Estimation of Physical and Mechanical Properties of Composite Board *via* Adaptive Neural Networks, Polynomial Curve Fitting, and the Adaptive Neuro-Fuzzy Inference System

H. Hüseyin Taş* and Bayram Cetişli

Several physical and mechanical properties of particle board were investigated using estimation modeling. Particleboards (0.65 g/cm^3) were produced for five experimental groups, in which lavender plant waste, red pine chips, and urea formaldehyde (UF) resin were mixed in different proportions. After immersing the particleboards in water for 24 h, several properties including thickness swelling (TS), modulus of rupture (MOR), modulus of elasticity (MOE), and internal bond strength (IBS) were determined. The statistical relevance of the experimental results was evaluated using multi-variance analysis (ANOVA), and the homogeneity between experimental groups was evaluated using Duncan tests. With the use of variable inputs and experimental results, estimation models using polynomial curve fitting (CF), adaptive neural networks (ANN), and an adaptive neuro-fuzzy inference system (ANFIS) were generated. The results obtained from the estimation models and experiments were then compared *via* root-mean-square error (RMSE) and R^2 values. The ANFIS estimation model was the best alternative to the costly, long-term experimental methods, as it produced more economical and reliable results in a shorter period of time.

Keywords: Composite material; Particleboard; Fuzzy logic

*Contact information: Süleyman Demirel University, Faculty of Technology, Department of Civil Engineering 32260 Isparta, Turkey; *Corresponding author: huseyintas@sdu.edu.tr*

INTRODUCTION

Particleboard is a composite product manufactured under elevated pressure and temperature from particles of wood or other lignocellulosic fibrous materials and a binder (EN 309 2005). The manufacture of modern particleboards goes back to the early 19th century. Production started with planer shavings and sawdust and progressed to the logs of all types (Bektaş *et. al.* 2005). In the building sector, particleboards with varying properties are especially useful for flooring and structural supporting walls (Kozlowski and Helwig 1998). With increasing populations and new application areas, the demand for wood has intensified the need for standing forest resources, which has stimulated a rise in the price of wood as a raw material. Thus, alternative biomasses or raw materials have been evaluated for their use in building and construction (Bektaş *et. al.* 2005).

In the particleboard production sector, botanical wastes that have been evaluated as cheaper alternatives to wood chips include groundnut shells (Jain *et al*. 1967), bagasse (Mitlin 1968; Turreda 1983), grain-wheat straw (Mosesson 1980; Han *et al*. 1998), bamboo (Rowell and Norimoto 1998), tea plant waste (Yalinkiliç *et al*. 1998; Filiz *et al*. 2011;

Batiancela *et al*. 2014), sunflower stalks (Khristova *et al*. 1998; Bektaş *et al*. 2005), vine branches (Ntalos and Grigoriou 2002), corn stalks (Güler *et al*. 2001), peanut shells (Batalla *et al*. 2005), almond shells (Gürü *et al.* 2006), agricultural waste (Arslan *et al*. 2007), giant reed (Garcia-Ortuna *et al*. 2011), kenaf (Xu *et al*. 2013), sunflower seed husks (Cosereanu *et al*. 2015), hazelnut husks (Avci *et al.* 2013), cotton and hemp stalks (Kollmann 1966), kiwi branches (Nemli *et al*. 2003), herbal greenhouse wastes (Karakuş 2007), banana peel wastes (Topbasli 2013), castor stalks (Grigoriou and Ntalos 2001), wheat straw and corn stalks (Wang and Sun 2002), kenaf and rubberwood (Halip *et al.* 2014), regenerated cellulose fibers (Kowaluk 2014), fibrous chips (Kowaluk *et al.* 2011), and ligno-cellulosic particles (Kowaluk *et al.* 2009).

Evaluating particleboard conformance to institutional standards by determining their physical and mechanical properties exhausts a great deal of time and effort, resulting in high costs to institutions and the loss of productive research time. Hence, the properties of wood-based composite panels should be determined with the most beneficial estimation method in terms of time, effort, and cost, *i.e.*, artificial neural networks, fuzzy logic, or Buckingham's p-theorem. Yapıcı *et al.* (2009) indicated that the nail- and screw-withdrawal resistances of OSB panel could be estimated, with error margins of 21.04% and 10.74% to their real values, respectively, through a fuzzy classification model. Neural networks reveal the material-quality process relationships during machine processing of laminated particleboards (Lacki *et al*. 2009). Arabi *et al.* (2011) reported that Buckingham's p-theorem estimates the bending strength and elasticity of particleboard with error margins of 7.06% and 11.27%, respectively. Using neural networks to estimate the properties of medium density fiberboards (MDF) board increases the efficiency of tests conducted in accordance with BS-EN standards (Ismail and Bakar 2012). Ismail and Bakar (2013) stated that producers could decrease the test period, in accordance with BS-EN quality standards, by simulating the test procedures for MDF board with a genetic algorithm neural network model. Finally, the fuzzy logic model can be used to estimate the load needed to drill MDF board (Prakash *et al.* 2014).

