İbrahim Karaman[1], Kenan Kılıç[2,3], Cevdet Söğütlü[4]

Prediction of Adhesion Strength of Some Varnishes Using Soft Computing Models

Predviđanje adhezivne čvrstoće nekih lakova uz pomoć modela mekog računalstva

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ABSTRACT • *The purpose of this study was to predict the adhesion strength of the varnish, which is applied as a protective coating/finish on the surface of wooden material using soft computing models. In this study, the soft computing approaches were applied to oak (Quercus Petrea L.), chestnut (Castanea sativa M.), and scotch pine (Pinus sylvestris L.) with water-based, polyurethane, and acrylic varnishes. The adhesion strength of the varnish was determined in accordance with the Turkish Standard Institute-24624 and ASTM D4541. The outcome of the experiment was used to develop artificial neural network (ANN) and fuzzy logic (FL) prediction models. The total number of 360 data points was split as 80 % of training and 20 % of test for the model development. During the application of the ANN, 6 features were used as an input, while the adhesion strength was used as an output of the model. The coefficient of determination values (R^2) for training and testing in the ANN models were 0.9939 and 0.9580, respectively. In the case of the ANFIS model, R^2 values for training and testing were 0.9917 and 0.9929, respectively. Considering the MAPE, RMSE, and R^2 values obtained from the results of both training and test values, it can be concluded that the ANFIS model showed a more successful performance in estimating varnish adhesion strength. Therefore, ANN and ANFIS have the potential to provide time and cost-efficient benefits in estimating wood adhesion strength.*

KEYWORDS: *artificial neural network, fuzzy logic, adhesion strength, wood, varnish*

SAŽETAK • *Cilj ovog istraživanja bio je uz pomoć modela mekog računalstva predvidjeti adhezivnu čvrstoću laka koji se nanosi kao zaštitni premaz na površinu drvnog materijala. Pristup mekog računalstva primijenjen je na uzorcima hrastovine (Quercus Petrea L.), kestenovine (Castanea sativa M.) i borovine (Pinus sylvestris L.) lakiranima vodenim poliuretanskim i vodenim akrilnim lakom. Adhezivna čvrstoća laka određena je prema normama TS EN 24624 i ASTM D4541. Rezultati istraživanja iskorišteni su za razvoj modela predviđanja umjetne neuronske mreže (ANN) i neizrazite logike (FL). Od ukupno 360 podatkovnih točaka razvoja modela 80 % njih upotrijebljeno je za trening, a 20 % za testiranje. Tijekom primjene ANN-a šest je svojstava poslužilo kao ulazna varijabla, dok je adhezivna čvrstoća primijenjena kao izlazna varijabla modela. Vrijednosti koeficijenta determinacije (R^2) za trening i testiranje u ANN modelima bile su 0,9939 i 0,9580. Pri primjeni ANFIS modela*

[1] Author is researcher at Yozgat Bozok University, Yozgat Vocational School, Computer Technology Department, Yozgat, Turkey. https://orcid.org/0000-0001-8396-9797
[2] Author is researcher at Gazi University, Graduate School Of Natural And Applied Sciences, Department of Wood Products Industrial Engineering, Ankara, Turkey. https://orcid.org/0000-0003-1607-9545
[3] Author is researcher at Yozgat Bozok University, Yozgat Vocational School, Design Department, Yozgat, Turkey. https://orcid.org/0000-0003-1607-9545
[4] Author is researcher at Gazi University, Faculty of Technology, Department of Wood Products Industrial Engineering, Ankara, Turkey. https://orcid.org/0000-0002-9359-1633

R^2 vrijednosti za trening i testiranje iznosile su 0,9917 i 0,9929. Uzimajući u obzir vrijednosti MAPE, RMSE i R^2, dobivene iz rezultata treninga i testiranja, moguće je zaključiti da se ANFIS model pokazao uspješnijim u procjeni adhezivne čvrstoće laka. Stoga se može reći da modeli ANN i ANFIS mogu imati vremenske i troškovne prednosti u procjeni adhezivne čvrstoće na drvu.

KLJUČNE RIJEČI: *umjetna neuronska mreža, neizrazita logika, adhezivna čvrstoća, drvo, lak*

1 INTRODUCTION
1. UVOD

The wooden material is defined as an indoor natural reinforcement engineering material as it can be processed and has high mechanical strength (Özgenç *et al*., 2022; Döngel *et al*., 2008; Hauptmann *et al*., 2013). Materials composed of wood are readily susceptible to physical and mechanical effects. Therefore, to increase the durability and aesthetics of the wooden material, synthetic and natural-based varnishes and resins are applied to the surface of the material (Kılıç, 2009). Moreover, the structure of the varnish and the heterogeneous property of the wooden material influence the adhesion strength of the varnish layers (Vitosyte *et al*., 2012; Marra, 1992). In the literature, there are several types of research about the adhesion strength of the varnish. According to the literature review, the adhesion strength of the water-based varnish is low while that of the polyurethane-based varnish is high (Vitosyte *et al*., 2012; Marra, 1992; Sönmez *et al*., 2004). Therefore, based on the previous research, the type of varnish is considered an important factor affecting the adhesion strength (Kılıç and Söğütlü, 2020; Söğütlü *et al*., 2016).

For that reason, the evaluation of the adhesion strength is important in terms of the analysis of wooden material-based product life cycle. Moreover, the adhesion strength is predicted using an artificial neural network (ANN) to decrease computation time and save energy for experimental evaluations. ANN is one of the artificial intelligence models used to solve complex and non-linear problems. The ANN consists of neurons and nodes that are activated by an activation function. Furthermore, the ANN can work with multi-input and output variables and create a relationship between non-linear parameters. The ANN is preferred rather than traditional statistical approaches because it is widely used in various engineering fields (Tiryaki *et al*., 2014b; Özşahin, 2013; Paliwal and Kumar, 2009). The ANNs and fuzzy logic (FL) have high computation ability for regression analysis and prediction compared to the traditional models (Kumar and Thakur, 2012; Londhe and Deo, 2003). Previous studies have developed the use of ANNs based on the properties of wooden materials. Budakci and Akkuş (2011) provided an ANN model to evaluate the average adhesion strength of the wooden material and laminated flooring. Tiryaki *et al*. (2014b) presented the ANN model for model surface roughness of wood in the machining process. Ceylan (2008) expressed an ANN model for the desiccation of wood, and Yang *et al*. (2015) demonstrated an ANN model to show the mechanical properties of heat-treated wooden material. Tiryaki *et al*. (2016) applied multilayered networks to predict the bonding strength of the different wooden materials. Bardak *et al*. (2016) estimated the bonding of wood materials with ANN models at four different temperatures depending on different pressing conditions. Tiryaki *et al*. (2014a) used different temperatures with various wooden materials to estimate the compression strength through the ANNs. However, Fuzzy Logic (FL) is widely used in household electrical appliances, industrial products, and manufacturing engineering (Mendel, 1995). According to the previous studies, several types of research have been implemented using FL. Yapıcı *et al*. (2009) presented an FL classification model to predict the tensile strength and elastic modulus of the flakeboard. Furthermore, Cha and Pearson, (1994) improved a model to estimate the elastic module of the laminated veneer lumber.

This study predicts the adhesion strength of different varnish types using ANN and FL models. During the experiment, different variables were used for these materials for the varnish adhesion strength test. In this study, varnish adhesion strength was estimated using ANN and ANFIS through data obtained in the experiments. By using the developed ANN model and FL methods, varnish adhesion strength was estimated, and the models were compared with the regression method.

