}$$

Hessian matrix can be computed as:

$$\bar{H} = \bar{J}^T \bar{J} + \mu \bar{I} \tag{3}$$

where: μ - Marquardt learning parameter,
I - unit matrix.

All weights of the network can be updated as:

$$\bar{W}^{(t+1)} = \bar{W}^{(t)} - \bar{H}^{-1}\bar{g} \tag{4}$$

where: g - gradient vector can be computed as:

$$\bar{g} = \bar{J}^T \bar{e} \tag{5}$$

Realise that when μ is large the algorithm becomes steepest decline, while for small μ the algorithm becomes Gauss-Newton. The Marquardt-Levenberg algorithm can be considered a trust-region modification to Gauss-Newton (Hagan and Menhaj 1994).

Adaptive Neuro-Fuzzy Infrence System (ANFIS)

The adaptive network-based fuzzy inference system was first introduced by Jang. ANFIS incorporates the human-like reasoning style of fuzzy inference systems (FIS) by the use of input–output sets and a set of IF–THEN fuzzy rules (Neshat et al. 2012).

Rule 1: IF x is A_1 and y is B_1, then $f_1=p_1+q_1+r_1$
Rule 2: IF x is A_2 and y is B_2, then $f_2= p_2+q_2+r_2$ (6)

where: x and y - inputs,
A_i and B_i - fuzzy sets,
f_i - outputs within the fuzzy region specified by the fuzzy rule,
pi, qi, ri - design parameters that are determined during the training process.

ANFIS architecture is as shown (Fig. 1) (Jang et al. 1997).

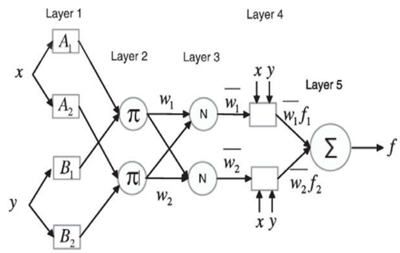

Fig. 1: ANFIS architecture.

ANFIS has five layers architecture as described below:

Layer 1: The first layer of this architecture is the fuzzy layer. Every node i in this layer is an adaptive node with a node function.

$$O_{1,i} = \mu_{A_i}(x), \text{ for i=1, 2, or}$$
$$O_{1,i} = \mu_{A_{i-2}}(y), \text{ for i=3, 4} \quad (7)$$

where: x, y - the input to node i

A_i, B_i - a linguistic label (such as "small" or "large") associated with this node.

In other words, $O_{1,i}$; - the membership function of A_i, and it specifies the degree to which the given x satisfies the quantifier A_i.

Layer 2: Every node in this layer is a circle node labeled. This layer involves fuzzy operators; it uses and operator to fuzzyfication the inputs. The output of this layer can be represented as:

$$O_{2,i} = w_i = \mu_{A_i}(x) * \mu_{B_i}(y), \quad i = 1,2 \quad (8)$$

Layer 3: Every node in this layer is a fixed node labeled N, representing the normalized firing weights of each rule. The ith node calculates the ratio of the it rule's firing weight to the sum of all rule's firing weights:

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1+w_2}, \quad i = 1,2 \quad (9)$$

where: $\overline{w_i}$ - an outputs of this layer which are called normalized firing weights.

Layer 4: Every node in this layer is an adaptive node with a node function, indicating the contribution of the its rule towards the overall output.

$$O_{4,i} = \overline{W_i} f_i = \overline{w_i}(p_i x + q_i + r_i), \quad i = 1,2 \quad (10)$$

where:

- the output of layer 3,

$\{p_i,q_i,r_i\}$ - the consequent parameter set.

Layer 5: The single node in this layer is a fixed node labeled Σ. This node computesthe overall output as the summation of all incoming signals.

$$O_{4,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad i = 1,2 \quad (11)$$

ANFIS used to hybrid learning algorithm that integrates Gradient Descent and Least Squares Estimation algorithm. The hybrid algorithm is composed to a forward pass and a backward pass.

