Predicting the Impacts of Various Factors on Failure Load of Screw Joints for Particleboard Using Artificial Neural Networks

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Innovations in the furniture industry have an important place in the global competitive environment. The use of mechanical joining techniques is rapidly increasing in the furniture industry. One of the most common mechanical joining techniques is screwing. This study investigated the impacts of screw diameter, screw length, and the distance between the screws on the failure load of screw joints in particleboard. Additionally, a model was developed on an artificial neural network model (ANN), based on experimental data, to predict the failure load of joints. The results indicated that the highest tension and compression strengths of joints were achieved when the distance is 140 mm between the screws. Joint strengths of all specimens were improved when the screw length and diameter were increased. It is necessary to estimate the effect of various factors to improve furniture joint performance. Coefficients of determination at 0.98 (tension strength test) and 0.96 (compression strength test) were predicted for the testing phase by the ANN model. All these findings established that the prediction was compatible with experimental data of tension and compression strengths. The results of the analysis showed that the neural network approach was effective in predicting the failure load of screw joints and showed that the ANN model has great potential in the design optimization of furniture assemblies.

Keywords: Screw; Joint; Furniture; Artificial neural networks

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INTRODUCTION

Furniture is much needed in daily life, and its design and construction is an applied art (Wang and Lee 2014). Its strength evaluation should start at the design process stage (Smardzewski *et al.* 2014). The strength and durability of furniture are some of the most important factors determining furniture value (Smardzewski and Majewski 2013). In furniture, the strength of joints plays a critical role in the quality. Furniture members are combined with different techniques (Kasal *et al.* 2016). The joints should always be carefully selected in the construction of wood-based furniture (Smardzewski *et al.* 2015). Structural failure may occur when the correct connection is overlooked (Haftkhani *et al.* 2011). For this reason, designers need to possess knowledge of how to select a suitable combination of members (the type of material, dimension, and geometry) and fasteners (nails, screws, dowels, and bolts) (Maleki *et al.* 2017).

L type Corner joints used in furniture production can be prepared with various materials. Some of these materials are wood, fiberboard, and particleboards. Especially today, particleboards are widely used in furniture production, because particleboards are much cheaper than wood fiberboards and plywoods. Minifix, dowel, screw, and glue can be used in the joining of L type corner in particleboard. Also, several of these joining methods can be used together. Many studies have been carried out on the advantages of furniture production with these joining methods. According to the results of the dowel design made by using particleboard and fiberboards in the box constructions furniture corner joints, the 8 mm diameter dowels gave better performance than the 10 mm diameter dowels. Moreover, the grooved surface dowels on the particleboards were found to be more successful than the flat surface dowels. However, the flat surface dowels on the fiberboards gave better results than the grooved surface dowels. The increase in the number of dowels indicates that the resultant corner joint increases the tensile strength and decreases the compressive strength (Efe 1998; Efe and Imirzi 2008). In another study, corner joints were used in the production of box-structured furniture; the authors investigated the strength properties of glue and glue-free joints. According to the results of the experiment, it was reported that glue-free joints outperformed glued joints, and the best results were given by unglued multifixed corner assemblies, while the second level of performance was obtained by unglued minifixed corner assemblies (Efe and Kasal 2000; Efe and İmirzi 2008). In a study by Kasal and his colleagues, particleboard coated with surface synthetic resin and fiberboard were used in the corners of the furniture. In addition, some of the screws used for joining the corner were used with polyurethane adhesive and some without adhesive. The corner joints obtained were examined for bending resistance under tensile and compressive loads. As a result of the work done, the bending strengths of the joints made using the fiberboard were higher than those using the chipboard. It has also been found that joints made using glue and screws enhance bending resistance (Kasal *et al.* 2006).

