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Prediction of Veneer Bonding Strength of Wood-Based Composites Through Soft-Computing Models

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An artificial neural network (ANN) and an adaptive neuro-fuzzy inference system (ANFIS) are used to predict the bonding strength of different wood-based composites and veneers. The dataset used for model creation is obtained from experimental setups. The experiments involved measuring the bonding strength of wood-based composites (Flakeboard, MDF, OSB) and veneer (beech, oak, pine) using different cutting directions and adhesive types. A total of 540 experiments were conducted. The main objective of this study is to propose AI-based models (ANN and ANFIS) that could reduce the cost of experiments and computational time. The ANN model achieved correlation coefficients (R2) of 0.91 and 0.94 for training and testing, respectively. The high R^2 values for both training and test datasets indicate that the ANN model is well-designed. On the other hand, the ANFIS model yielded R2 values of 0.88 and 0.85 for training and testing, respectively. Based on these results, the ANN models exhibited a stronger correlation than the ANFIS models. Overall, this study demonstrates the effectiveness of using artificial intelligence models, specifically ANN and ANFIS, to predict the bonding strength of wood-based composites and veneer. By employing these models, researchers can reduce the need for extensive experimentation and save computational time, making the process more efficient and cost-effective.

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Introduction

Wooden materials possess unique characteristics such as hygroscopicity, anisotropy, heterogeneity, fibrous structure, and cellular composition. These properties contribute to their widespread use in human society. Wood is favored for its lightweight nature, affordability, ease of processing, and ornamental appeal. Flakeboard, MDF, and OSB are particularly important types of wood-based composites due to their favorable mechanical and physical properties (Demirkir *et al.* 2013; Esteban *et al.* 2011).

The bonding strength between coatings is mainly determined by the properties of the resins. Currently, synthetic resins such as urea-formaldehyde (UF) and phenol formaldehyde (PF) are widely used in plywood production due to their low price, high bond strength, and desirable water resistance. Diphenylmethane diisocyanate (MDI) can be applied to produce formaldehyde-free plywood, but is widely

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applied in fiberboard rather than in the plywood industry. Renewable biomass-based resins have been reported as promising candidates for producing formaldehyde-free plywood (Li *et al*. 2019). However, due to its uneconomical price and low water resistance, its large-scale application in industry has been limited. Besides the properties of resins, the bond strength between coatings is closely related to hot pressing techniques. Researchers rely on optimizing hot pressing techniques to improve bond strength. They have found that the effect of moisture content is more important than the amount of resin applied (Zhang *et al.* 2016). In a study presenting a new crosslinking agent to improve the water-resistance of soy-based adhesive, plywood produced with thermal-hydro-mechanically modified veneers exhibited better durability than pure veneers (Liu *et al*. 2018).

Understanding the relationship between the quality and durability of wooden materials is crucial, and adhesion quality plays a significant role in this regard (Hass *et al.* 2014; Horman *et al.* 2010). Adhesive materials are used to bond wooden components together (Akyüz *et al.* 2019). The bonding strength of wooden materials is influenced by factors such as the type of wood, adhesive, and surface friction (Sogutlu 2017). In addition, parameters such as wood species, specific gravity, surface quality, pressure and pressure duration affect the bond strength. These variables should be selected according to the intended use of the materials (Hiziroglu *et al.* 2014; Hiziroglu *et al.* 2013).

Consequently, numerous studies have been conducted to investigate and enhance the bonding strength of wooden materials (Bustos *et al.* 2004; Aydin 2004). This research aims to improve the overall performance and longevity of wooden products.

However, experimental applications using real materials can lead to delays in production in industry (Cook *et al.* 2000). In addition, experimental studies involve time-consuming and costly operations. To overcome these shortcomings and obtain optimum bonding strength, model soft computing-based approaches have been implemented in the last decades (Esteban *et al.* 2011). Prediction models provide fast computation time and very close approximation to the actual results, and are therefore preferred to overcome the drawbacks of the experimental approach (Fernández *et al.* 2012).

There are several studies related to the prediction of the bonding strength of wooden materials. Demirkir *et al.* (2013) presented a bonding strength model based on the various temperature applications of a wooden material. Tiryaki *et al.* (2014) described different approaches to estimating bonding strength based on a wooden material's surface friction, using an artificial neural network (ANN). In a study by Bardak *et al.* (2016a), an ANN and multivariable regression analysis were utilized to develop a model that considered the effects of pressure before and after assembly in both open and closed assembly lines. The models achieved a 0.977 correlation coefficient for bonding strength. Furthermore, an ANN model has been proposed to predict the effects of different pressing temperatures and times on the bonding strength of solid wood (Bardak *et al.* 2016b). Furthermore, Tiryaki *et al.* (2016) assessed the prediction of bonding strength in heat-treated woods using the Matlab Neural Network Toolbox. In another study, ANN and multiple linear regression applied to different wooden materials with various vacuum, diffusion, and pressure times were used to predict bonding strength (Akyüz *et al.* 2019). Additionally, an adaptive neuro-fuzzy inference system (ANFIS) has been considered as a way to estimate the bonding strength of a wooden material (Demirkir *et al.* 2013; Esteban *et al.* 2011).

The present study aimed to utilize ANN and ANFIS models for predicting the bonding strength of wooden materials, so as to reduce operational time and costs. A total of 540 samples were prepared, consisting of wood-based composites (Flakeboard, MDF, and OSB) and veneers (beech, oak, and pine), with different cutting directions (radial/tangential). Various adhesives, including polyvinyl acetate (PVAc), urea-formaldehyde adhesive (UF), and contact adhesives, were also employed.

Tensile strength perpendicular to the surface is measured to determine the quality of the adhesive and gluing. To increase the tensile strength perpendicular to the surface, it is suggested that the board surfaces should be suitably coated (Ozdemir 1996).

The performance of the cross-section of some wood species with different adhesives has previously been investigated, and it was determined that radial-shear gave the best result, tangent-shear the second best result, and miter-nose joint the worst result in a comparison of results for the cross-section directions (Bircan 2020). In an investigation of adhesion properties using oak, fir, beech, and yellow pine trees, radial surfaces achieved 13.4% better adhesion performance than tangential surfaces (Balkiz 2000).