RESULTS AND DISCUSSION

The density and moisture content values of OSBs were determined according to the related standards (TS EN 323, 1999) (TS EN 322, 1999). The average density and moisture content of panels were obtained as 0.61 g.cm^{-2} and 7.2 %, respectively. It was found that the aimed and obtained values of these properties were within the ranges specified in the standards.

Tab. 1: Modulus of elasticity values of test specimens.

Manufacturing conditions			MOE (Nmm^{-2})					
			30 (kg.cm^{-2})		40 (kg.cm^{-2})		50 (kg.cm^{-2})	
Pressing time (min.)	Pressing temperature (°C)	Adhesive ratio (%)	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
3	175	3	2869.14	402.03	3924.31	1941.99	2221.24	240.00
		6	5945.95	374.54	4153.64	809.89	2435.12	124.44
		9	3033.56	252.03	3790.98	402.19	3300.45	320.60
		12	2395.81	403.46	2179.14	199.85	3580.86	275.17
	185	3	1830.01	321.05	3776.44	952.57	2382.31	112.80
		6	4818.82	239.38	6541.96	310.83	5759.62	178.85
		9	5126.72	496.58	5839.49	396.24	6524.34	340.80
		12	2747.84	200.35	2471.89	461.74	3161.67	763.29
	195	3	2478.95	226.78	1386.84	236.41	1802.72	118.93
		6	5402.99	305.62	3500.32	155.69	4778.77	462.95
		9	3206.22	543.17	2325.23	120.88	2997.64	425.16
		12	4334.65	242.52	2170.40	577.74	2308.46	510.86
6	175	3	5627.47	160.01	6938.44	188.57	3980.86	888.42
		6	6453.90	235.43	7437.03	284.16	6223.24	275.73
		9	7102.53	498.93	8018.89	615.23	8221.52	462.43
		12	5737.12	319.59	2632.46	771.76	5405.68	392.37
	185	3	4434.88	548.19	5627.90	419.63	3668.79	246.61
		6	6816.69	539.27	7653.40	609.12	7067.88	1212.46
		9	8066.52	646.98	6800.63	529.77	8909.73	917.46
		12	3655.24	463.60	4113.38	294.12	4017.14	779.64
6	195	3	5496.89	174.53	5754.53	437.84	4371.90	273.47
		6	6401.64	103.64	6795.64	226.66	6284.33	220.08
		9	4537.02	325.04	7876.06	679.39	6976.25	491.43
		12	4932.49	671.14	6722.35	1547.92	3943.22	389.37
9	175	3	4427.01	341.41	5852.06	505.87	5380.34	551.48
		6	6014.76	344.79	6769.27	422.12	6507.54	394.35
		9	7236.19	401.98	7489.78	383.04	6914.86	693.77
		12	6904.46	530.87	6130.86	321.84	7442.27	918.72
	185	3	6195.36	539.26	5323.26	268.55	3499.18	181.72
		6	7976.49	224.70	6444.19	198.53	5641.34	396.32
		9	7747.40	413.56	8943.46	568.81	6227.26	854.15
		12	5390.55	245.01	7047.13	197.01	5237.55	338.87
	195	3	5243.40	582.77	5258.65	341.57	4496.68	423.12
		6	5204.43	318.30	6231.14	328.71	5363.00	521.78
		9	7536.75	849.17	6583.83	375.28	7850.35	674.96
		12	5404.27	844.39	6971.23	994.58	4169.37	446.37

The average and standard deviation of the value modulus of elasticity (MOE) determined according to manufacturing conditions of test panels is given in Tab. 1.