There are many artificial intelligence methods. Some of them are systems such as artificial neural networks (ANNs), fuzzy systems, multiple linear regression, and deep learning. In real life, artificial intelligence techniques are used in many areas such as predicting egg production based on energy consumption (Sefeedpari *et al.* 2016), modeling of groundwater level fluctuations (Gholami *et al.* 2015), neural network river forecasting through baseflow separation and binary-coded swarm optimization (Taormina *et al.* 2015), dimension reduction using semi-supervised locally linear embedding for plant leaf classification (Zhang and Chau 2009), assessment of river water quality based on theory of variable fuzzy sets and fuzzy binary comparison method (Wang *et al.* 2014), a split-step particle swarm optimization algorithm in river stage forecasting (Chau 2007), predictive performance of artificial neural network and multiple linear regression models in predicting adhesive bonding strength of wood (Bardak *et al.* 2016a), and neural network prediction of wood bonding quality (Bardak *et al.* 2016b). Lately, artificial neural networks is one of the most popular methods in the field of the artificial intelligence, and it is used to solve pattern recognition, prediction, classification, and optimization problems in engineering applications (Kumar and Thakur 2012; Tiryaki and Hamzacebi 2014). In contrast to commonly used modelling methods, artificial neural networks can help us to learn how to store their bias values and weights from examples or training patterns, and it guides how to use this knowledge to predict future values (Londhe and Deo 2003 and Tiryaki *et al.* 2016). Artificial neural networks (ANNs) can help designers in this regard. Artificial neural networks are usually information processing systems that mimic some features of biological neurons. An input layer, hidden layer(s), and an output layer of neurons are the main parts of each ANN structure (Saffari *et al.* 2009; Tracey *et al.* 2011). The ANNs can be used to estimate new data through learning from some series of experimental data without outside help (Akincioglu *et al.* 2013). This technique is capable of handling incomplete data and can deal with nonlinear problems. ANN can make predictions and generalizations at high speeds once it is trained (Yuste and Dorado 2006; Rajendra *et al.* 2009; Garaga and Latha 2010). Modern researchers use ANNs to solve complex engineering problems. Previous studies have found a successful use for ANNs in mechanical engineering (Chau 2006; Kmet *et al.* 2011; Verma *et al.* 2017).

Research on estimating the performance of furniture joints with artificial neural networks is limited. However, most of the current scientific literature is focused on experimental investigations of the screwing process. In this study, the impacts of various factors (screw diameter, screw length, and the distance between the screws) on the failure load of screw joints are modelled. As a result, the designed model has been estimated with high accuracy.

EXPERIMENTAL

Materials

An 18 mm × 50 mm × 300 mm surface-coated chipboard was used as a wood material. Bartin University in Bartin, Turkey supplied the particleboards. All particleboards were kept for 7 days under standard air conditions (environment temperature 20 °C ± 2 °C, relative air humidity 65% ± 5%).

Sample preparation and testing

Each experimental sample consisted of two members. The butt member was 270 mm × 132 mm, and the face member was 270 mm × 150 mm. The screw sizes, which are commonly used in the particleboard assemblies in industry, were taken into consideration. Screw lengths of 30 mm and 40 mm and screw diameters of 3 mm, 3.5 mm, and 4 mm were selected. Figure 1 shows the screws used in this study.

Fig. 1. Screw samples

Specially prepared moulds were used when the experimental specimens were combined with screws. The screws were mounted by the drill. In many studies, the distance between the screws was chosen differently (Efe and Imirzi 2008; Efe *et al.* 2011;

Demirci *et al.* 2011). Therefore, in this work the spacing of the screws was varied in steps of 20 mm from 100 to 200 mm to find the optimum resistance distance. The experimental setup for determining compression (a) and tension (b) strengths is shown in Fig. 2.