The objectives of this research are as follows:

1. To predict the bonding strength of different wood-based composites and wood veneers.
2. To reduce the cost of experiments and computational time by creating artificial intelligence-based models (ANN and ANFIS) with the data obtained from experiments.
3. To determine which is more effective by comparing the prediction accuracies of ANN and ANFIS models.

Significance of the research:
1. It provides artificial intelligence-based predictive models that can replace costly and time-consuming physical experiments.
2. It has been shown that the ANN model increases the accuracy of the experiments, obtaining high R^2 values, and achieves stronger performance than ANFIS.
3. This study reveals that the use of artificial intelligence models for the bonding strength of wood-based composites and coatings will make industrial processes more efficient.

A study on "Veneer Bonding Strength of Wood-Based Composites" using soft-computing models can provide significant benefits both scientifically and industrially. Such a study aims to optimize manufacturing processes by improving prediction accuracy, introducing new methods, and contributing to the literature in the field.

Material and methods

1. Experimental materials

This research used Flakeboard, MDF, and OSB-based boards with a thickness of 18 mm. Additionally, samples were prepared using different adhesive types, including PVAc and UF. The cutting direction was determined as either radial or tangential. Veneer samples with a thickness of 0.6 mm were chosen, specifically beech (*Fagus Orientalis* L.), Scotch pine (*Pinus Sylvestris* L.), and oak (*Quercus Petrea* L.).

A total of 27 draft pieces measuring 13 cm x 140 cm, with 9 pieces for each type of board, were cut parallel to the long sides of 210 cm x 280 cm particleboard and fiberboard and 122 cm x 244 cm OSB boards. In addition, 9 veneer draft pieces measuring 14 cm x 141 cm were cut for each veneer type and cutting direction, with one surface of each draft piece being radial and the other tangential intersection veneer.

POLİSAN brand D3 was used as a PVAc adhesive in the coating bonding process. MİKROKİM UF 1080 brand adhesive was used as a UF formaldehyde adhesive. KLEBT K-7000 adhesive was used as a contact adhesive.

In addition, Henkel's Thomsit R-625 polyurethane based adhesive was used for bonding the steel test cylinders. The polyurethane-based adhesive used has two components, and adhesion is realized by chemical means. The first component is the adhesive resin, and the second is a hardener that initiates the chemical reaction.

2. Experimental method

The setup for the adhesion experiments on each sample involved a pneumatic adhesion machine, as depicted in Figure 1. The tests were performed following the guidelines specified in TS EN 311 (2005). A surface strength test was applied to the samples using the adhesion machine for a duration of 60 seconds, with a maximum pressure of 1 kg/cm².

3. Preparation of experimental samples

A total of 540 experimental samples were prepared, with variations in the following factors: boarding type (3 options), adhesive type (3 options), coating type (3 options), and cutting direction (2 options). There were 10 samples for each combination. The complete

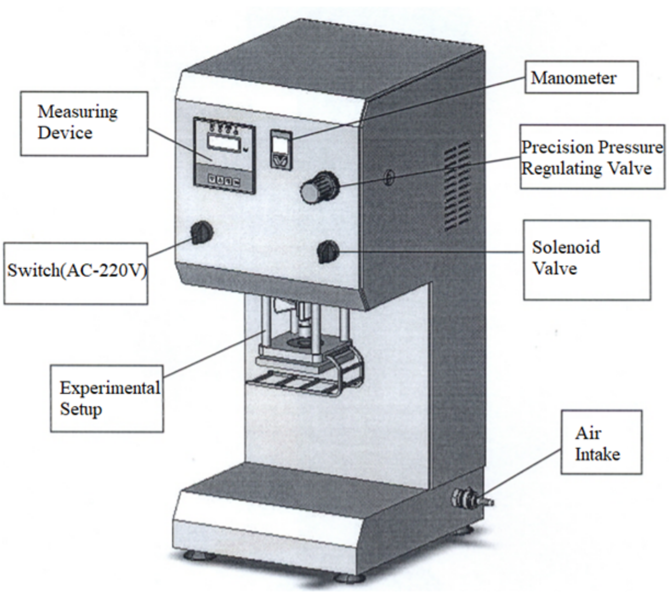


Fig. 1. Pneumatic adhesion machine (Budakci 2003)

Table 1. Bonding strength test conditions

Adhesive type	Viscosity (Cp)*	Amount of adhesive (gr/m²)	Pressure (kg/cm²)	Pressure time (min)	Pressure table temperature (⁰C)
PVAc	160 – 200	160	8	60	20
UF	400 – 600	160	8	4	80
Contact	-	250	8	2	-

* **Cp**: Centipoise

experimental design can be represented as (3x3x3x2x10). Table 1 presents the results of the bonding strength tests conducted on the joint surfaces based on this experimental design.

The prepared parts were stacked in a closed place without direct sunlight or air circulation, by placing a stacking bar between the boards, and the coatings were stacked horizontally in the form of balls and allowed to air-dry. The process of adhering the air-dried draft veneers to the board surfaces with adhesive types was carried out in accordance with the points specified in Table 1, taking into account the manufacturers' recommendations regarding the adhesives.

After the coated draft pieces were removed from the press and cooled down, they were kept for three weeks in a closed place with direct sunlight and air circulation to allow the adhesives to harden completely.

The draft parts which had been kept for three weeks were grouped, and after one edge had been smoothed on a planing machine, they were cut with 0.1 mm precision to specified dimensions (120 x120 mm) according to the TS EN 311 standard on a circular tray saw machine with a plotter. The samples were then grouped and kept in an air conditioning environment at 200 °C ± 20 °C and at 65% ± 5% relative humidity, until they reached constant weight and the moisture differences that arose during the gluing phase and the preparation of the samples were eliminated. Next, the experimental procedures were carried out.

4. Experimental results

Table 2 presents the statistical results of the veneer bonding strength tests, indicating different values for board type, adhesive type, coating type, and cutting direction. The table provides an overview of the bonding strength values obtained from the experiments, highlighting the variations based on the aforementioned factors.

The table provides statistical results from the veneer bonding strength tests for different combinations of wood-based composite types (Flakeboard, MDF, OSB), adhesive types (PVAc, UF, Contact), veneer types (beech, pine, oak), and veneer section directions (radial, tangential). For each combination, the table presents the minimum (Xmin), maximum (Xmax), mean ($\bar{x}$), and standard deviation (S) values of the bonding strength in N/mm^2.