In this study, medium-density particleboard were produced after mixing waste lavender, red pine chips, and urea formaldehyde resin in different proportions. The physical and mechanical properties of the particleboards were investigated using the polynomial curve fitting method, adaptive neural networks, and an adaptive neuro-fuzzy inference system. By this way, the laboratory tests can be decreased and some of the unmeasured physical and mechanical values of particleboards are estimated by mathematical and artificial intelligence based methods.

EXPERIMENTAL

Materials and Methods

Red pine (RP) chips were obtained from the production line of the Isparta Orma factory and were used for the core layer of the particleboard. Lavender plant (LP) chips were obtained from the waste stalks of lavender plants grown and harvested in the village of Kuyucak, located in Isparta, Turkey. Lavender and red pine chips were treated in a drying oven at 102 ± 3 °C until the moisture level reached 2 to 3%. Five different groups were formed for experimental studies, and the mixing ratios of UF resin, red pine, and lavender plant waste are given in Table 1.

Table 1. Mixing Ratios of Chips and Resin for the Experimental Groups

Board Group	Mixing Ratio of Chips (%)		Glue Ratio (%)
	Lavender Stem	Red Pine	
A	0	100	12
			10
			6
B	25	75	12
			10
			6
C	50	50	12
			10
			6
D	75	25	12
			10
			6
E	100	0	12
			10
			6

The chips were weighed according to mixing ratios of the experimental groups and then mixed to homogeneity. The chips were blended with 12 or 10 or 6% UF resin with a 65% solid content. The glued chips were poured into a wood form and placed on top of a rectangle metal sash with a 12 mm thickness and dimensions of 31 × 35 cm^2. Next, the chips were pre-pressed at room temperature. Particleboard mats were removed from the wood form sash and incubated for 4 min in a hot-press machine (CEMILUSTA, SSP-180T, Istanbul, Turkey) at a temperature of 155 to 160 °C and pressure of 2.6 to 3.0 N/mm^2.

After cooling, particleboards were removed from the hot-press machine and cut to 50 × 300 mm and 50 × 50 mm samples. The final dimensions were measured with digital calipers (Mitutoyo, P&G Industrial Co., Ltd., City, China) to an accuracy of 0.01 mm.

Thickness swelling (TS), modulus of rupture (MOR), modulus of elasticity (MOE), and internal bond strength (IBS) were determined in accordance with the testing standard TS-EN-312 (2005) on a Zwick/Roell Z050 Universal testing machine (Ulm, Germany) with a 5000 kg load capacity and a 5 mm/min load rate.

The experimental data were evaluated statistically *via* SPSS 20.0 software (Chicago, USA), and the relevance of the results obtained was investigated *via* multi-variance analysis (ANOVA) at a 5% significance level. The Duncan test was used to determine the minor differences between all the variables within groups that were found to have a relationship (Taş and Sevinçli 2015).

Design of the CF, ANNs, and ANFIS Systems

Polynomial curve fitting (CF)

Curve fitting is the process of constructing a curve, or a mathematical function, that contains the best fitting function to a series of data points, which are possibly subjected to constraints. Curve fitting can involve either interpolation, where an exact fit to the data is required, or smoothing, in which a "smooth" function approximately fits the data (Jang *et* *al.* 1997; Kivsalaas 2010). A related topic is regression analysis, which focuses more on the question of statistical inference, such as how much uncertainty is present in a curve that is fit to the data observed and the inclusion of random errors. Fitted curves can be used to facilitate data visualization, to infer values of a function where no data is available, or to summarize the relationships among two or more variables. Extrapolation refers to the use of a fitted curve beyond the range of the observed data and is subject to a degree of error because it may reflect the method used to construct the curve as much as it reflects the observed data. The parameters of the fitted curve were determined through least square estimation (LSE) (Esteban *et al.* 2009).

Adaptive neural networks (ANNs)

Adaptive neural networks are parallel processing structures that solve a wide range of problems. A neural network is a system composed of many cross-linked simple processing units called neurons. The neurons consist of a series of interconnected functions in a multiple regression, wherein the importance lies not so much in the relationship that exists among the functions but is instead focused on achieving an output that is within an acceptable margin of error (Esteban *et al.* 2009; Kranthi and Satapathy 2010).