2 MATERIALS AND METHODS
2. MATERIJALI I METODE

2.1 Materials
2.1. Materijali

In this study, three types of wooden material were used for prediction models, namely scotch pine, chestnut and oak. According to the age period, both 100 years and new (young age) oak (*Quercus Petrea L.*), chestnut (*Castanea sativa M.*) and scotch pine (*Pinus sylvestris L.*) were selected as experimental materials. After the material selection, water-based varnish, polyurethane, and acrylic varnish were applied to the surface of the samples.

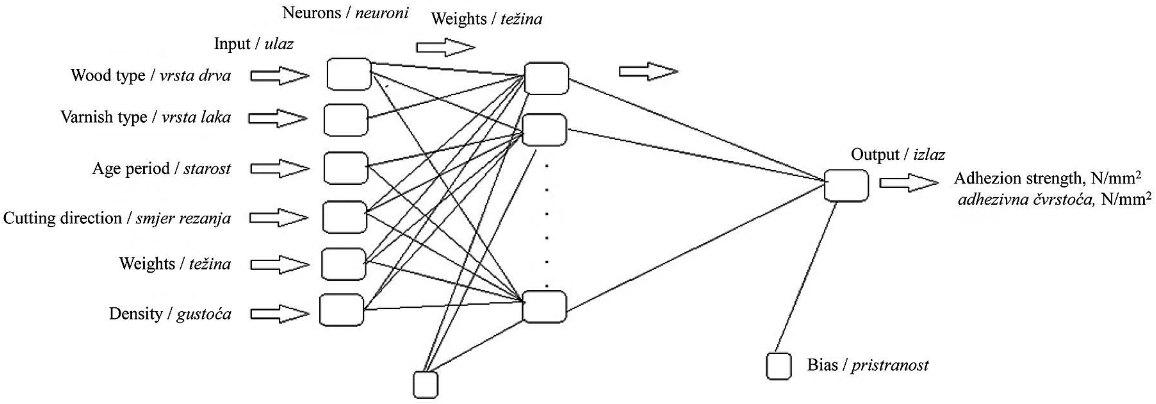


Figure 1 Model of adhesion strength neural network
Slika 1. Model neuronske mreže adhezivne čvrstoće

2.2 Methods
2.2. Metode
2.2.1 Neural Networks
2.2.1. Neuronske mreže

Artificial intelligence (AI) is commonly used in different engineering disciplines with different parameters to interpret the output (dependent) parameter(s). In this study, commonly accepted artificial neural networks (ANN) and FL models were employed. Moreover, different models were implemented to predict the adhesion strength with various input features such as wood type, age period, cutting direction, varnish type, weight, and density. The models were created in Matlab R2016a software for predicting the adhesion strength. As a result of the test process, the actual (measured) values of adhesion strength and the predicted values were obtained and compared with each other. The Mean Square Error (*MSE*), Mean Squared Error (MSE) and Mean Absolute Percentage Error (*MAPE*) were calculated according to Eqs. 1–3 below.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n}} \tag{1}$$

$$MSE = \frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n} \tag{2}$$

$$MAPE = \frac{\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|}{n} \cdot 100 \tag{3}$$

Where n is the number of data, A_t is the actual value, and F_t is the predicted value.

In this study, feed-forward backprop, cascade feed-forward backprop, elman backprop, layer recurrent and NARX neural networks were applied. Feed neural networks and cascade feed-forward provided significant regression results. Besides, the models were trained as Traincgf, Trainlm and Trainrp. Using the K-fold technique, the training dataset was divided into 5 groups, 1 of which was reserved for the test and rest for the training, and the average of the performance values obtained was taken.

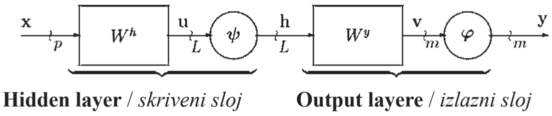


Figure 2 Multilayered neural network with two neurons
Slika 2. Višeslojna neuronska mreža s dva neurona

ANNs are inspired by the human brain sensorial activities, and the sensorial neurons can be created by computers (Hedayat *et al*., 2009). Figure 1 shows an artificial neural network consisting of nodes, neurons, and transfer functions.

Feedforward backprop neural networks include an input layer, an output layer and one or more hidden layers (Hedayat *et al*., 2009). According to the structure of the feed-forward neural network, the first layer is the link to the entrance neuron and the forward neurons are connected to the previous layer connections, whereas the last layer is linked to the output. Figure 2 indicates the multilayered neural networks that consist of a combination of the single-layer neural networks.

The output of the hidden layers in a multilayered neural network is expressed in Eq. 1 (Hounmenou *et al*., 2021).

$$u_j = \sum_{i=1}^{p} w_{ji}^{h} \cdot x_i \tag{4}$$

Furthermore, the output is shown in Eq. 2.

$$v_k = \sum_{j=1}^{L} w_{kj}^{y} \cdot h_j \tag{5}$$

Where p is the number of input layers, h is the number of hidden layers, and L is the number of data.

The structure of the Cascade-Feed Forward Neural Network (CFFNN) is similar to the feed-forward neural network, and it is a type of supervised learning algorithm (Hedayat *et al*., 2009). Moreover, the CFFNN include the weight of each neuron connection (Wadkar *et al*., 2021).

ANN models consist of 1 hidden layer and 32 neurons. Different neuron numbers were used in the

ANN models until optimum results were obtained. The reason for the application of the different number of neurons is related to the black box of the neural networks. While creating the model in ANN, different neuron numbers were obtained by trial and error to obtain the best results. In the study, K-Folds cross validation technique was used to reduce the bias of the model, and the k value was determined as 5. This 5 different test groups were created from the data set, with 20 % of the tests. The data outside of 20 % for each group was used as the training set. 5 different training and test sets were created from the data set used for the experiments. The test rate used was determined as 20 %. The remaining 80 % was divided into two parts - with 25 % validation and 75 % training. Validation set was randomly selected from 80 % of each k cycle.

2.2.2 Fuzzy Logic
2.2.2. Neizrazita logika

The FL algorithm uses fuzzy outcomes from rules with numerical and language datasets. The FL performs a membership function for the language process. Furthermore, fuzzy logic has two different approaches - Mamdani and Sugeno (Chen and Liou, 1999). Mamdani is widely used for FL algorithm because it provides fuzzification, fuzzy rules and defuzzification. The membership function is often used to represent linguistic terms. The membership function is expressed as the closeness of the input values to the membership degree. The membership value of the input is used to determine fuzzy inference with rules. When the membership value is 0, it indicates that the fuzzy set is not a member, and when it is 1, it indicates that it is a full member of the fuzzy set. Values between 0 and 1 represent the degree of membership in the fuzzy set (Zhao and Bose, 2002). An Adaptive Neuro-Fuzzy Inference System (ANFIS) is based on a combination of the FL and an artificial neural network. The ANFIS model works with fuzzification and neural network training ability to create rules for the dataset.

In this model, 80 % data were selected for training, and the remaining 20 % data was used for testing. The data were randomly selected and used for training and testing.

2.2.3 Preparation of samples
2.2.3. Priprema uzoraka

Each wood was cut radially and tangentially with 100 mm ×100 mm ×10 mm scales and 10 pieces, and the 360 total number of the experimental samples were prepared as the type of wood (3), cutting direction (2), age period (2), and varnish type (3). According to the (TS EN-26624, 1996) and (ASTM D4541, 2009), the adhesion strength of the varnish was measured using the pneumatic adhesion equipment, as shown in Figure 3.