Bonding strength values vary depending on the wood-based composite type, adhesive type, veneer type, and veneer section direction. Generally, the bonding strength values are higher for MDF and OSB than for Flakeboard. Among the adhesive types, PVAc and UF generally yield higher bonding strength than the Contact adhesive. The bonding strength values may differ for different veneer types (beech, pine, oak) within each combination. The adhesion strength values may also vary depending on the veneer section direction (radial or tangential). These statistical results provide insights into the variation of bonding strength based on different factors, which can be useful in understanding the performance and suitability of different wood-based composites, adhesives, veneers, and veneer section directions for specific applications. Some images from the wood veneer soundness test are given in Figure 2.

5. Artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS)

Artificial intelligence has been applied in various engineering fields due to the versatile properties of algorithms, such as the ability to include a large number

Fig. 2. Some images from the wood veneer strength test

Table 2. Statistical values for veneer bonding strength (N/mm²)

WOOD-BASED COMPOSITE TYPE	Type of adhesive	Veneer type	VENEER SECTION DIRECTION							
			Radial				Tangential			
			Xmin	Xmax	$\bar{x}$	S	Xmin	Xmax	$\bar{x}$	S
FLAKEBOARD	PVAc	Beech	1.33	1.75	1.56	0.14	1.08	1.51	1.23	0.14
		Pine	1.24	1.54	1.42	0.09	0.98	1.32	1.11	0.12
		Oak	1.15	1.46	1.29	0.11	1.20	1.59	1.45	0.11
	UF	Beech	1.18	1.53	1.38	0.11	1.13	1.39	1.27	0.10
		Pine	1.16	1.45	1.31	0.08	0.99	1.44	1.10	0.15
		Oak	1.28	1.60	1.38	0.10	1.24	1.54	1.38	0.10
	CONTACT	Beech	1.00	1.65	1.29	0.23	0.73	1.03	0.87	0.10
		Pine	1.09	1.36	1.24	0.10	1.04	1.51	1.33	0.16
		Oak	0.94	1.44	1.19	0.18	1.08	1.60	1.31	0.15
MDF	PVAc	Beech	1.46	2.40	1.88	0.31	1.47	2.73	1.84	0.37
		Pine	1.37	2.25	1.69	0.27	1.83	2.62	2.13	0.28
		Oak	1.43	2.73	1.82	0.39	1.50	2.26	1.80	0.24
	UF	Beech	1.53	1.99	1.73	0.15	1.44	2.20	1.80	0.22
		Pine	1.55	1.96	1.78	0.13	1.49	2.51	1.84	0.34
		Oak	1.54	2.65	1.95	0.34	1.54	1.99	1.77	0.14
	CONTACT	Beech	0.77	1.77	1.10	0.29	0.57	1.03	0.77	0.18
		Pine	1.34	1.65	1.48	0.10	1.04	1.67	1.29	0.24
		Oak	0.95	1.39	1.17	0.15	0.75	1.14	0.88	0.15
OSB	PVAc	Beech	1.43	2.57	1.91	0.35	1.43	2.17	1.73	0.26
		Pine	1.08	1.78	1.28	0.21	1.26	1.77	1.51	0.18
		Oak	1.61	2.05	1.76	0.13	1.25	1.82	1.59	0.20
	UF	Beech	1.95	2.60	2.21	0.23	1.23	1.82	1.41	0.17
		Pine	1.25	1.78	1.51	0.19	1.34	2.21	1.72	0.24
		Oak	1.60	2.13	1.76	0.16	1.43	1.90	1.67	0.14
	CONTACT	Beech	0.70	1.42	1.04	0.20	0.82	1.41	1.10	0.20
		Pine	0.72	1.15	0.91	0.15	0.78	1.49	1.10	0.27
		Oak	0.78	1.29	0.93	0.17	0.75	1.37	0.95	0.21

of features (Jenis *et al.* 2023). An artificial neural network consists of nodes, neurons, and a transfer function, as seen in Figure 3. A veneer bonding strength prediction model was created using ANN and ANFIS. The models were designed using Matlab 2016Ra Toolbox. According to the outcomes of the ANN and ANFIS models, wood type, adhesive type, cutting direction, and coating type influence the bonding strength. The artificial neural network (ANN) achieved a correlation coefficient (R^2) ranging from 0.91 to 0.94, while the adaptive neuro-fuzzy inference system (ANFIS) produced an R^2 value of 0.88. In ANN models, the data are randomly selected, and the training is carried out by separating 70% of the data, with 30% used for testing. With K-Fold cross-validation in ANN models, the dataset is divided into training and test data for each iteration. Here, our data are divided into *k* different subsets. First, the dataset is randomly selected. The dataset is then divided into *k* groups. A selected group is used for validation, while the other (k-1) group is used for training.

Root Mean Squared Error (RMSE) and Mean Squared Error (MSE) are error measures that quantify how far the predictions deviate from the true values. Mean Absolute Percentage Error (MAPE) measures how inaccurate the estimates are as a percentage of the actual values. Low MAPE values indicate that the model makes predictions close to the actual values. These calculations are performed according to equations (1)–(3) as given below.

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

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

$$MAPE = \frac{\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|}{n} x100 \tag{3}$$

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

Results and discussion

1. Neural networks

An ANN consists of an input layer, an output layer, and one or more hidden layers, as seen in Figure 3. In this study, the estimation of bonding strength was modeled using the Neural Networks Toolbox in the Matlab 2016Ra program. The available networks are feed-forward neural network (FFNN), cascade feed-forward neural network (CFFNN), Elman neural network (ENN), Layer Recurrent neural network (LRNN), and NARX neural network (NARXNN). The models were trained using the Traincgf, Trainlm, and Trainrp algorithms.

The first layer creates the connection at the network inputs in feedforward networks. In these networks, each layer has a connection to the previous layer. Thus, the input data is multiplied by the weights to produce an output. Moreover, several ANN models were used to estimate the bonding strength measurement results. Table 3 presents some of the applied ANN models. Based on Table 3, the models that produced the highest correlation coefficient were selected to create a model for bonding strength. FFNN-lm, FFNN-rp, CFNN-lm, and CFNN-rp algorithms with one hidden layer with 30 neurons demonstrated reasonable results. In addition, the correlation coefficient (R^2) values of the models were improved with a first hidden layer of 30 and a second hidden layer of 20 neurons.