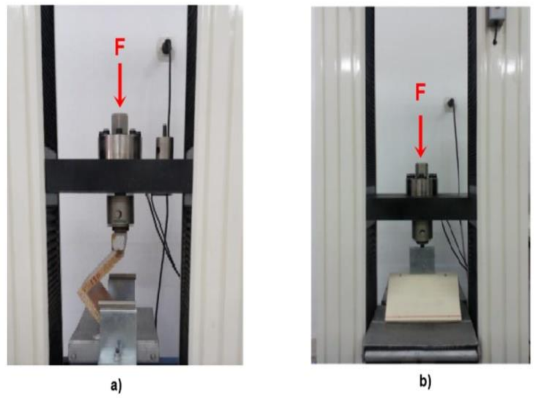

Fig. 2. Experimental setup for determining compression (a) and tension (b) strengths

Compression and tension strength tests were conducted according to the procedure outlined in the ASTM 1037 (1998) standard. This standard has been used in determining the compression and tension strengths in this work since the ASTM 1037 standard is mostly used in determining the resistance properties of particleboard and fiberboard joints (Atar and Ozciftci 2008; Çetin-Yerlikaya 2013). The tests were performed on a universal testing machine with a capacity of 10,000 kg and a loading speed of 2 mm/min. The loading was continued until separation occurred on the surface of the test samples. The strength of the joints was characterized by the bending moment force. The bending moment in compression (M_c) and in tension (M_t) = Moment (Nmm), and $F_{\max}$ = Maximum force at the moment of breaking (N). The parameter L is the Arm of Moment (mm). The M_t and M_c values were calculated with Eqs. 1 and 2:

$$M_t \text{ (Nmm)} = \text{Fmax} / 2 \times \text{L} \tag{1}$$

$$M_c \text{ (Nmm)} = \text{Fmax} \times \text{L} \tag{2}$$

Methods

Development of artificial neural networks procedure

RapidMiner is mostly used in many studies (Geetha and Nasira 2014; Yadav *et al.* 2015; Celik and Basarır 2017) and popular commercial software (RapidMiner, Inc. Headquarters, version 7.4, Boston, MA, USA) has been developed by Ralf Klinkenberg, Ingo Mierswa, and Simon Fischer in 2001 (Yadav *et al.* 2015). Therefore, the RapidMiner software was selected for this work. Rapidminer is applied for ANNs based the prediction of the failure load of screw joints. The software has modules and operators that make it possible to analyze data sets for predicting. At the same time, this software is used to measure prediction performance. The ANNs are computed based on the independent variables that experimental data provide. The screw diameter, screw length, and distance between values were the inputs of the neural network, while the failure load of the screw joint was its output. The reported data were separated into two parts: training (80%) and testing data (20%). Figure 3 shows the RapidMiner operation for model production with operators. In addition, the method known in the literature as k-fold cross validation has been used to measure the success of the ANN model. In this method, data set were separated into two parts: training (90%) and testing data (10%).

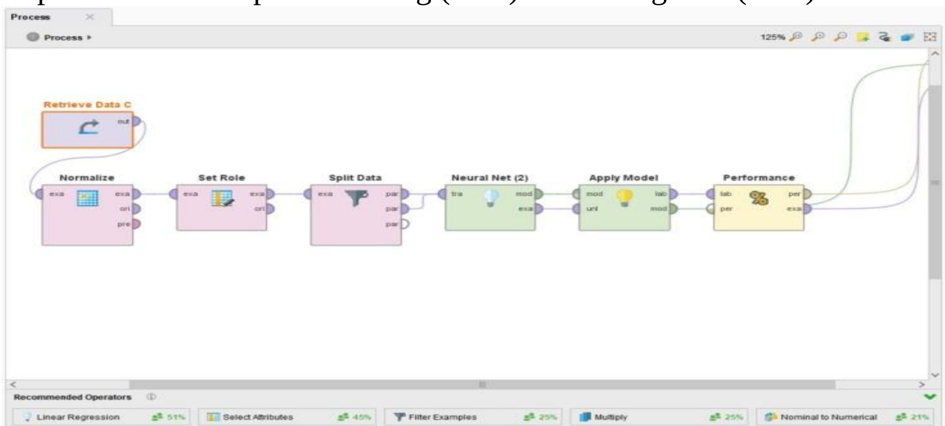

Fig. 3. RapidMiner operation for model production with operators

There are no rules for the number of neurons needed in artificial neural networks. The number of neurons required in each hidden layer can only be determined by trial (Akdag *et al.* 2016; Garcia *et al.* 2017). In this study, the employed neural network architecture is shown in Fig. 4.