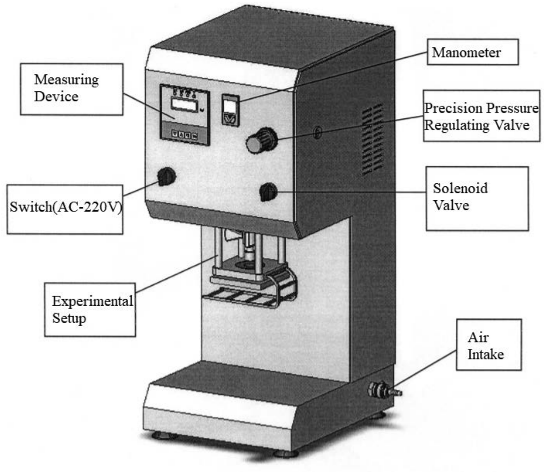


Figure 3 Adhesion tester (Budakçi, 2006)
Slika 3. Uređaj za ispitivanje adhezije (Budakçi, 2006)

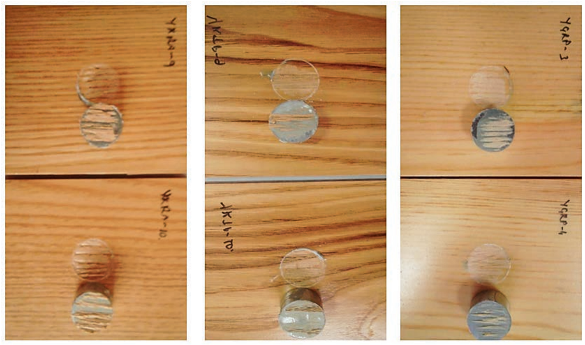


Figure 4 Post-adhesion test of some samples
Slika 4. Prikaz uzoraka nakon ispitivanja adhezije

After the experiment, Figure 4 shows the results of adhesion strength of varnish layers.

3 RESULTS AND DISCUSSION
3. REZULTATI I RASPRAVA

3.1 Adhesion Test Results
3.1. Rezultati ispitivanja adhezije

Table 1 presents the results of the pneumatic adhesion test equipment for the “F; Fresh and NA; Natural aged” wood type and their statistical outcomes.

According to Table 1, the adhesion strength values show different results based on the wood type, age period, cutting direction and type of varnish. The results were evaluated to check the result reliability using analysis of variance through MSTAT-C with a 95 % confidence interval. Table 2 illustrates the results of analysis of variance.

According to the results of the analysis of variance, the age period is statistically insignificant. The interaction between wood species age and period-section direction was insignificant. It can be seen that the interaction of cross-section direction and varnish type is not effective on adhesion strength (p=0.05).

Table 1 Results of adhesion strength after the experiment
Tablica 1. Rezultati adhezivne čvrstoće

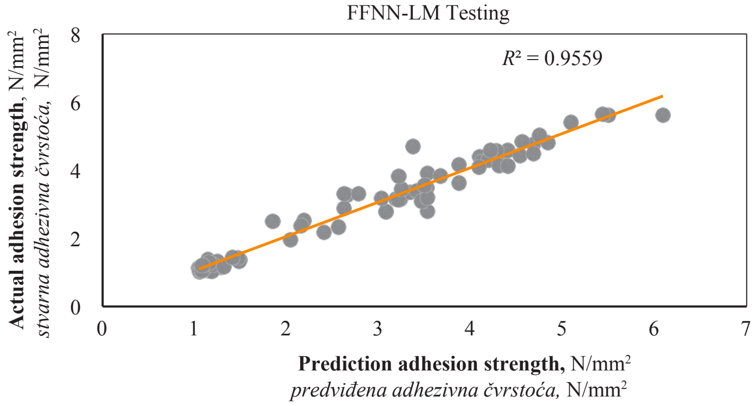
Wood type/ Age period *Vrsta drva / starost*	**Water-based** / *Vodeni lak*				**Polyurethane** / *Poliuretanski lak*				**Acrylic** / *Akrilni lak*			
	Radial		**Tangential**		**Radial**		**Tangential**		**Radial**		**Tangential**	
	$\bar{X}$	*s*	$\bar{X}$	*s*	$\bar{X}$	*S*	$\bar{X}$	*S*	$\bar{X}$	*s*	$\bar{X}$	*s*
F. scotch pine *F. borovina*	1.340	0.46	1.939	0.54	3.101	0.50	3.642	0.80	2.995	0.70	2.570	0.88
NA. scotch pine *NA borovina*	1.234	0.60	1.318	0.18	3.529	0.77	3.257	0.68	2.702	0.71	2.342	0.65
F. oak *F. hrastovina*	1.068	0.25	0.953	0.13	3.239	0.82	3.951	0.82	4.694	0.90	5.150	0.96
NA. oak *NA. hrastovina*	1.177	0.37	0.959	0.16	5.228	1.24	4.525	0.92	3.832	0.71	3.517	0.52
F. chestnut *F. kestenovina*	1.352	0.32	1.783	0.40	3.816	1.11	4.522	1.01	3.738	0.66	4.725	1.07
NA. chestnut *NA. kestenovina*	1.259	0.49	1.056	0.24	4.385	1.11	4.650	1.01	3.873	0.69	4.903	1.11

$\bar{X}$ – Arithmetic averages, s – Standard deviation, F – fresh, NA – Natural aged
$\bar{X}$– aritmetičke sredine, s – standardna devijacija, F – svježe drvo, NA – prirodno ostarjelo drvo

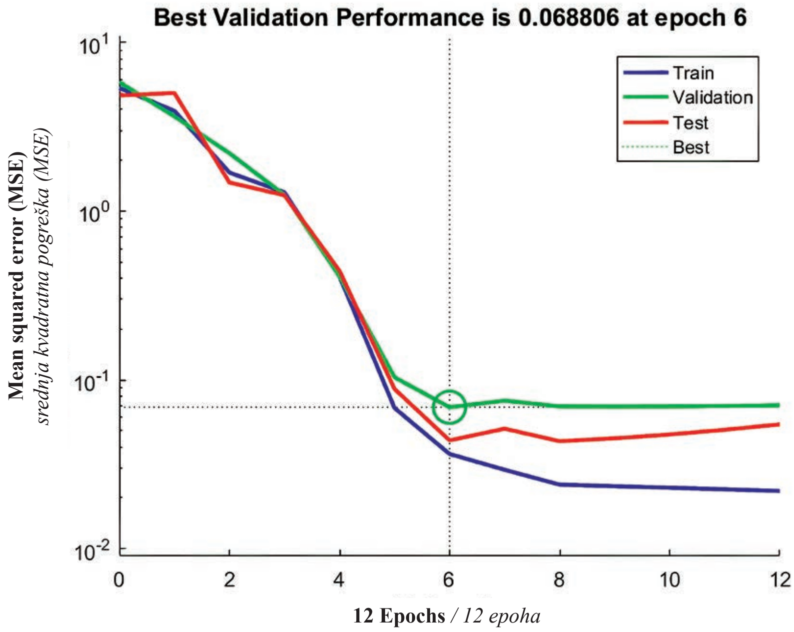
Table 2 Variance results of adhesion strength
Tablica 2. Rezultati varijance za adhezivnu čvrstoću