Figure 4 shows the configuration of the ANN models for the prediction of veneer bonding strength. ANN-lm and ANN-rp produced higher correlation coefficient values than the other ANN models. The models had one hidden layer with 30 neurons (a, b), or two hidden layers with 30 and 20 neurons (c, d), which gave more realistic results. The ANN models also had 4 input layers and one output neuron. The graphic

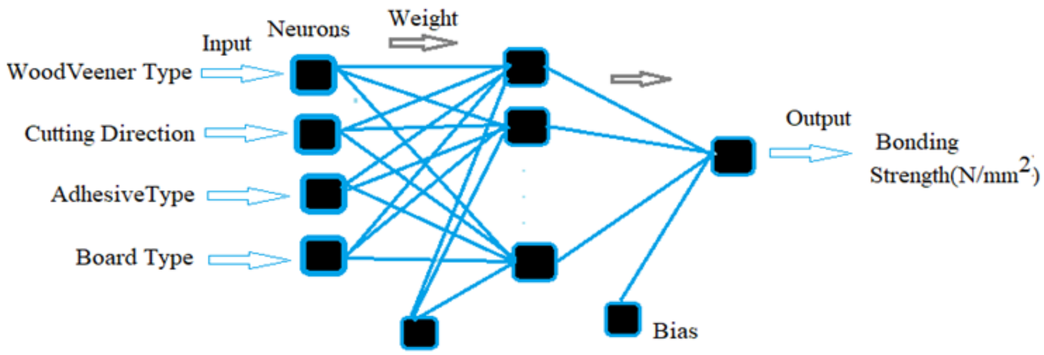


Fig. 3. Bonding strength neural network model

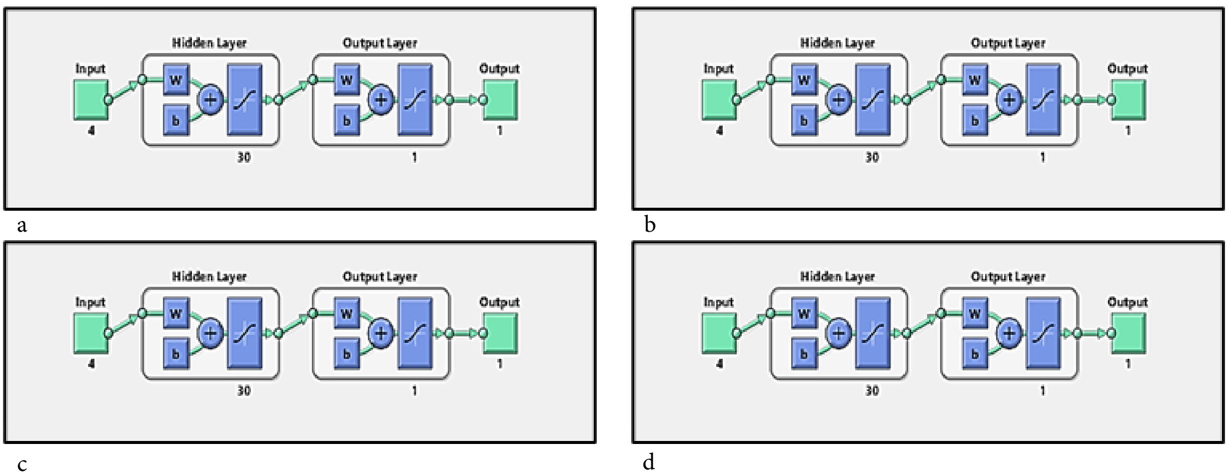


Fig. 4. ANN models for veneer bonding strength: (a) FNNN, (b) CFNN, (c) ENN, and (d) LRNN

Table 3. ANN models for veneer bonding strength

Neural networks	Algorithm	Neurons	Epoch	R^2
FINN	Trainlm	30 (1 hidden layer)	7	0.9342
FINN	Trainlm	30-20 (2 hidden layers)	10	0.9349
FFNN	Trainrp	30 (1 hidden layer)	39	0.9329
FFNN	Trainrp	30-20 (2 hidden layers)	56	0.9359
CFFNN	Trainlm	30 (1 hidden layer)	9	0.9350
CFFNN	Trainlm	30-20(2 hidden layer)	5	0.9358
CFFNN	Trainrp	30 (1 hidden layer)	68	0.9343
ENN	Trainrp	30 (1 hidden layer)	56	0.9102
NARXNN	Trainlm	30 (1 hidden layer)	6	0.9224
LRNN	Trainlm	30 (1 hidden layer)	5	0.9156