Adaptive neural networks are generally made up of three layers: the input, hidden, and output layers. If the problem is more complex, the number of hidden layers can be increased, as illustrated in Fig. 1. The input layer receives the initial values of the variables, the output layer shows the results of the network for the input, and the hidden layer carries out the operations designed to achieve the output. The number of neurons in the input layer must correspond to the number of entry variables, and the output layer must have as many neurons as the number of outputs produced by the network. However, there is no rule to allow prior decisions to be made on the number of neurons the hidden layer should contain or whether the hidden layer must consist of more than one sub-layer (Esteban *et al.* 2009; Kranthi and Satapathy 2010). The hidden layer is obtained through trial and error.

Neural computation based on artificial neural networks involves database training to predict the input of the initial values of the variables, while the output layer shows the results of the network for the two-dimensional problems because it is able to imitate the learning capability of human beings. Thus, the network learns directly from the examples without any prior formula regarding the nature of the problem and can independently generalize knowledge, which then can be applied to new cases.

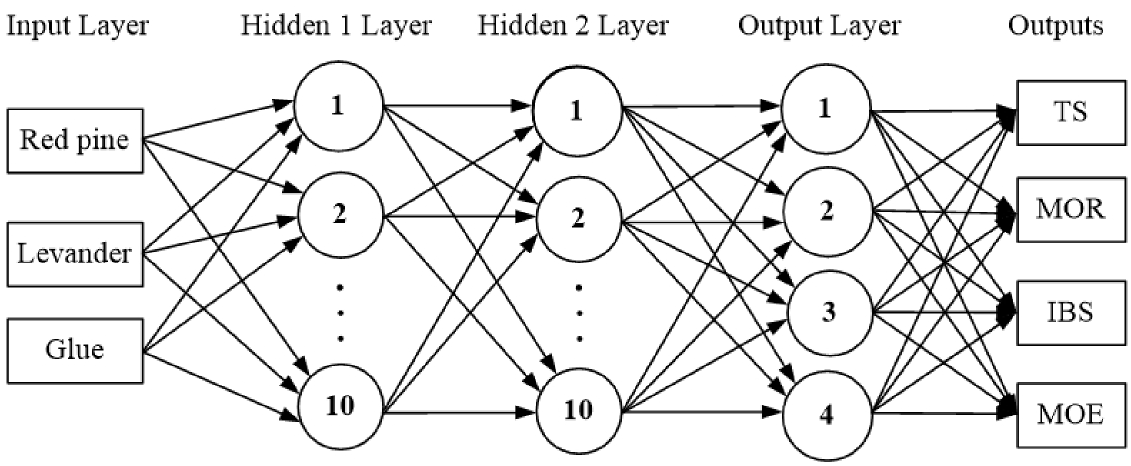

Fig. 1. Figure modified from adaptive neural network architecture (Esteban *et al.* 2009)

Adaptive neuro-fuzzy inference system (ANFIS)

One way to represent data and knowledge is to use fuzzy rules instead of exact rules (Kasabov 1998). Fuzzy systems are rule-based expert systems based on fuzzy rules and a fuzzy inference system. A fuzzy inference system is a real-time expert system used to model and utilize the knowledge and experience of a human operator or process engineer (Esteban *et al.* 2009). Fuzzy logic can model nonlinear functions of arbitrary complexity, and it provides an alternative solution to nonlinear modeling because it is closer to the real world. For this purpose, a variety of fuzzy rules should be defined for local fuzzy regions instead of global nonlinear functions. Nonlinearity and complexity are handled by rules, membership functions, and the inference process, which results in improved performance, simpler implementation, and reduced design costs. The ANFIS network system is based on the Sugeno model, which consists of fuzzy nodes and first-order polynomials (Jang *et al.* 1997).

A hybrid learning algorithm, consisting of gradient descent and least square estimation, was proposed by Jang *et al.* (1997). ANFIS is more powerful than simple fuzzy logic algorithms and neural networks because it provides a method for fuzzy modeling to learn information about the data set and thereby computes the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data (Kranthi and Satapathy 2010). ANFIS is composed of five layers: fuzzification, rule, normalization, de-fuzzification, and output (Fig. 2).