Factors / *Čimbenici*	**Degree of Independence** *Stupanj neovisnosti*	**Sum of Squares** *Zbroj kvadrata*	**Mean of Squares** *Srednja vrijednost kvadrata*	***F* Values** *F-vrijednost*	***P***
Wood type (A) *vrsta drva (A)*	2	50.206	25.103	45.9771	0.0000*
Age period (B) *starost drva (B)*	1	0.089	0.089	0.1638	NS
Interaction (AB) *interakcija (AB)*	2	1.322	0.661	1.2107	0.2993**
Cross-section (C) *presjek (C)*	1	2.395	2.395	4.3857	0.0370*
Interaction (AC) *interakcija (AC)*	2	4.915	2.457	4.5009	0.0118*
Interaction (BC) interakcija (BC)	1	6.529	6.529	11.9581	0.0006*
Interaction (ABC) *interakcija (ABC)*	2	0.567	0.284	0.5197	NS
Varnish type (D) *vrsta laka (D)*	2	542.640	271.320	496.9330	0.0000*
Interaction (AD) *interakcija (AD)*	4	50.601	12.650	23.1693	0.0000*
Interaction (BD) *interakcija (BD)*	2	18.335	9.168	16.7907	0.0000*
Interaction (ABD) *interakcija (ABD)*	4	18.542	4.635	8.4901	0.0000*
Interaction (CD) *interakcija (CD)*	2	0.264	0.132	0.2417	NS
Interaction (ACD) *interakcija (ACD)*	4	7.188	1.797	3.2913	0.0115*
Interaction (BCD) *interakcija (BCD)*	2	2.312	1.156	2.1173	0.1220**
Interaction (ABCD) *interakcija (ABCD)*	4	1.691	0.423	0.7742	NS
Error / *pogreška*	324	176.901	0.546		
Sum / *zbroj*	359	884.497			

* – Difference is significantly based on (p<0.05). / *razlika je značajna pri p<0,05*
** – Difference is insignificantly based on (p>0.05) / *razlika nije značajna pri p>0,05*
NS (Nonsignificant) – Insignificant / *nije značajno*



a)



b)

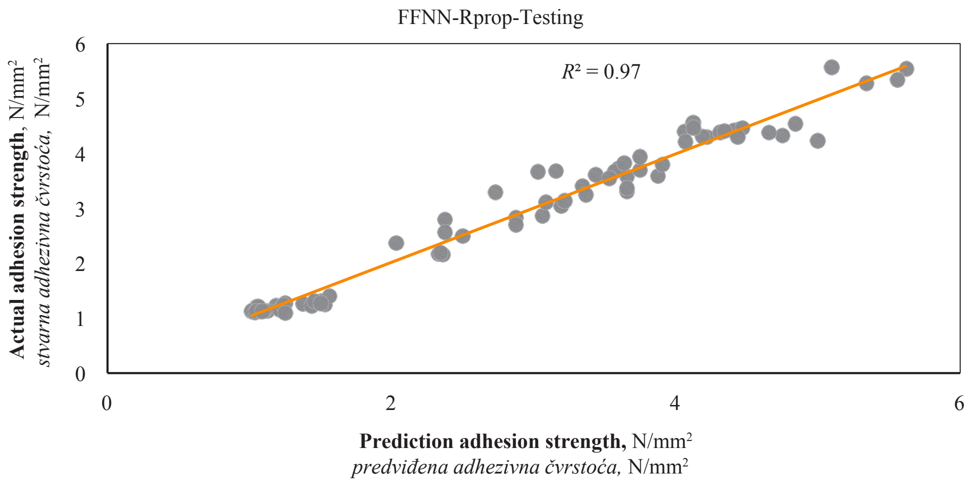
Figure 5 Relationship between FFNN-LM model with actual and predicted adhesion strength (a) and model *MSE* performance (b)
Slika 5. Odnos između FFNN-LM modela sa stvarnom i s predviđenom adhezivnom čvrstoćom (a) te *MSE* svojstva modela (b)

3.2 Soft computing models for adhesion strength
3.2. Modeli mekog računalstva za adhezivnu čvrstoću

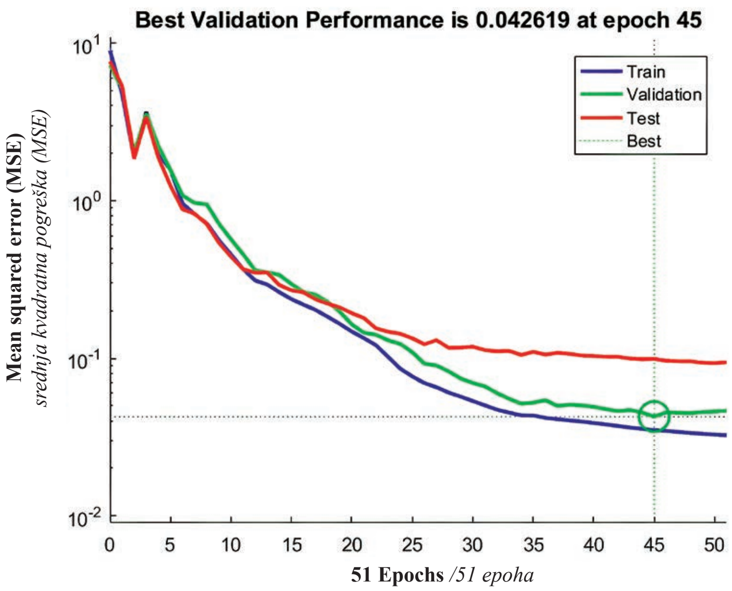
3.2.1 Feed forward backprop ANN (FFNN)
3.2.1. Aciklična umjetna neuronska mreža s propagacijom unatrag

In this model, a training algorithm was used based on a Levenberg-Marquardt (LM) optimization with updating weight and standard deviation of the values. Although the LM provides the fastest backpropagation, it needs high memory for the process. According to the outcome of the LM algorithm, the best results were obtained with 32 hidden neurons. Figure 5(a) shows the model providing R^2=0.9811 and R^2=0.9559 coefficients of determination for the training and test, respectively. In this model, the ratio of the vector was divided 0.8 for training and 0.2 for testing. Figure 5(b) shows that the model with the best performance and the lowest error rate obtained using the K-Fold technique was achieved with 6 epochs.

Moreover, two hidden layers FFNN backpropagation algorithms were applied with 10 hidden nodes in Layer 1 and 32 hidden nodes in Layer 2. Figure 6(a) demonstrates that the FFNN-Rprop had an R^2=0.9775 coefficient of determination for training and an R^2=0.9700 coefficient of determination for testing. In this model, the ratio of the vector was divided into 0.6 for training, 0.2 for validation, 0.2 for testing. Figure 6(b) shows that the model with the best performance and the lowest error rate, obtained using the K-Fold technique, was achieved with 45 epochs.



a)



b)

Figure 6 Relationship between FFNN-Rprop model with actual and predicted adhesion strength (a) and model *MSE* performance (b)
Slika 6. Odnos između FFNN-Rprop modela sa stvarnom i s predviđenom adhezivnom čvrstoćom (a) te *MSE* svojstva modela (b)