One of the most important factors that effect on the properties of OSB is adhesive type. Phenolic adhesives are mainly used for providing strong and durable bonds in wood composites. Modulus of elasticity value is a very important property of wood composite panels in many applications; that is, especially in construction's sectors. OSB panels are commonly used in building sectors. In this study, it was found that the MOE values changed between 1802.72 and 8943.46 $N.mm^{-2}$. The highest value of MOE was 8943.46 $N.mm^{-2}$ (9 % adhesive ratio, 185°C pressing temperature, 40 $kg.cm^{-2}$ pressing pressure and 9 min. pressing time). It was shown that there was a critical increase after increasing the adhesive ratio and pressing time. But, it can state that when the increase of pressing pressure, the MOE values of panel's decrease that used 12 % adhesive ratio and 3 min. pressing time. It can be said that when the used to 12 % adhesive ratio, pressing time inadequate for curing time especially using 3 min. pressing time. In a similar study, it was found out that by increasing the adhesive level from 3 to 6 %, modulus of elasticity value was increased by about 25.92 % in flexure parallel with the length of the layers (Gökhan et al. 2011). Avramidis and Smith (1989) and Tang et al. (1984) both stated that mechanical properties of OSB increased as resin ratio increased from 4 to 5 then 6 %. In addition, water absorption, thickness swelling and linear expansion properties improved with increasing of resin ratio. The Multiple variance analysis was applied on data belong to EMO, which was determined experimentally was shown in Tab. 2.

Tab. 2: The results of variance analyze.

Source	Type III Sum of squares	Df	Mean square	F- value	Sig. Level ($P<0.05$)
Corrected Model	1807956337.69	107	16896788.20	58.44	0.00
Intercept	14792741358.04	1	14792741358.04	51164.10	0.00
Pressing pressure (PP)	23589628.37	2	11794814.19	40.80	0.00
Pressing time (PM)	777938176.56	2	388969088.28	1345.34	0.00
Pressing temperature (PT)	29927267.32	2	14963633.66	51.76	0.00
Adhesive ratio (AR)	423391180.52	3	141130393.51	488.13	0.00
PP * PM	15460742.49	4	3865185.62	13.37	0.00
PP * PT	3863133.22	4	965783.30	3.34	0.01
PM * PT	30833872.26	4	7708468.07	26.66	0.00
PP * PM * PT	75258673.87	8	9407334.23	32.54	0.00
PP * AR	35001250.24	6	5833541.71	20.18	0.00
PM* AR	95084012.68	6	15847335.45	54.81	0.00
PP *PM * AR	32218225.58	12	2684852.13	9.29	0.00
PT* AR	65972207.23	6	10995367.87	38.03	0.00
PP * PT* AR	71439974.58	12	5953331.21	20.59	0.00
PM* PT *AR	46052935.20	12	3837744.60	13.27	0.00
PP * PM* PT* AR	81925057.58	24	3413544.07	11.81	0.00
Error	124901323.38	432	289123.43		
Total	16725599019.11	540			

Many of parameters affect the final mechanical and physical properties of OSB. Nearly almost all factors interact with each other in one way or another. Consequently, each factor cannot be thought of as an individual entity that can be manipulated to control panel properties. The situation is rather complex and necessitates a more complete understanding of the entire process before any improvement can be made (Basturk 1999). According to the variance analysis, the effects of the pressing pressure, pressing temperature, pressing time and adhesive ratio and the interaction of them on MOE values wasfound statistically significant. To comparisons of these means were done by employing a Duncan test to identify which groups were significantly different from other groups, and the results were given in Tab. 3.

Tab. 3: The results of Duncan test.

Manufacturing conditions		**EMO ($N.cm^{-2}$)**	
		Mean	**HG**
Pressing pressure ($kg.mm^{-2}$)	50	4973.71	A
	30	5242.62	B
	40	5485.45	C
Pressing time (min.)	3	3541.79	A
	6	5963.99	B
	9	6195.99	C
Pressing temperature (°C)	195	4919.41	A
	175	5296.63	B
	185	5485.73	C
Adhesive ratio (%)	3	4231.47	A
	12	4489.17	B
	6	5949.00	C
	9	6266.06	D

According to Duncan's test, the MOE values were determined changing between 3541.79 and 6266.06 $N.mm^{-2}$. Because of all manufacturing conditions of panels had affected on MOE, and it was seen that each of them fell within different homogenous groups. Determination of the relationships for prediction of MOE value of OSB panels produced different conditions by using multiple regressions, artificial neural network and ANFIS models, and also we compared the models. Firstly, basic statistics were shown Tab. 4. Pressing pressure values changed between 30 and 50 with an average value of 40. While the average value of pressing time was 6 min., values varied from 3 to 9 min. The average values of pressing temperature and adhesive ratio were 185°C and 7.5 % respectively. And, the maximum and minimum values of pressing time and the adhesive ratio were 3-9 min., 3-12 %, respectively.