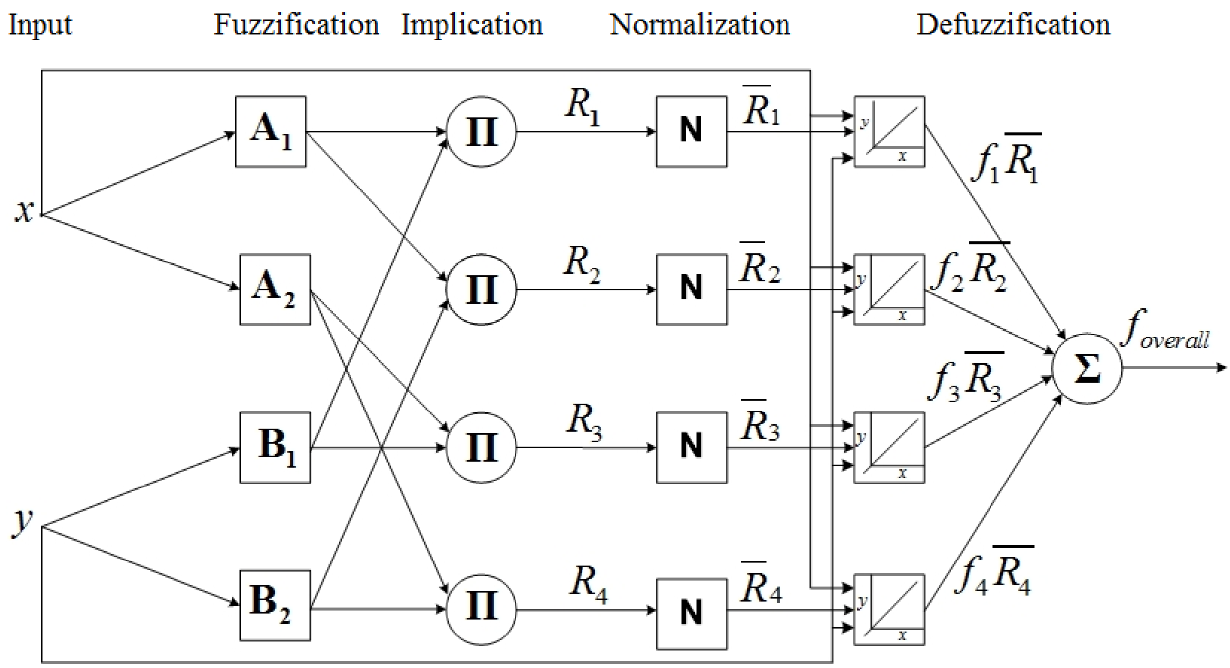

Fig. 2. Figure modified from typical ANFIS architecture (Jang *et al.* 1997)

In this study, experimental data was estimated using ANFIS, ANN, and second-order polynomials. ANFIS had 20, 7, 9, and 5 rules for TS, MOR, IBS, and MOE, respectively. These rule numbers were determined through trial and error. ANN had two hidden layers consisting of 3-10-10-4 neurons for each layer. The activation functions of layers were “logsig”, “tansig”, and “purelin”. The “trainscg” function was used for network training. Second-order polynomials were fitted using LSE. The ANFIS and ANN results denote the mean values of 10 runs. For ANFIS and ANN training, the experimental data were equally divided into training and test data. Training data were used for the training models, and the test data was used for a comparison of the methods.

RESULTS AND DISCUSSION

According to ANOVA of the experimental results (Table 2), the differences between all experimental groups were statistically significant ($P < 0.05$) in terms of mixture and glue ratio. Duncan’s multiple range test comparison was used to determine the importance of the smallest, significant differences between the groups (Tables 3 and 4).

Table 2. Variance Analysis of TS, MOR, IBS, and MOE

Source	DV	Sum of Squares	Degrees of freedom	Mean Square	F
Corrected Model	TS	12822.838[a]	14	915.917	2469.569
	MOR	426.137[b]	14	30.438	9066.227
	IBS	1.295[c]	14	0.093	1020.399
	MOE	3581868.480[d]	14	255847.749	18231.431
Intercept	TS	244294.413	1	244294.413	658686.192
	MOR	9798.596	1	9798.596	2918565.161
	IBS	8.535	1	8.535	94130.882
	MOE	167976887.520	1	167976887.520	11969849.467
Mixture (M)	TS	4086.531	4	1021.633	2754.608
	MOR	39.840	4	9.960	2966.677
	IBS	0.188	4	0.047	517.169
	MOE	174035.947	4	43508.987	3100.403
Glue (G)	TS	8368.009	2	4184.005	11281.249
	MOR	375.788	2	187.894	55965.234
	IBS	1.105	2	0.552	6091.074
	MOE	3324685.520	2	1662342.760	118456.729
M x G	TS	368.297	8	46.037	124.129
	MOR	10.508	8	1.314	391.251
	IBS	.003	8	0.000	4.346
	MOE	83147.013	8	10393.377	740.621
Error	TS	22.253	60	0.371	
	MOR	0.201	60	0.003	
	IBS	0.005	60	9.067E-005	
	MOE	842.000	60	14.033	
Total	TS	257139.504	75		
	MOR	10224.934	75		
	IBS	9.835	75		
	MOE	171559598	75		
Corrected Total	TS	12845.091	74		
	MOR	426.338	74		
	IBS	1.301	74		
	MOE	3582710.480	74		