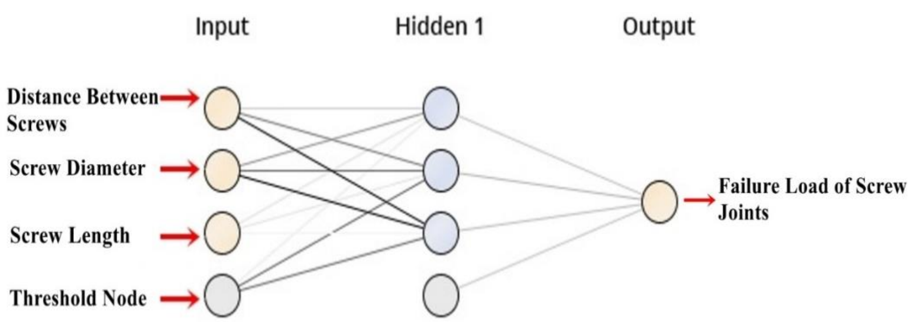

Fig. 4. The employed neural network architecture

RESULTS AND DISCUSSION

Moment Capacity under Compression and Tension Loads

The screw diameter, the screw length, and the distance between the screws affected the tension and compression strengths of joints. The distance was varied to find the best value in the steps of 20 mm from 100 to 200 mm. The results showed that the highest tension and compression strengths of joints were achieved when the distance is 140 mm between the screws. The worst results were obtained at 100 mm configuration. For the test of the screw length and diameter, the screw length values were chosen as 30 and 40 mm, while the screw diameter was used 3, 3.5, and 4 mm. Joint strengths of all specimens improved when the screw length and diameter were increased. Therefore, Table 1 indicates that the best results were reached with 140 (the distance), 40 (the screw length), and 4 (the screw diameter). On the other hand, the worst parameters were 100 (the distance), 30 (the screw length), and 3 (the screw diameter), as expected. Moment capacities were found to be greater for joints loaded in tension than the ones loaded in compression, which was also reported by Zhang and Eckelman (1993). These results were consistent with previous studies (Kasal 2008; Smardzewski *et al.* 2015). Table 1 presents the moment capacity variability determined by the compression and tension tests depending on changes in the diameter, length, and distance between the screws.

Table 1. Results of the Duncan and Experimental Tests for Process Variables of Moment Capacity under Compression and Tension Loads

Numbers are in units of mm.				Moment Capacity (Nmm)					
				Under Compression			Under Tension		
Distance between screws	Screw length	Screw diameter	N	Mean	SD	HG	Mean	SD	HG
100	30	3	5	742	43	A	1762	30	A
		3.5	5	1095	118	A	3597	130	BC
		4	5	2104	151	CD	6079	108	EF
	40	3	5	5004	86	H	13321	673	G
		3.5	5	5967	101	I	14073	472	GH
		4	5	9794	548	MN	15886	758	IJ
120	30	3	5	836	62	A	2909	592	B
		3.5	5	2162	139	CD	3736	147	BC
		4	5	2143	238	CD	7081	350	F
	40	3	5	6953	277	J	15015	590	HI
		3.5	5	10265	474	NO	15809	917	IJ
		4	5	10783	875	O	19172	517	M
140	30	3	5	1270	113	AB	6050	180	EF
		3.5	5	3117	109	EF	6934	139	F
		4	5	4203	100	G	7205	403	F
	40	3	5	8223	171	K	22040	2007	N
		3.5	5	11597	1894	PQ	28154	1482	O
		4	5	11750	1002	Q	33497	1692	Q
160	30	3	5	1256	61	AB	5123	90	DE
		3.5	5	2230	154	CD	6778	218	F
		4	5	2488	112	DE	7244	282	F
	40	3	5	9931	576	MN	16624	1004	JK
		3.5	5	11022	92	OPQ	19105	1512	M
		4	5	10910	543	OP	30225	2455	P
180	30	3	5	807	22	A	5042	76	DE
		3.5	5	2003	959	BCD	5272	580	DE
		4	5	3847	84	FG	6264	165	EF
	40	3	5	6048	1353	I	14046	1008	GH
		3.5	5	8670	268	KL	17190	427	KL
		4	5	8592	1436	KL	22238	1607	N
200	30	3	5	1568	156	ABC	4756	162	CD
		3.5	5	3573	643	FG	6796	607	F
		4	5	4053	142	G	6673	314	F
	40	3	5	9105	175	LM	14961	510	HI
		3.5	5	9106	239	LM	18029	253	LM
		4	5	9736	449	MN	22273	1744	N