Tab. 4: Basic statistics of the results.

	Pressing pressure ($kg.cm^{-2}$)	**Pressing time (min.)**	**Pressing temperature (°C)**	**Adhesive ratio (%)**
Minimum	30	3	195	3
Maximum	50	9	175	12
Average	40	6	185	7.5
Std.Dev.	8.17	2.45	8.17	3.35

The multiple regression analysis was performed for this study. Statistically significant and strong correlations were found to be linear. MOE value was used as independent values, descriptive statistics (minimum, maximum, mean, mode, median, variance, etc.) were calculated using SPSS. Tab. 5 shows that the MOE as an independent value shows that almost normal distribution. It can be seen that skewnessand kurtosis values of -0.143 and -0.738 were very slow, and this result shows that the analyses will work well.

Tab. 5: Descriptive statistics for MOE as an independent value.

N	**Valid: 540**
	Missing: 0
Mean	5233.9245
Median	5442.53
Mode	2009.54
Std. deviation	1893.67
Variance	3586006.7
Kurtosis	-0.738
Skewness	-0.143
Maximum	9945.82
Minimum	486.41
Sum	2826319.22

Multiple regression analysis was performed to correlate the MOE to pressing conditions and adhesive ratio (Tab. 6).

Tab. 6: Model summaries of multiple regressions for prediction of MOE.

Independent variables	Coefficient	Std. error	t-value	Sig. level
Constant	6334.34	1554.95	4.07	0.000
Pressing pressure	-13.44	8.12	-1.65	0.099
Pressing time	442.36	27.08	16.33	0.000
Pressing temperature	-18.86	8.12	-2.32	0.021
Adhesive ratio	36.33	19.77	1.83	0.067

Multiple regression model to predict reflectance is given below.

Y=6334.34-(13.44 x pressing pressure) + (442.36 x pressing time) - (18.86 x pressing temperature) + (36. 33 x adhesive ratio).

According to multiple regression analysis, the coefficient of correlation between the actual and predicted values is a good indicator to check the prediction performance of the model. Fig. 2 shows the relationships between experimental and predicted values for the multiple regression models for MOE value of OSB panels.

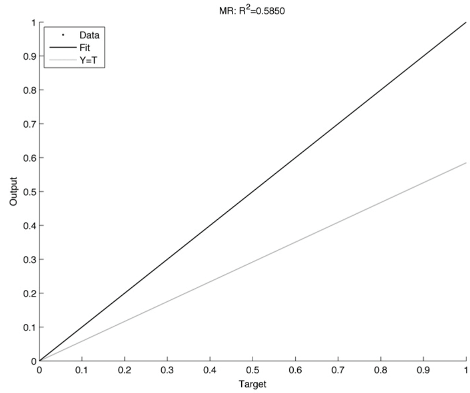

Fig. 2: Relationships between experimental and predicted values for the multiple regression model for MOE.

In this study values account for (VAF) and root mean square error (RMSE) were calculated to control the performance of the prediction capacity of the predictive model developed for the study as employed by Yilmaz and Kaynar (2011):

$$VAF = \left[1 - \frac{\mathrm{var}(y - y')}{\mathrm{var}(y)}\right] x100$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y - y')^2}$$

Where y and y´ are the calculated and predicted values, respectively. The calculated indices are given in Tab. 7. If the values account for (VAF) is 100, R^2 is 1.00 and root mean square error (RMSE) is 0, the model will be shown excellent performance.

In this equation, where A_i is the actual value and P_i is the predicted value. The obtained values of RMSE and VAF given in Tab. 7 indicated high prediction performances.

Tab. 7: Performance indices (RMSE, VAF and R^2) for models.