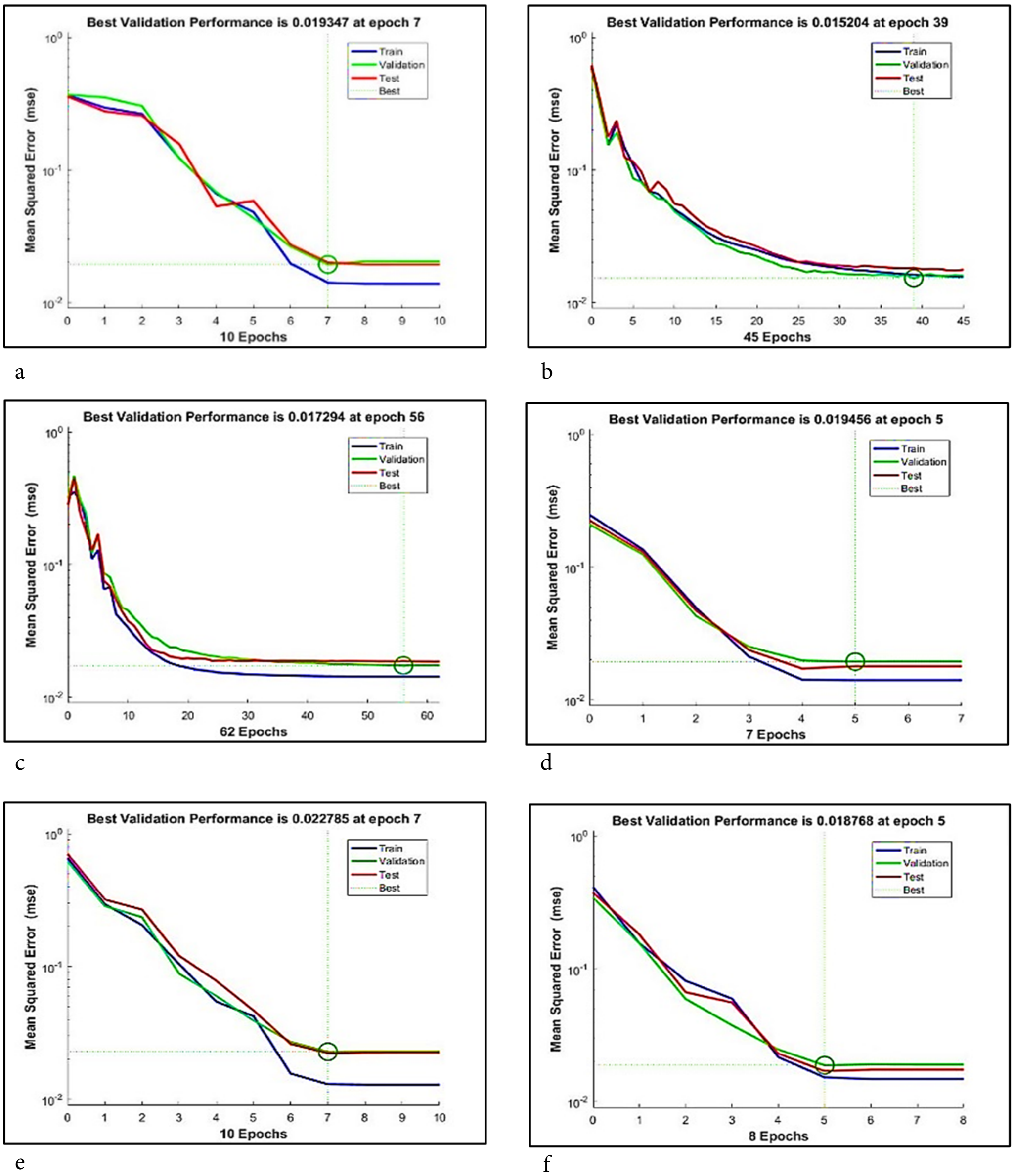
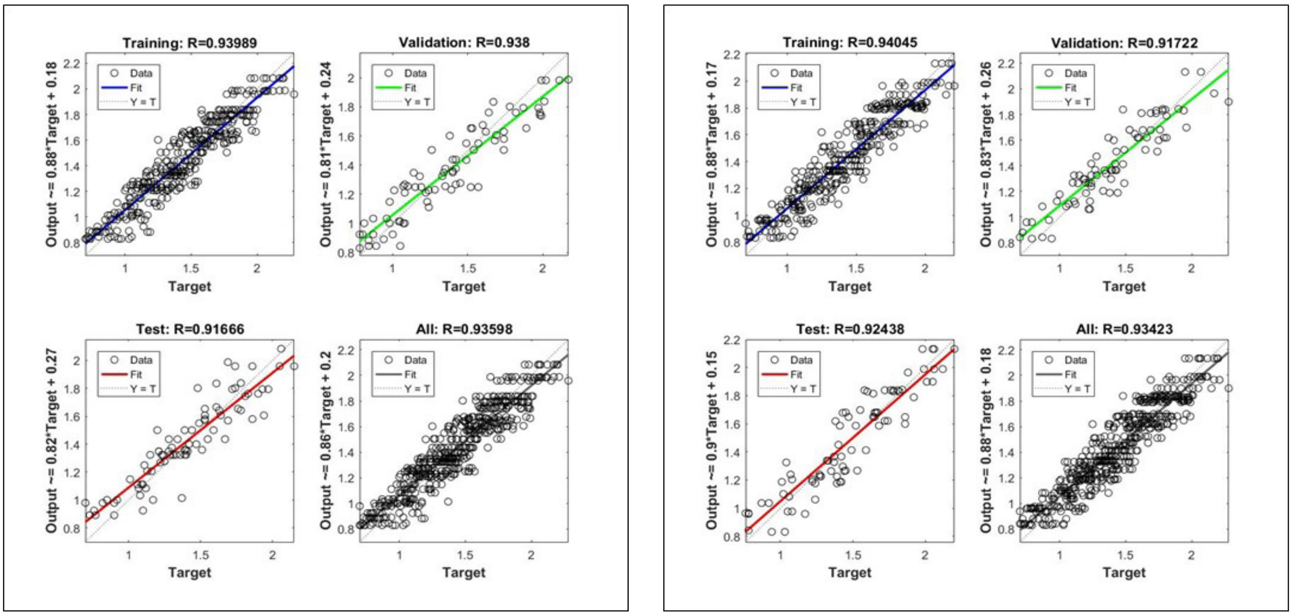


Fig. 5. MSE of ANNs for bonding strength: (a) FFNN-lm, (b) FFNN-rp, (c) CFNN-lm, (d) CFNN-rp, (e) ENN-lm, and (f) LRNN-lm