DV: Dependent Variable (Taş and Sevinçli 2015)

a. R^2 = 0.998 (Adjusted R^2 = 0.998)
c. R^2 = 0.996 (Adjusted R^2 = 0.995)
b. R^2 = 1.000 (Adjusted R^2 = 0.999)
d. R^2 = 1.000 (Adjusted R^2 =1.000)

Note: all values tested had a *P*-value of 0.000

Table 3. Duncan Mean Separation Tests for Mixture Ratios

Particleboard Group	A	B	C	D	E
MOR (N/mm^2)	12.22^a	12.21^b	11.41^c	10.94^d	10.34^d
MOE (N/mm^2)	1553.46^a	1528.53^b	1506.13^c	1482^d	1412.66^e
IBS (N/mm^2)	0.41^a	0.36^b	0.33^c	0.30^d	0.26^e
TS (%)	46.82^a	52.64^b	57.21^c	59.72^d	68.94^e
[a,b,c,d,e] Values with the same letter are not significantly different (Duncan test). (Taş and Sevinçli 2015)					

Table 4. Duncan Mean Separation Tests for Glue Ratio

Glue Ratios (%)	6	10	12
MOR (N/mm^2)	8.36^a	12.28^b	13.64^c
MOE (N/mm^2)	1199.24^a	1631.28^b	1659.16^c
IBS (N/mm^2)	0.16^a	0.39^b	0.44^c
TS (%)	71.56^a	52.95^b	46.69^c
[a,b,c,] Values with the same letter are not significantly different (Duncan test). (Taş and Sevinçli 2015)			

Table 5. Comparison of Estimation Methods using RMSE Values for Experimental Data

	ANFIS	ANN	CF
TS	0.862	3.127	2.513
MOR	0.072	0.186	0.418
IBS	0.009	0.009	0.012
MOE	5.005	85.045	33.932
Mean	1.487	22.092	9.219
Std. Dev.	2.377	41.99	16.512

Table 6. Comparison of Estimation Methods using R^2 Values for Experimental Data

	ANFIS	ANN	CF
TS	0.995	0.942	0.962
MOR	0.999	0.993	0.968
IBS	0.994	0.994	0.991
MOE	0.999	0.840	0.974
Mean	0.997	0.942	0.974
Std. Dev.	0.002	0.072	0.012

The approximation of the ANFIS, ANN, and CF estimation models, where variable inputs and results of the study were used to represent the real experimental data, are given in Tables 5 and 6 by comparison analysis, using RMSE and R^2 values, respectively. The models were run 10 times, and the obtained average results are given in Tables 5 and 6. Although 38 samples were used as training data, 37 samples were used as test data. The tables show the results of test data. In Table 6, R^2 values are bigger than 0.9. This result could be regarded as suspicious. But the methods were run many times and gave similar results. Also RMSE and error rate results support the R^2 results. ANFIS provided the best estimation results. Although ANNs uses parameters more than ANFIS, it is insufficient in relation to the ANFIS because the ANFIS is used for the estimation of particleboard features. Third- and fourth-order polynomials were used for TS and MOE estimations. However, these polynomials proved insufficient for true estimation.

Experimental data were estimated using ANFIS, ANN, and CF methods. The obtained results for thickness swelling, for modulus of rupture, internal bond strength, and modulus of elasticity are given in Figs. 3, 4, 5, and 6, respectively. When the real experimental values and the ANFIS, ANN, and CF curves were compared, it was clear that the ANFIS model produced estimate values that were closest to the experimental ones.