3.2.2 Cascade-feed forward neural network (CFFNN)
3.2.2. Kaskadna aciklična neuronska mreža

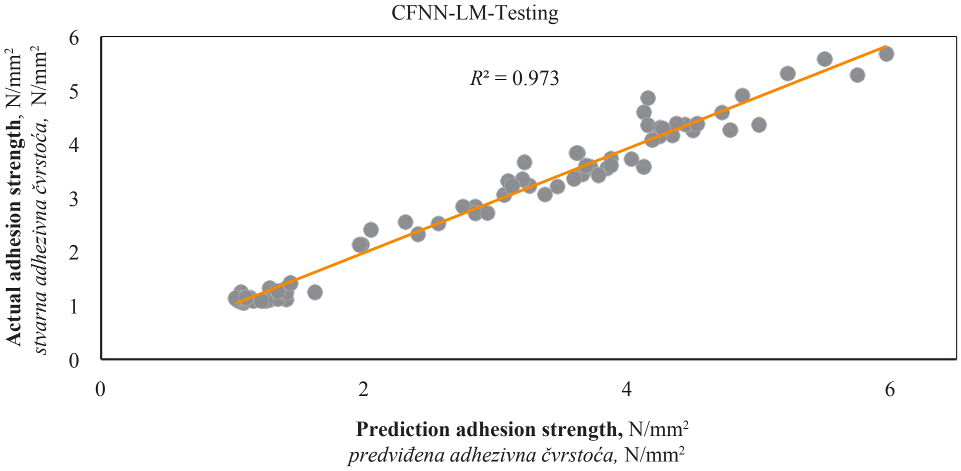
CFFNN-LM model for prediction of adhesion strength consists of 2 layers and 32 hidden neurons. The outcome of the model is shown in Figure 7(a) The CFFNN-LM provided R^2=0.9808 and R^2=0.9601 coefficients of determination for training and test, respectively. In CFFNN-LM model, the ratio of the vector was divided into 0.8 for training and 0.2 for testing. Figure 7(b) shows that the model with the best performance and the lowest error rate, obtained using the K-Fold technique, was achieved with 12 epochs.

A series of neural networks were used until the number of neurons in the hidden layer reached the minimum mean square error (*MSE*) of the output. Considering the predicted results among the proposed ANN models, *MSE* 0.046, *RMSE* 0.215 and *MAPE* 4.83 % showed the best performance in the FFNN-LM model.

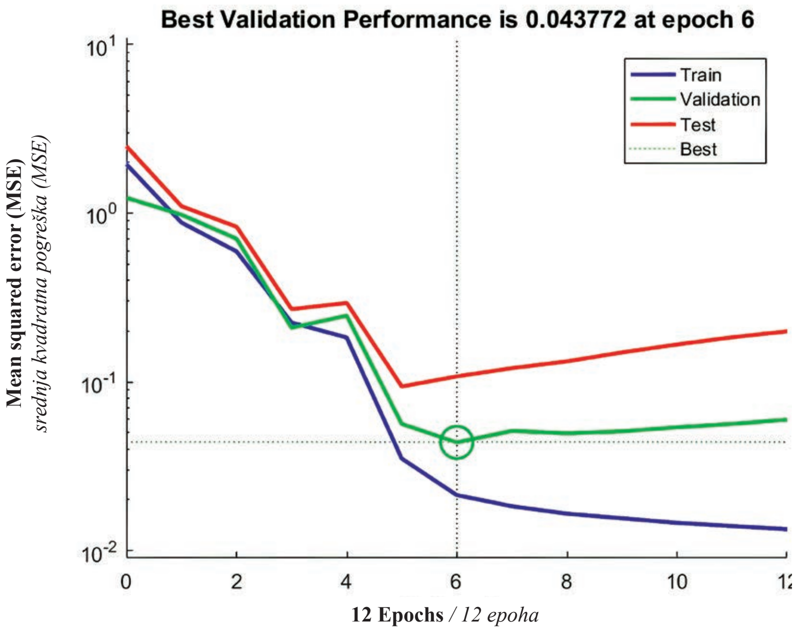
3.2.3 Fuzzy inference systems
3.2.3. Sustavi neizrazitog zaključivanja

To obtain the FL model, wood type, cutting direction and type of varnish were used as inputs. The model is illustrated in Figure 8. Fuzzification is applied to the input parameters to train the proposed model. After applying fuzzification, 18 different rules were obtained. After obtaining the table of rules, the output was acquired using defuzzification.

Figure 9 presents the adhesion strength related to the varnish and wood type.



a)



b)

Figure 7 Relationship between CFFNN-LM model with actual and predicted adhesion strength (a) and model *MSE* performance (b)
Slika 7. Odnos između CFFNN-LM modela sa stvarnom i s predviđenom adhezivnom čvrstoćom (a) te *MSE* svojstva modela (b)

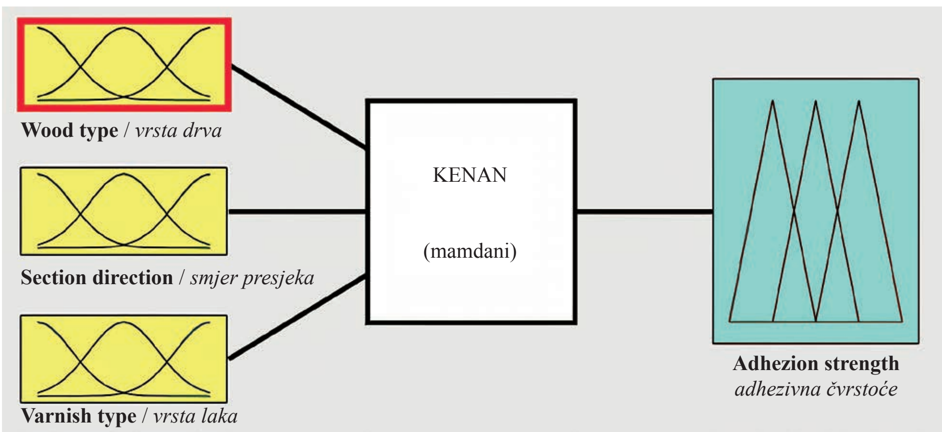


Figure 8 FIS model for adhesion strength
Slika 8. FIS model za adhezivnu čvrstoću

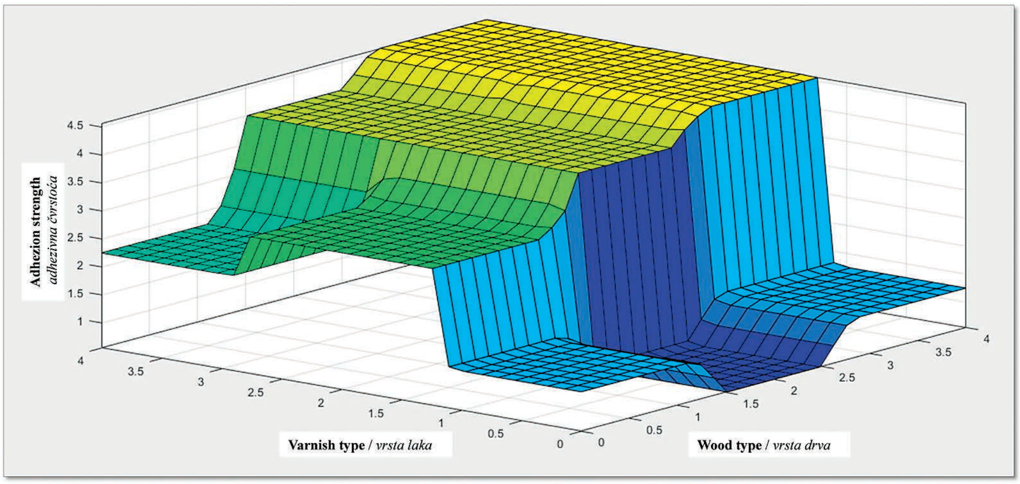


Figure 9 FIS surface view for inputs and adhesion strength
Slika 9. FIS izgled površine za ulaze i adhezivnu čvrstoću