a

b

Fig. 6. Results of ANN-based bonding strength model (a) CFNN-lm and (b) FFNN-lm

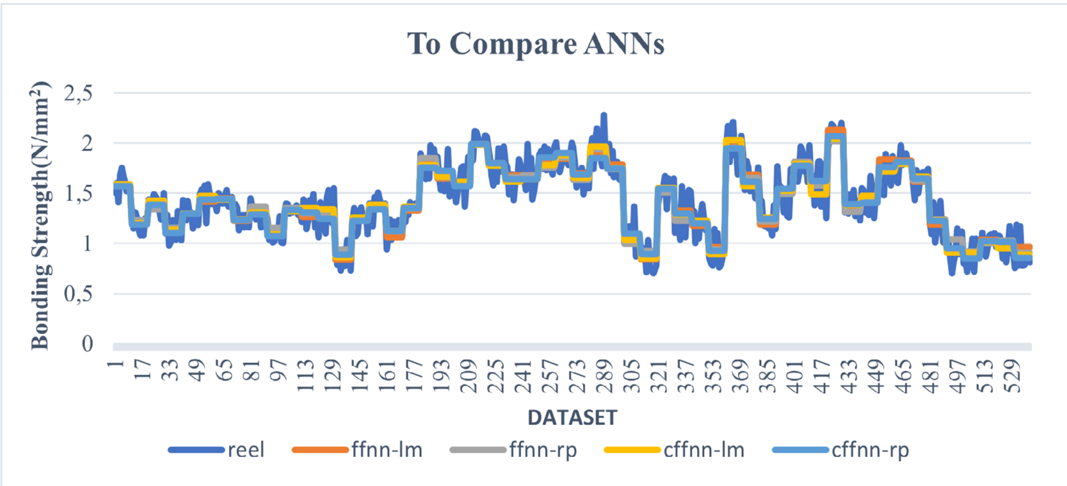


Fig. 7. Comparison of the ANN models

shows visually the structural differences of these models, indicating how different ANN models are structured with parameters such as the number of input and hidden layers, the number of neurons, and their effects on prediction performance.

Figure 5 shows the MSE, train, validation, test and epoch results of FFNN-lm, FFNN-rp, CFNM-lm, CFNM-rp, ENN-lm, and LRNN-lm ANN models.

In this research, the CFNN-lm and FFNN-rp ANN models achieved the best results for prediction of the veneer bonding strength. Figure 6 shows the training and test results for CFNN-lm and FNN-lm. The dataset was split into training (70%) and testing (30%) sets. Furthermore, the neural network was optimised according to the regularisation weight and standard deviation of the models using the Levenberg-Marquardt algorithm. Although this is generally the fastest backpropagation algorithm, it requires more memory (Hedayat *et al.* 2009).

Figure 7 presents a comparison of the ANN models for the prediction of bonding strength. The bonding strength of the veneer for various input features can be predicted by these models.

2. Adaptive neuro-fuzzy inference system (ANFIS)

Rule-based fuzzy logic, which consists of fuzzy inferences, uses both numerical and linguistic data. There are two different methods, called Mamdani and Sugeno. Moreover, ANFIS is a combination of ANN and fuzzy logic based on the fuzzy inference method (Precious *et al.* 2021). When ANFIS training takes place, both ANN learning and fuzzy logic rules are used together. The ANFIS consists of 6 main layers, known as the rule

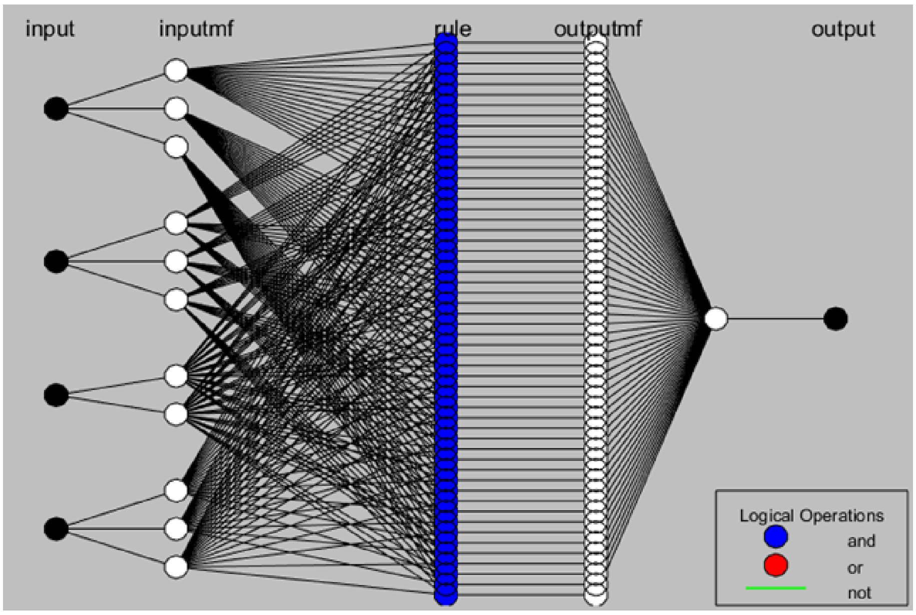


Fig. 8. ANFIS model for adhesion strength of veneer

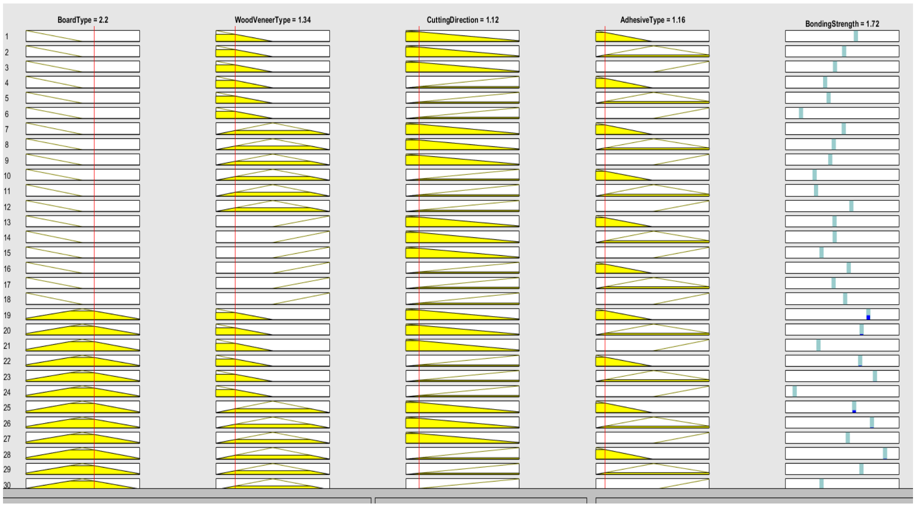


Fig. 9. Rules for veneer adhesion strength

layer, normalization, membership function, clarification, and output. Figure 8 demonstrates the configuration of the ANFIS model for prediction of the bonding strength. In this model, the input features are board type, coating type, cutting direction, and adhesive type, while the output is the bonding strength of the veneer.

A total of 540 data were used to create the model. The dataset was split into training (70%) and test (30%) sets. Figure 9 presents the bonding strength model, consisting of 54 different rules.