Notes: SD: standard deviation; HG (Homogeneity group): A group of observational units similar to each other in terms of an observed feature; different letters in columns represent statistical differences ,and same letters in columns indicate that there is no statistical difference between the samples according to the Duncan's multiply range test at 95% confidence level. Groups in HG column with more than one letter show no statistically significant difference with groups with common letter but groups that do not contain a letter in common are statistically different.

ANN

Thirty-six different inputs were presented to the ANN, and an experimental output (predicted failure load of screws) was obtained for each input for the testing phase (Table 2) of the tension and compression strength tests.

Table 2. Input and Output Parameters in Moment Capacity under Tension and Compression Loads for Testing Phase

Numbers are in units of mm.			Moment Capacity (Nmm)			
			Under Tension		Under Compression	
Distance between screws	Screw Length	Screw diameter	Experimental	Predicted	Experimental	Predicted
100	30	3.0	1758	2171	761	882
100	30	3.5	3515	4829	1293	1666
100	30	4.0	6105	6498	2358	2983
100	40	3.0	13551	13156	5021	4628
100	40	3.5	14555	14342	6086	6536
100	40	4.0	16280	15337	10346	8966
120	30	3.0	2510	3961	751	1074
120	30	3.5	3839	5590	2358	2280
120	30	4.0	7185	6456	2440	3287
120	40	3.0	15465	14269	6618	7325
120	40	3.5	14338	17094	11106	9376
120	40	4.0	19333	19017	10090	11036
140	30	3.0	5810	5174	1293	1400
140	30	3.5	6753	6158	3119	2849
140	30	4.0	6938	6642	4184	3535
140	40	3.0	20489	21272	8216	8992
140	40	3.5	26594	27587	13236	10833
140	40	4.0	32260	33695	12171	11743
160	30	3.0	5134	5933	1293	1490
160	30	3.5	7076	6516	2358	2993
160	30	4.0	7400	6793	2586	3701
160	40	3.0	15170	15798	10574	8668
160	40	3.5	17899	20724	11106	10231
160	40	4.0	33069	28637	10041	10835
180	30	3.0	5033	6406	781	807
180	30	3.5	4839	6743	1521	2315
180	30	4.0	6429	6898	3956	3424
180	40	3.0	12609	13526	7683	7923
180	40	3.5	16698	16576	8976	8844
180	40	4.0	20280	22069	6618	9117
200	30	3.0	4585	7012	1826	1724
200	30	3.5	7649	7126	4488	3199
200	30	4.0	6450	7153	4184	4466
200	40	3.0	15818	14113	9281	8084
200	40	3.5	17656	17424	8976	8522
200	40	4.0	20194	22591	10346	8602

When Table 2 is examined, it can be seen that the moment capacity results under both tensile and compressive loads are close to each other when the experimental and predicted results of the model are considered. Various performance measures related to the ANN model are shown in Table 3.