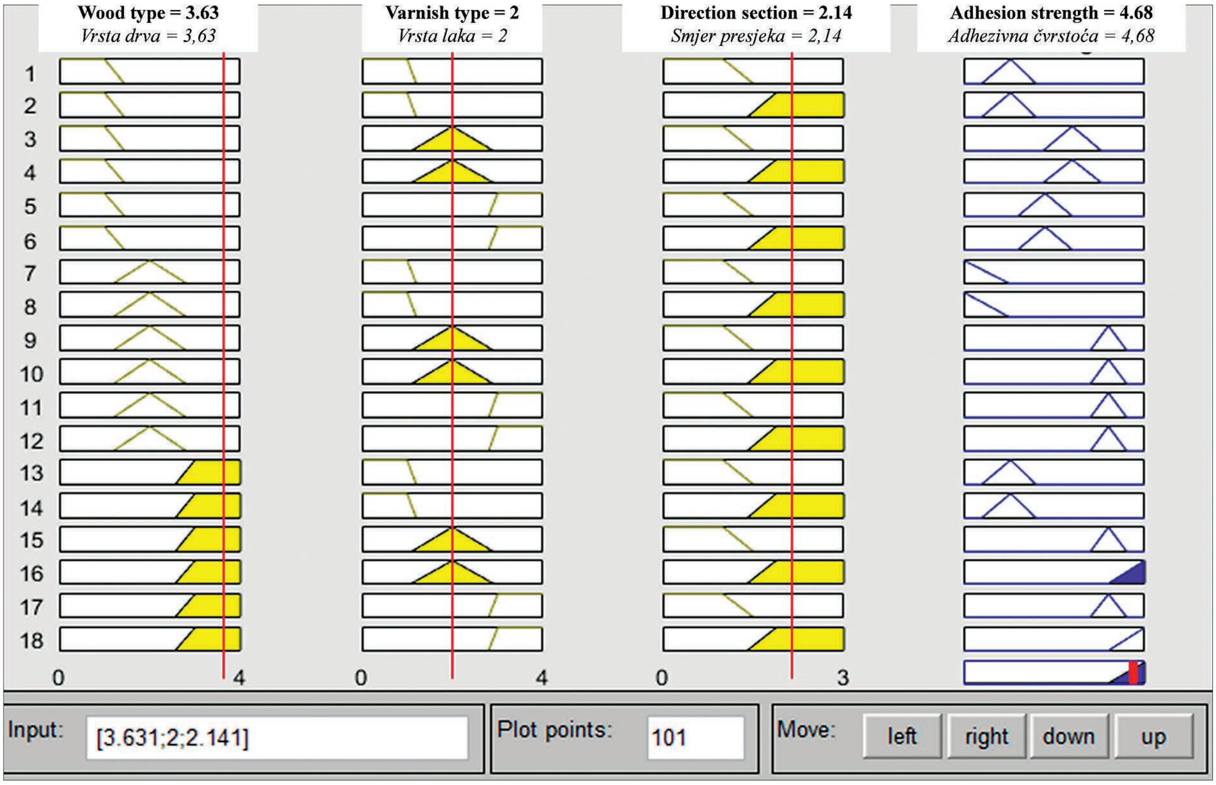


Figure 10 FIS rules for 3 inputs and 1 output
Slika 10. FIS pravila za tri ulaza i jedan izlaz

Furthermore, Figure 10 illustrates the feature importance of the input parameters with the FIS surface map.

3.2.4 Adaptive neuro-fuzzy inference system (ANFIS)
3.2.4. Prilagodljivi sustav neuro-neizrazitog zaključivanja

The ANFIS consists of 6 different layers that are input, rules, normalization, member, defuzzification and output layers, respectively. The ANFIS model input values were used with wood type, age period, direction section, varnish type, density and weight of adhesion strength. Figure 11 shows the adhesion strength changing with wood type, varnish type and cutting direction through the ANFIS model.

A total of 360 data points were split as 80 % for training and 20 % for testing in the ANFIS model. Figure 12 and 13 show the results of the ANFIS model, the proposed model had R^2=0.9917 and R^2=0.9929 coefficients of determination for training and test results.

Moreover, the ANFIS can provide feature importance using an FL surface map. Figure 14 shows im-

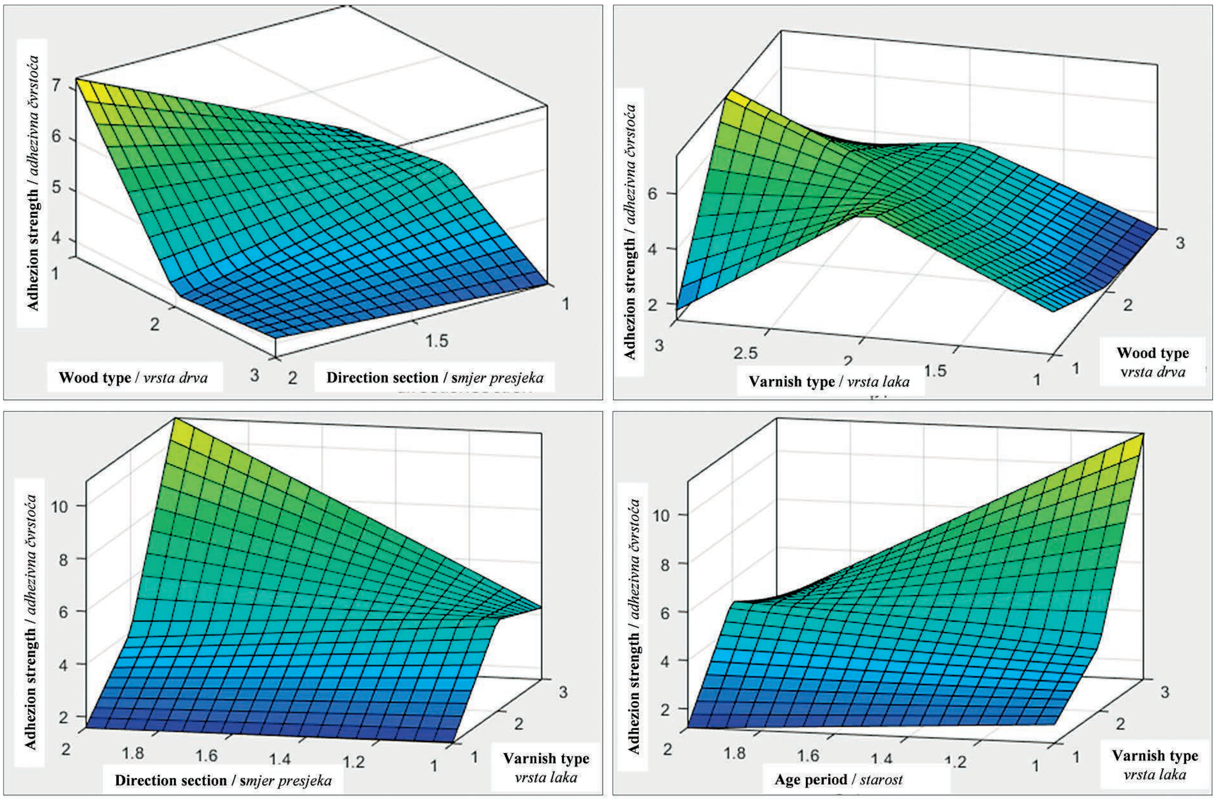


Figure 11 ANFIS surface view for inputs and adhesion strength
Slika 11. ANFIS izgled površine za ulaze i adhezivnu čvrstoću