Figure 10 shows surfaces for the interaction of veneer bonding strength, veneer type, board type, cutting direction, and adhesive type. It is observed that when the veneer type is pine and the board type is Flakeboard, the bonding strength of the veneer to decrease. On the other hand, when the veneer type is oak and the board type is MDF, the bonding strength of the veneer shows an increase. When the tangential cutting direction is combined with Flakeboard, the bonding strength of the veneer again decreases.

Figure 10 shows the graphs and interactions obtained as a result of the analysis of all experimental variables—bonding strength, adhesive type, board type, cutting direction and wood veneer type—using fuzzy logic. Surface models obtained in ANFIS based on different variables are presented.

Figure 11 illustrates the correlation coefficients (R^2) for the results of the ANFIS model with training and test datasets. The values of R^2 were 0.8837 for the training set and 0.8551 for the test set.

Figure 12 indicates the actual and ANFIS predicted values for bonding strength. This model returns reasonable values for veneer bonding strength, although its results are weaker than those of the ANN models.

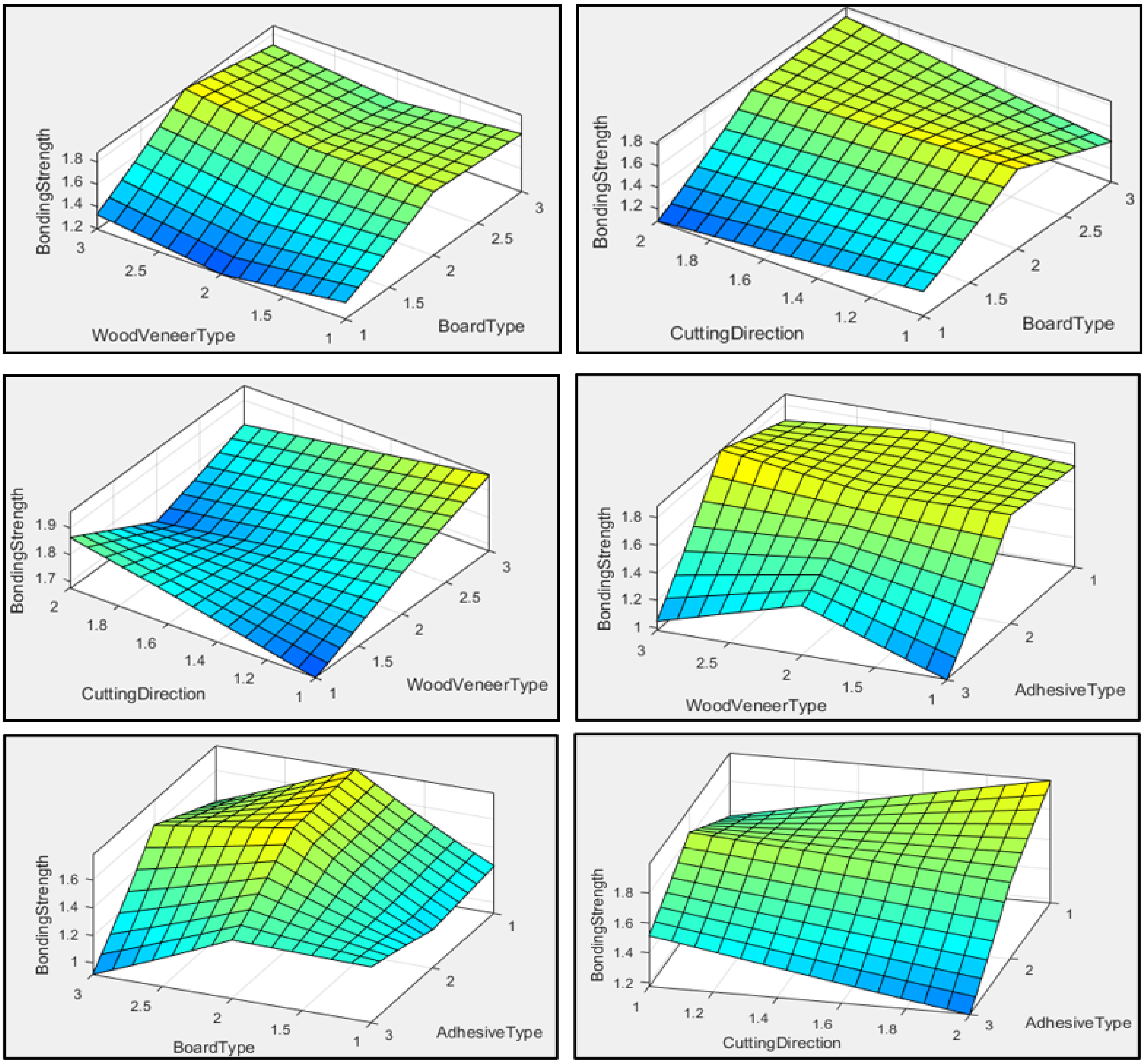
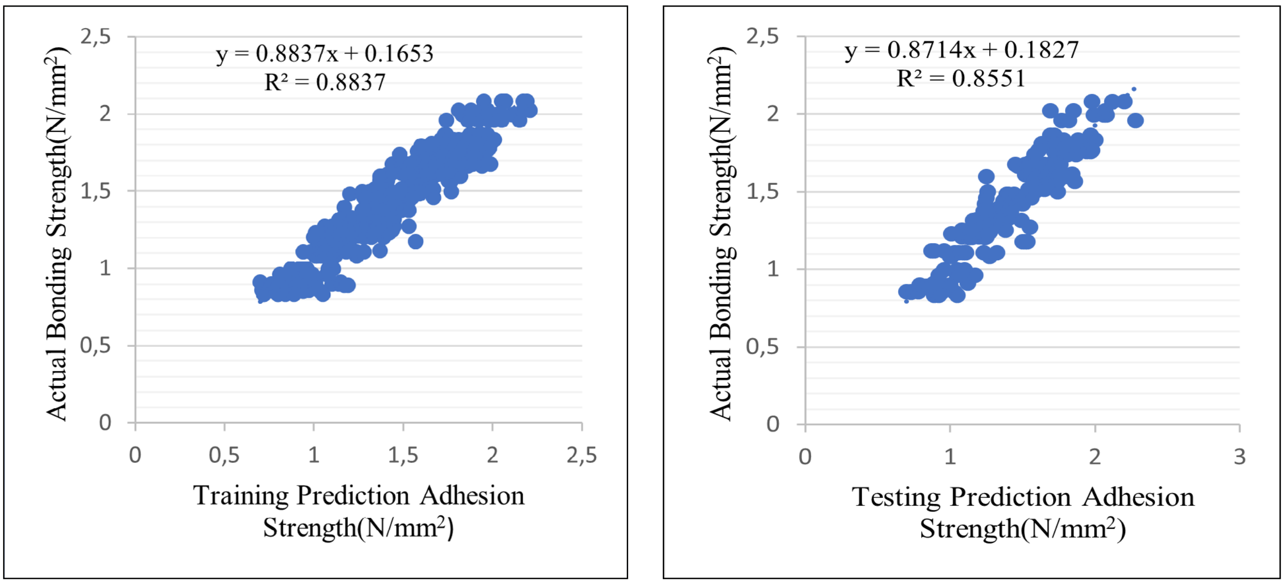