Table 3. Various Performance Measures Related to ANN Model

Test Type	ANN Model	Coefficient of Determination (R^2)	Root mean squared error	Absolute error	Relative error	Spearman Rho	Kendall Tau
Tension strength test	Testing	0.984	1462.168	1139.490	14.06%	0.942	0.816
	K-fold cross-validation	0.987	1699.144	1391.811	16.45%	0.958	0.875
	Training	0.990	1226.112	960.457	11.44%	0.955	0.844
Compression strength test	Testing	0.969	992.412	761.529	16.28%	0.952	0.838
	K-fold cross-validation	0.978	1044.642	805.377	23.47%	0.971	0.889
	Training	0.980	995.524	749.861	22.47%	0.978	0.887

The coefficient of determination, R^2, collectively can give an indication of the ANN performance. The R^2 values were within range of 0 and 1, and prediction accuracy increases when R^2 gets closer to 1 (Ozsahin 2012; Tiryaki *et al.* 2015). Generally, a R^2 value greater than 0.9 indicates a highly satisfactory model (Heng and Suetsugi 2013; Cranganu *et al.* 2015). In other words, there was a good agreement between the experimental and the prediction results. For tension strength, the values of R^2 in testing, cross-validation, and training were 0.984, 0.987, and 0.990, respectively, while the values of R^2 in testing, cross-validation, and training for compression were 0.969, 0.978, and 0.980, respectively. R^2 values calculated in the present study with the ANN modeling technique were found to be greater than 96% for all data sets. The R^2 value obtained from the tension strength test was better than the compression strength test for the testing phase. All these findings showed that the prediction was compatible with experimental data of tension and compression strengths at least 96%. Root Mean Squared Error, which is calculated by quadrature sum of all errors, is the standard deviation of the residuals (prediction errors) (Hyndman and Koehler 2006). Mean absolute error is the average absolute deviation of the prediction from the actual value, and it is commonly used for forecast error in time series analysis (Hyndman and Athanasopoulos 2014). Relative error is the mean of the absolute deviation between the experimental and the predicted values. Spearman's Rho is the linear relationship between the measured and predicted quantities, which is the rank correlation between them (Spearman 1904). On the other hand, the last parameter is Kendall's Tau. The strength of the relationship between two quantities can be measured by Kendall’s Tau, which refers the rank correlation as it does for Spearman's Rho (Kendall 1938; Celik and Basarır 2017).

CONCLUSIONS

Experiments were performed by varying three furniture joint process parameters: the screw diameter, the length, and the distance between the screws.

1. It was found that these parameters significantly affected the strength of joints.
2. Though the ANN method was satisfactory in the modeling of the joint process, the prediction for the joints of the tension strength test was better for the testing phase than the compression strength test.
3. In this study, ANN was shown to be successful for decreasing designers' and engineers' time for analyzing the performance of different furniture joints.
4. This method ensures an optimum selection of the screw diameter, the length, and the distance between the screws as a failure load of screws, generating maximum strength.
5. Finally, it is possible to say that ANNs are more economical to determine the effects on the strength of joints of various factors (screw diameter, screw length, and the distance between the screws). This work can be extended by testing different distance between screws, different screw lengths and diameters, or by adding different factors such as the number of screws and the type of wood material.

REFERENCES CITED

Akdag, U., Komur, M., and Akcay, S. (2016). "Prediction of heat transfer on a flat plate subjected to a transversely pulsating jet using artificial neural networks," *Applied Thermal Engineering* 100, 412-420. DOI: 10.1016/j.applthermaleng.2016.01.147

Akincioglu, S., Mendi, F., Cicek, A., and Akincioglu, G. (2013). "Prediction of thrust forces and hole diameters using artificial neural networks in drilling of AISI D2 tool steel with cemented carbide tools," *Academic Platform Journal of Engineering and Science* 1(2), 11-20. DOI: 10.5505/apjes.2013.87597

ASTM D1037 (1998). "Wood-base fiber and particle panel strength testing," ASTM International, West Conshohocken, PA, USA.