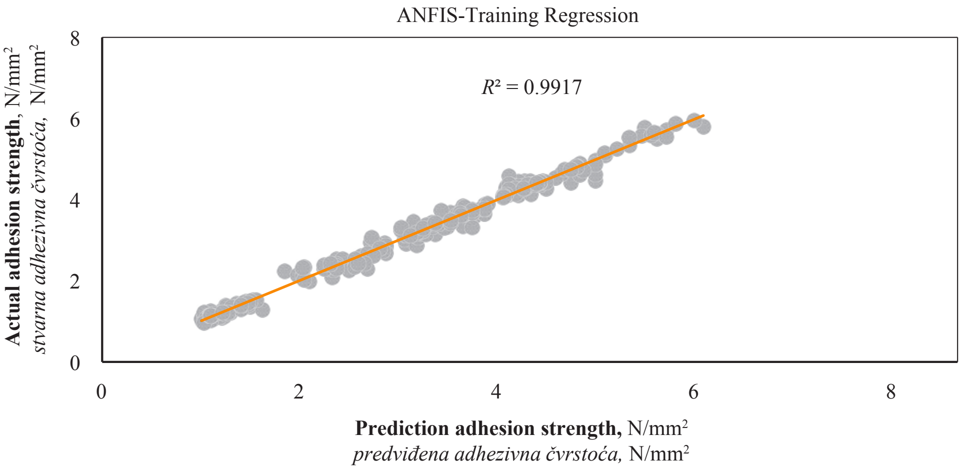


Figure 12 Relationship between actual and predicted adhesion strength by ANFIS model for training
Slika 12. Odnos između stvarne i predviđene adhezivne čvrstoće u ANFIS modelu za trening

portant features for predicting adhesion strength. In this model, wood type, age period, cross-section direction, varnish type, density and weight showed high importance for the prediction of the varnish adhesion strength.

Furthermore, Figure 15 presents 324 rules for the ANFIS model with 6 inputs and 3 Gaussian values. This figure shows the consistency of the varnish adhesion strength with the actual value and the estimated FIS values.

Triangle, sigmoid, and Gaussian membership functions are generally used in fuzzy logic applications and the functions are associated with the cause and effect of the rules. These membership functions take values in the range from 0 to 1 and the corresponding number in this range represents the membership function. In this study, Gaussian was used to determine membership functions. Figure 16 and 17 demonstrate the comparison of the ANN and ANFIS models, in terms of the training and test. It has been determined that the predicted results are very close to the real values. Although the CFNN model diverges from the real values, it can be noticed that all models give optimum results.

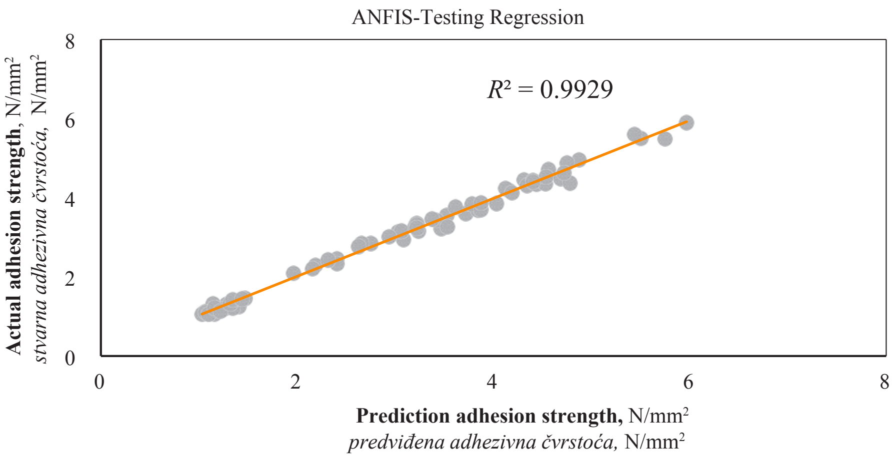


Figure 13 Relationship between actual and predicted adhesion strength by ANFIS model for testing
Slika 13. Odnos između stvarne i predviđene adhezivne čvrstoće u ANFIS modelu za testiranje

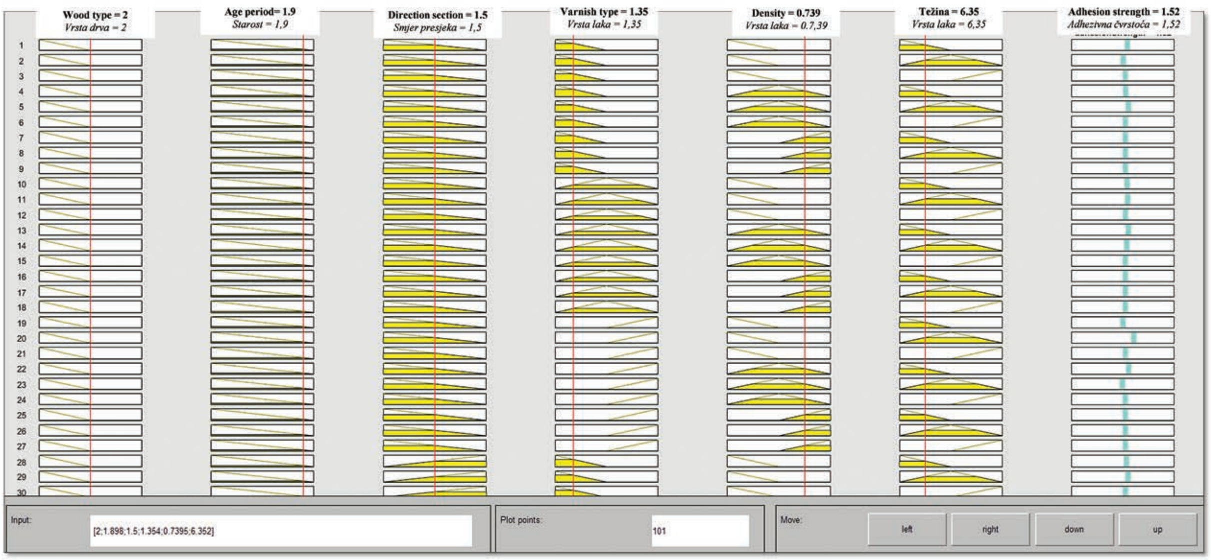


Figure 14 ANFIS rules for 6 inputs and 1 output
Slika 14. ANFIS pravila za šest ulaza i jedan izlaz

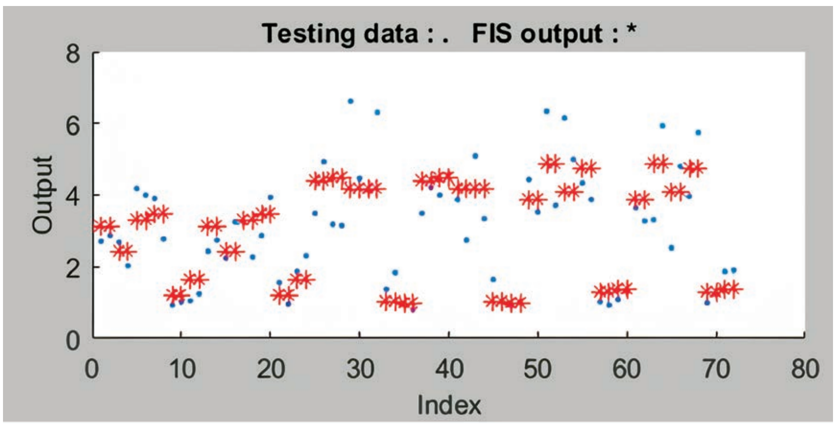


Figure 15 ANFIS rules for 6 inputs and 1 output
Slika 15. ANFIS pravila za šest ulaza i jedan izlaz