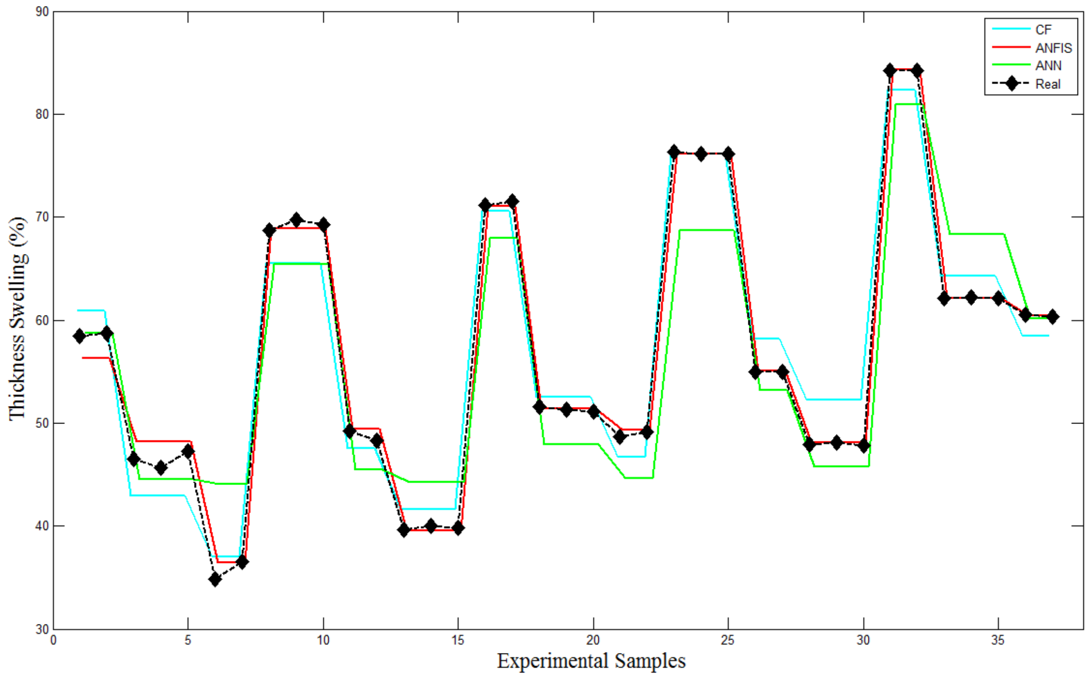

Fig. 3. Thickness swelling estimation results

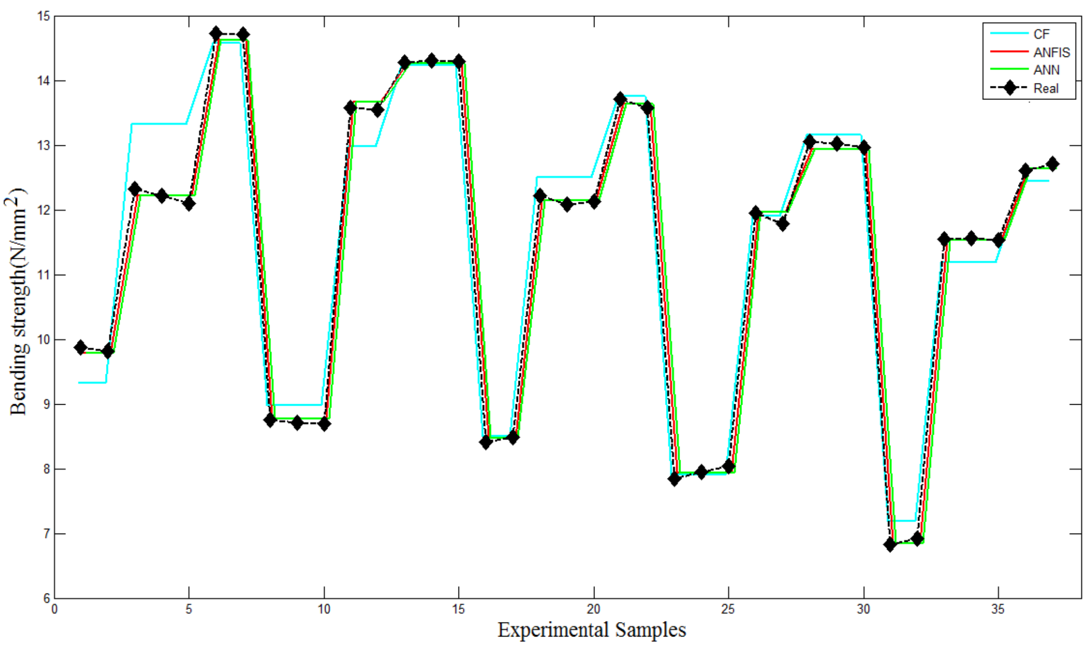

Fig. 4. MOR estimation results

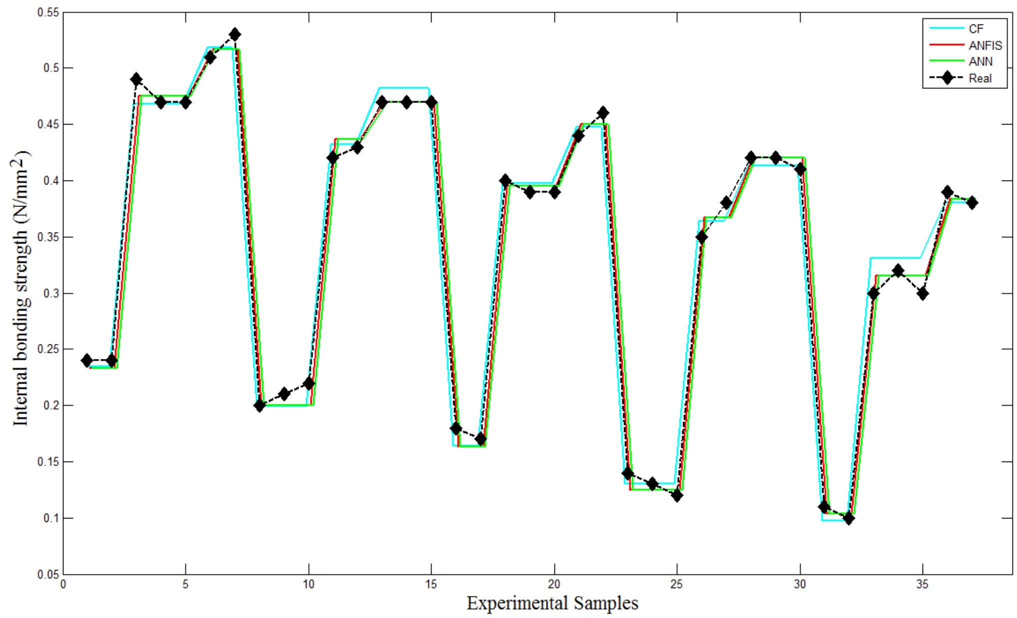

Fig. 5. IBS estimation results

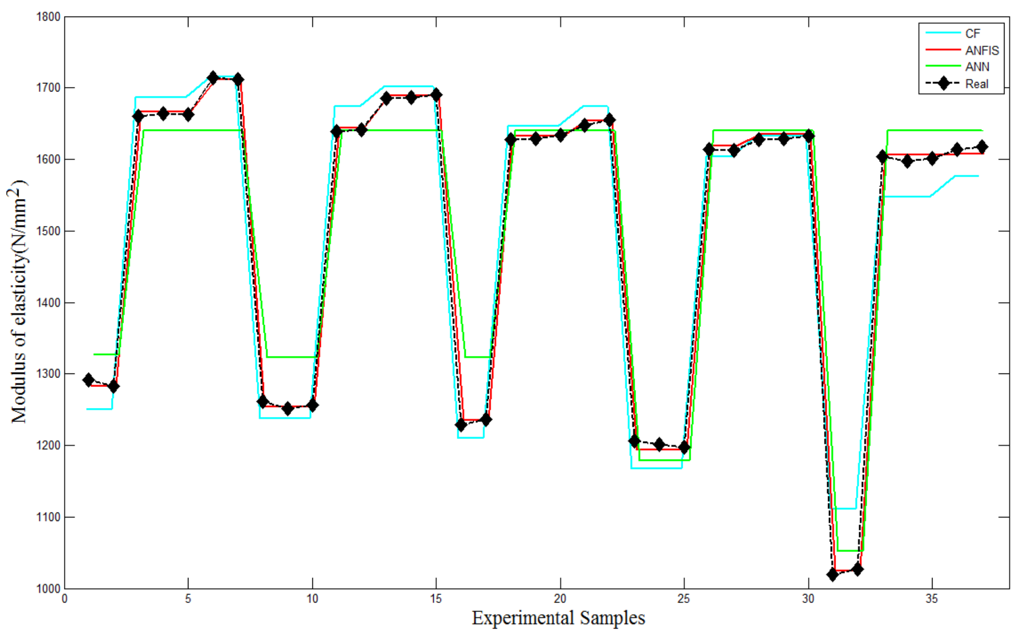

Fig. 6. MOE estimation results

The ANFIS estimation surfaces were determined according to the lavender and resin ratios (Fig. 7). The TS values decreased as the ratio of lavender plant waste decreased and the ratio of red pine and resin increased. MOR and MOE values increased to their maximum levels as the ratio of lavender plant waste decreased and the ratio of red pine and resin) increased. IBS values increased to the maximum level as the ratio of lavender plant waste decreased and the ratios of red pine and resin increased. However, the increased resin ratio was not significant.