Model	RMSE		VAF (%)		R^2	
	Train	Test	Train	Test	Train	Test
ANN-MLP	0.0575	0.0814	92.5922	84.7671	0.9623	0.9208
ANFIS	0.0490	0.0699	94.6207	88.7550	0.9727	0.9424
MR	0.1684	0.1769	36.4519	28.3422	0.6038	0.5329

RMSE; root mean square error. VAF; value account for.

In this research, performance of ANFIS (3*3*3 membership functions) was better than ANN-MLP (Levenberg-Marquardt backpropagation - trainlm; 20 hidden neurons) and multiple regressions. The best RMSE and VAF values were found by using ANFIS model in the both train and test samples. The RMSE and VAF of ANFIS model for train and test were 0.0490, 0.0699, 94.6207 and 88.7550 % respectively. The best R^2 was found 0.9727 at ANFIS in Fig. 3 shows that relationship between actual and predicted MOE for ANN and ANFIS models.

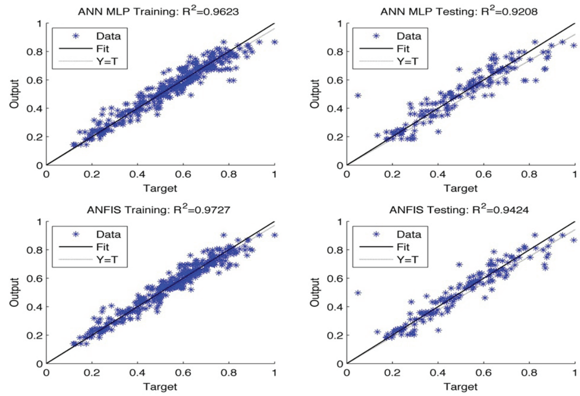

Fig. 3: Relationship between actual and predicted MOE for ANN and ANFIS models.

The deviations from the MOE value, the distances of the predicted MOE from the models were also calculated and graphics were drawn according to all and randomly selected 50 data (Fig. 4). These graphics shows that the deviation interval for all and first 100 data were (-1 to +1) of the predicted MOE from ANFIS is smaller than the deviation interval of multiple regression (-1 to +1) and ANN (-1 to +1).

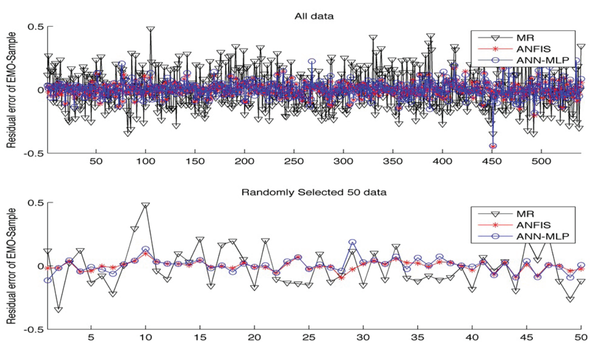

Fig. 4: The variation of the MOE predicted by multiple regression, ANN and ANFIS models for all and first 100 data.

According to this results, the multiple regression model for prediction of MOE (R^2=0.5850) was a good performance, but it was not as good as ANN-MLP and ANFIS especially. The ANN model has got a good performance (train R^2=0.9623, test R^2=0.9208) when compared with the multiple regression model. ANFIS model (train R^2=0.9727, test R^2=0.9424) has the highest performance for the prediction of MOE.

CONCLUSIONS

In this study, multiple regression, artificial neural network and adaptive neuro-fuzzy inference system were used to prediction of modulus of elasticity of oriented strand board panels, and these systems were compared to eachother's. The research developed the ANFIS and compared to the artificial neural network (ANN) model and multiple regression models. ANFIS estimated the MOE with higher accuracy. ANFIS model has a higher performance than ANN and multiple regressions for predicting MOE values of oriented strand board.

ANN and ANFIS have got higher accuracy and lower fault than traditional statistical models. The ANN and ANFIS can provide new approaches than simple statistics for highly precision mechanical and physical properties of wood-based practices, and this approach can recommend method in similar studies. The performance comparison showed that the ANFIS is a good tool for minimizing the uncertainties in the wood-based engineering projects.

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