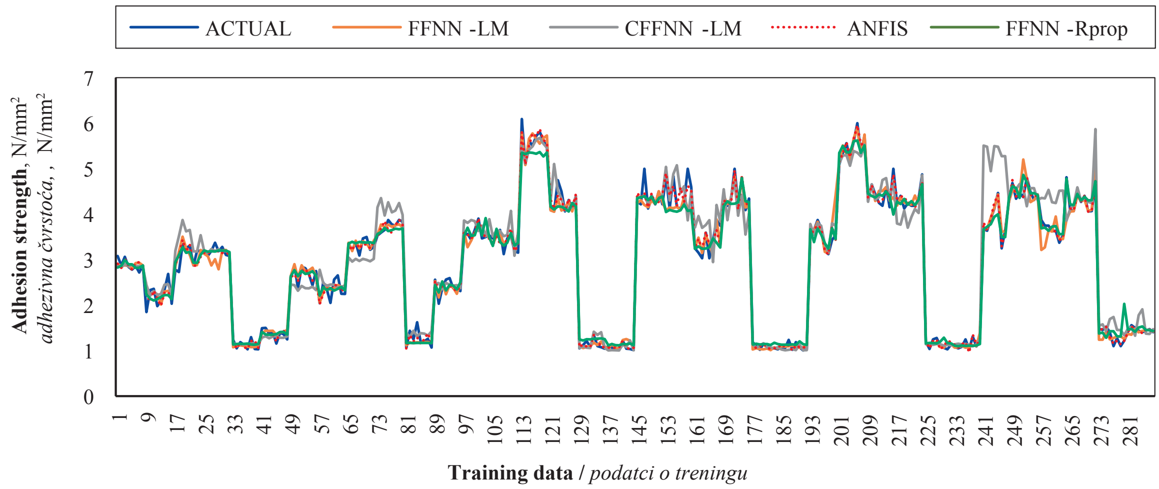


Figure 16 Comparing ANN and ANFIS values with actual values (training)
Slika 16. Usporedba ANN i ANFIS vrijednosti sa stvarnim vrijednostima (treninga)

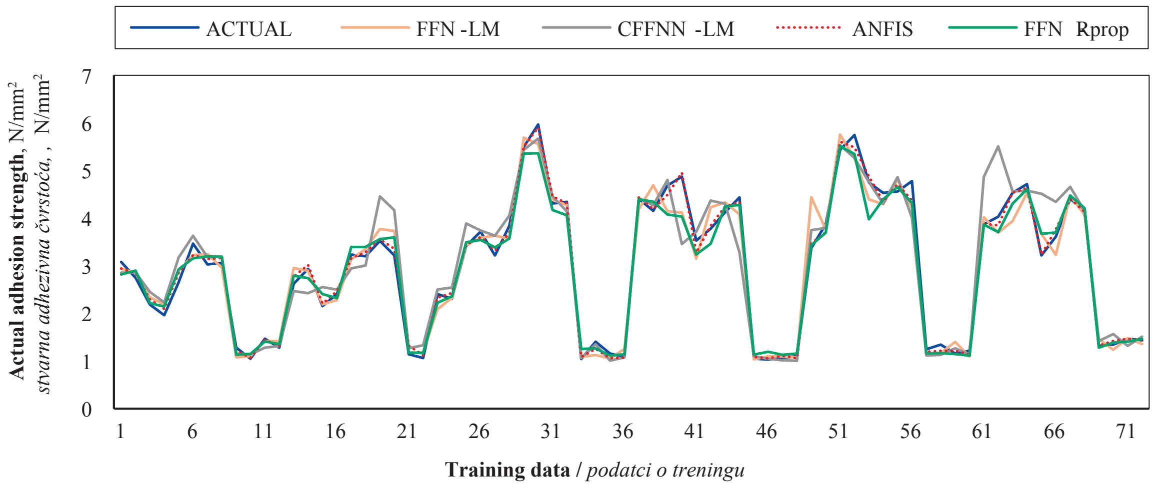


Figure 17 Comparing ANN and ANFIS values with actual values (testing)
Slika 17. Usporedba ANN i ANFIS vrijednosti sa stvarnim vrijednostima (testiranja)

Table 3 presents the training and testing evaluation results in ANN and ANFIS, with determination coefficient (R^2), Mean Square Error (*MSE*), Mean Absolute Percentage Error (*MAPE*) and Root Mean Square Error (*RMSE*). In this table, *MSE*, *MAPE* and *RMSE* values give the average results of 5 different groups with the K-Fold technique. In addition, the determination coefficent values were added to the best results obtained.

Tiryaki *et al*. (2016) predicted the bond strength of solid wood exposed to heat treatment using ANN. In this model, as a result of testing, they found the *RMSE* value of 0.217 and the *MAPE* value of 6.253 %. In this study, Anfis testing *RMSE* and *MAPE* values were low-

Table 3 Results of performance evaluation criteria for ANNs and ANFIS models
Tablica 3. Rezultati kriterija ocjenjivanja uspješnosti za modele ANN i ANFIS

Modelling	R^2	*MSE*	*RMSE*	*MAPE*, %
FFNN-LM(training)	0.9811	0.1406*	0.315*	7.65*
FFNN-LM(testing)	0.9559	0.1806*	0.4096*	9.586*
FFNN- Rprop (training)	0.9775	0.068*	0.2552*	8.024*
FFNN- Prop (testing)	0.9700	0.1584*	0.3782*	9.938*
CFFNN-LM (training)	0.9808	0.0422*	0.196*	5.454*
CFFNN-LM (testing)	0.9730	0.158*	0.3808*	9.672*
Anfis (training)	0.9917	0.004	0.064	2.22
Anfis (testing)	0.9929	0.014	0.12	3.60

*5 test group average values / *srednje vrijednosti pet ispitnih grupa* er. Esteban *et al.* (2009) predicted the bond strength of particle boards using ANN thickness, density, moisture, swelling and absorption. In this study, the test results were MAPE 7.86 %, while the R^2 value was 0.85. In our study, on the other hand, higher *MAPE* values were obtained in all models with R^2 values and a better *MAPE* result was obtained in Anfis models.

4 CONCLUSIONS
4. ZAKLJUČAK

Due to the heterogeneous properties of the wooden materials, the prediction of the adhesion strength is an important area of research in wood industry. In this research, the adhesion strength was predicted using ANN, FL and ANFIS. According to the proposed model results:

- FFNN, CFNN, FIS and ANFIS were used to predict the adhesion strength.
- The best estimate of adhesion strength in the ANN models was obtained for 32 neurons.
- In ANN-based models, TrainLM and TrainRp provided reasonable results compared to TrainCFG.
- The coefficient of determination values in the ANFIS model was obtained by creating 324 rules using the Gauss membership function. Additionally, testing in the ANFIS model showed the highest coefficient of determination in estimating adhesion strength. In this model, the results of *MAPE* 2.22 % (training) and 3.60 % (testing) seem to be a reasonable result. Additionally, *RMSE* and *MSE* results indicate that fuzzy logic can be applied in this area.
- The ANN model provided significant results for tangensoidal function in the Levemberg Marquardt algorithm.
- In the ANN models, the lowest *MAPE* value was 5.45 % in the FFNN training data, while the *RMSE* value was 0.196.
- The ANFIS model was used for the first time in the wood industry field in estimating varnish adhesion strength. The model was successful in performance predictions in both training and testing.

This result shows that artificial intelligence models can be improved using high-dimensional datasets in the future. Moreover, the life span of the wooden material can be increased, while decreasing the processing time for wooden material. Furthermore, the combination of the different artificial intelligence models can increase the prediction accuracy of the adhesion strength.

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Corresponding address:

İBRAHIM KARAMAN
Yozgat Bozok University, Yozgat Vocational School, Computer Technology Department, 66200, Yozgat, TURKEY, e-mail: ibrahim.karaman@bozok.edu.tr