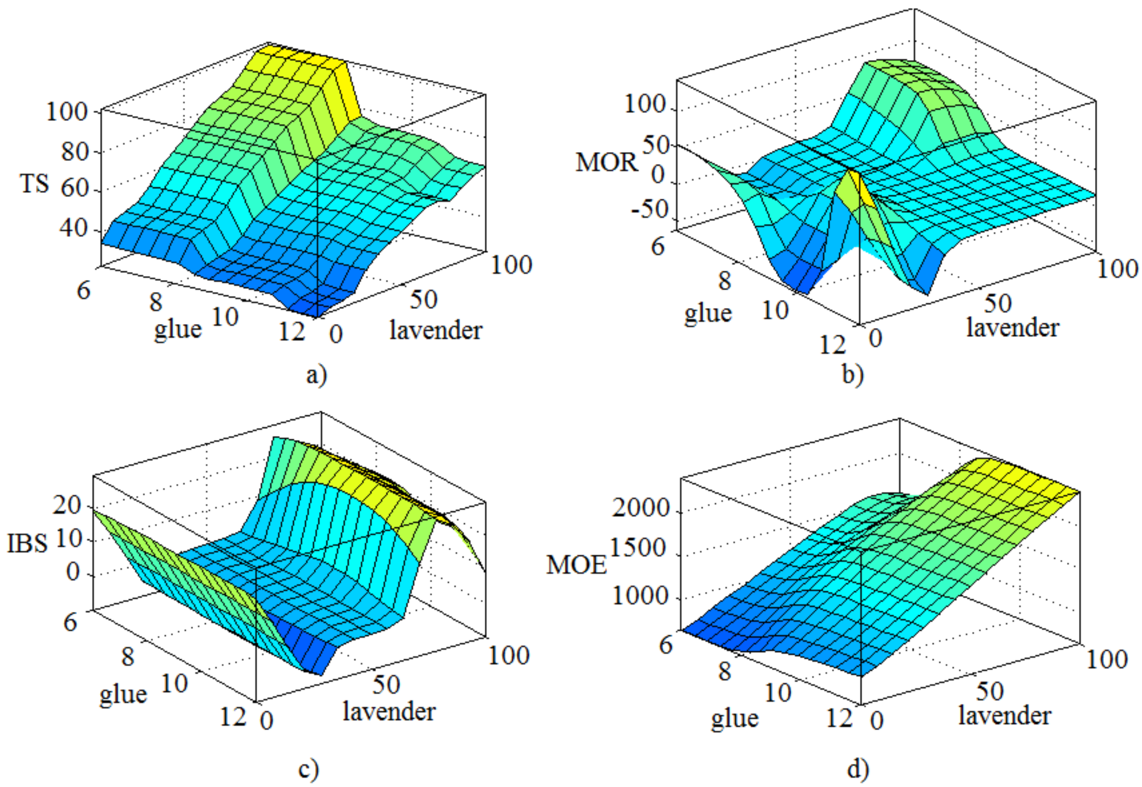

Fig. 7. ANFIS estimation surfaces according to lavender and resin ratios. a) TS, b) MOR, c) IBS, and d) MOE

Percentage error results of the estimation methods are given in Table 7.

Table 7. Percentage Error Rates of Estimation Methods for Experimental Data

Output	ANFIS (%)	ANN (%)	CF (%)
TS	0.99	5.87	4.11
MOR	0.53	0.54	2.69
IBS	2.92	3.57	3.47
MOE	0.29	1.92	1.98
Mean	1.18	2.97	3.06
Std. Dev.	1.19	2.29	0.92

Although all methods give sufficient error rates, the ANFIS is very close to the real values.

Similar studies using the other estimation models such as Fuzzy Logic to determine some mechanical and physical characteristics of the particleboards and other wood-based panels reported that the closest results were found to the actual values with minimum margin of error. For example, the elasticity and flexural strength values of the particleboards were reported to be closest to the actual values with 7.06% and 11.27% margin of error, respectively, using the Buckinghams p-theorem estimation model (Arabi *et al.* 2011). Similarly, nail and screw withdrawal resistances of the OSB panels were reported to be the closest values to the actual values with 21.04% and 10.74% margin of error, respectively, using the Fuzzy logic estimation model (Yapıcı *et al.* 2009).

CONCLUSIONS

1. Medium-density particleboards were produced using different proportions of lavender plant waste, red pine chips, and urea formaldehyde resin. The physical and mechanical properties of the particleboards were determined through experimental methods, and the results were statistically evaluated.
2. With the use of variable inputs and experimental results, CF, ANN, and ANFIS models were used to estimate the physical and mechanical properties of particleboards.
3. The results obtained from the estimation models were compared with real experimental results. The ANFIS estimation model performed the best and was easier than the ANN and CF estimation models with 1.18% error relative to the real data.

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