Fig. 10. ANFIS surface models for veneer bonding strength



a b

Fig. 11. ANFIS model prediction results: (a) training and (b) test

Table 4. Results for performance evaluation criteria for ANNs and ANFIS models

Model	MSE	RMSE	MAPE (%)
FFNN-LM	0.019	0.137	8.58
FFNN- Rprop	0.019	0.136	8.33
ENN	0.170	0.413	26.86
LRNN	0.326	0.571	29.84
NARXNN	0.053	0.231	13.65
ANFIS	0.018	0.135	8.20

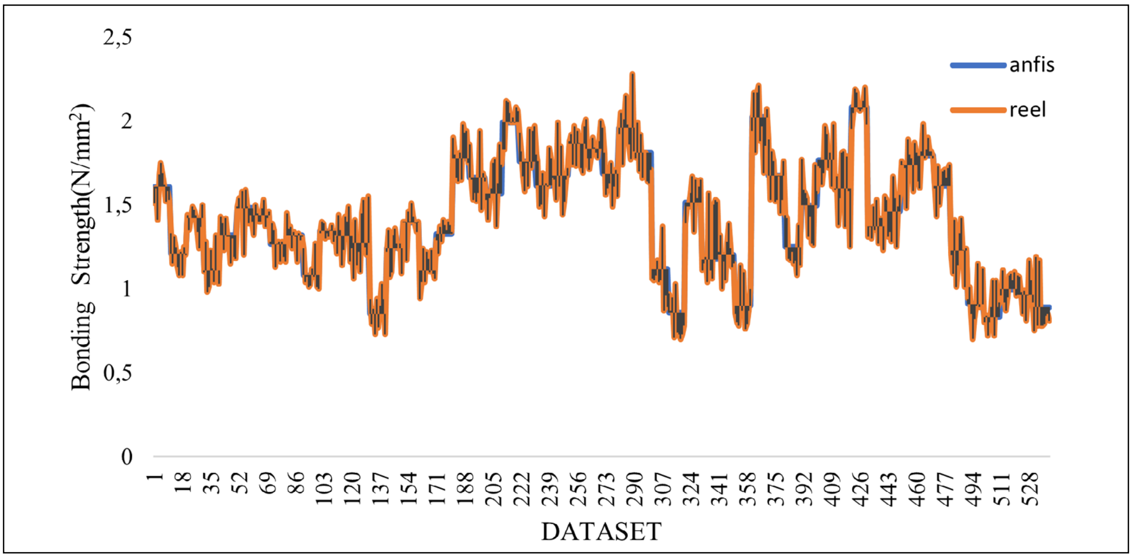


Fig. 12. Actual values and ANFIS predictions for veneer bonding strength

Table 4 presents training and testing evaluation results in ANN and ANFIS in terms of Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE).

The table presents the performance metrics MSE (Mean Squared Error), RMSE (Root Mean Squared Error), and MAPE (Mean Absolute Percentage Error) for different artificial neural network (ANN) models. The FFNN-LM and FFNN-Rprop models have low MSE, RMSE, and MAPE values. This indicates that these models have predictions that are close to the actual values. Additionally, the MAPE value for the FFNN-Rprop model is slightly lower than that of FFNN-LM, indicating better performance. The ENN and LRNN models have higher MSE, RMSE, and MAPE values than other models. This suggests that these models have predictions that deviate further from the actual values, and thus demonstrate lower performance. The NARXNN model performs better than the other models: its MSE, RMSE, and MAPE values are lower than those of the other models, indicating better predictive power. The ANFIS model has low MSE, RMSE, and MAPE values compared with the other models. This indicates that the ANFIS model's predictions are closer to the actual values, demonstrating better performance.

In conclusion, the FFNN-LM, FFNN-Rprop, and ANFIS models achieved the best performance, while the ENN and LRNN models exhibited lower performance.

Conclusions

Due to the usage conditions of wooden materials, bonding strength is important for indsutrial producers and consumers. In this study, experiments were carried out using wood coating type, adhesive type, cutting direction, and panel type as features, while the bonding strength was used as an output. Regression analysis was carried out using ANN and ANFIS. The models provided the following observations:

1. The ANN models provided more realistic results.
2. Although ANFIS presented a strong correlation, it produced weaker results than the other models.
3. The ANN model with the tangential function and Levenberg–Marquardt (lm) algorithm provided more significant results.

4. The ANN models achieved R^2 values between 0.91 and 0.94.
5. The coefficient of determination values in the ANFIS model were obtained by creating 54 rules using the Gauss membership function. Additionally, testing in the ANFIS model led to the highest coefficient of determination in the estimation of bonding strength. In this model, the MAPE value of 8.20% seems to be a reasonable result. Additionally, RMSE and MSE results indicate that fuzzy logic can be applied in this area.
6. In the ANN models, the lowest MAPE value is 8.58% for the FFNN training data, and the RMSE value was 0.137.
7. The ANN and ANFIS results indicated how the cutting direction, coating type, panel type, and adhesive type influenced the veneer bonding strength. The MDF panel in the radial cutting direction with PVAc and UF adhesives produced the best veneer bonding strength.

It is seen that the bonding strength of wood materials can be predicted with high accuracy using soft calculation methods. This will contribute to more efficient production and consumption processes in industry. In our next studies, it is planned to add different features and apply different soft computing models to increase prediction accuracy for veneer bonding strength.

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