Atar, M., and Ozciftci, A. (2008). "The effects of screw and back panels on the strenght of corner joints in case furniture," *Materials and Design* 29, 519-525. DOI: 10.1016/j.matdes.2007.01.015

Bardak, S., Tiryaki, S., Bardak, T., and Aydin, A. (2016a). "Predictive Performance of artificial neural network and multiple linear regression models in predicting adhesive bonding strength of wood," *Strength of Materials* 48(6), 811-824. DOI: 10.1007/s11223-017-9828-x

Bardak, S., Tiryaki, S., Nemli, G., and Aydin, A. (2016b). "Investigation and neural network prediction of wood bonding quality based on pressing conditions," *International Journal of Adhesion & Adhesives* 68, 115-123. DOI: 10.1016/j.ijadhadh.2016.02.010

Celik, U., and Basarır, C. (2017). "The prediction of precious metal prices via artificial neural network by using RapidMiner," *The Journal of Operations Research, Statistics, Econometrics and Management Information Systems* 5(1), 45-54. DOI: 10.17093/alphanumeric.290381

Cetin-Yerlikaya, N. (2013). “The effect of dowel and minifix on the bending moment in the cabinet-type furniture,” *Artvin Coruh University Journal of Forestry Faculty* 14(1), 36-49.

Chau, K. (2006). “A review on integration of artificial intelligence into water quality modelling,” *Marine Pollution Bulletin* 52(7), 726-733. DOI: 10.1016/j.marpolbul.2006.04.003

Chau, K. W. (2007). “A split-step particle swarm optimization algorithm in river stage forecasting,” *Journal of Hydrology* 346, 131-135. DOI: 10.1016/j.jhydrol.2007.09.004

Cranganu, C., Luchian, H., and Breaban, M. E. (2015). *Artificial Intelligent Approaches in Petroleum Geosciences*, Springer International Publishing, Cham, Switzerland. DOI: 10.1007/978-3-319-16531-8

Demirci, S., Efe, H., Kasal, A., Imirzi, H. O., and Ozen, E. (2011). “The Moment capacity of disassembled “l” type furniture corner joints produced with various connection elements,” *Kastamonu University Journal of Forestry Faculty* 11(2), 138-145.

Efe, H. (1998). “Kutu Konstrüksiyonlu Mobilya Köşe Birleştirmelerinde Rasyonel Kavela Tasarımı,” *Journal of Polytechnic* 1(1), 17-23 (In Turkish).

Efe, H., Diler, H., and Kasal, A. (2011). “The bending moment resistance of screw joints on furniture corner joints for case construction,” *Afyon Kocatepe University Journal of Science* 6(1), 97-110.

Efe, H., and Imirzi, H. O. (2008). “Moment capacity of corner joints for case furniture constructed with different joint techniques and board thickness,” *Journal of Polytechnic* 11(1), 65-75. DOI: 10.2339/2008.11.1.65-75

Efe, H., and Kasal, A. (2000). “Tension resistance of stable and demontable corner joints in case construction of furniture,” *The Journal of the Industrial Arts Education Faculty of Gazi University* 8, 61-74.

Garaga, A., and Latha, G. M. (2010). “Intelligent prediction of the stress-strain response of intact and jointed rocks,” *Computers and Geotechnics* 37(5), 629-637. DOI: 10.1016/j.compgeo.2010.04.001

Garcia, J. J., Garcia, F., Bermúdez, J., and Machado, L. (2017). “Prediction of pressure drop during evaporation of R407C in horizontal tubes using artificial neural networks,” *International Journal of Refrigeration* 85, 292-302. DOI: 10.1016/j.ijrefrig.2017.10.007

Geetha, A., and Nasira, G. M. (2014). “Artificial neural networks’ application in weather forecasting – using RapidMiner,” *International Journal of Computational Intelligence and Informatics* 4(3), 177-182.

Gholami, V., Chau, K. W., Fadaee, F., Torkaman, J., and Ghaffari, A. (2015). “Modeling of groundwater level fluctuations using dendrochronology in alluvial aquifers,” *Journal of Hydrology* 529, 1060-1069. DOI: 10.1016/j.jhydrol.2015.09.028

Haftkhani, A. R., Ebrahimi, G., Tajvidi, M., Layeghi, M., and Arabi, M. (2011). “Lateral resistance of joints made with various screws in commercial wood plastic composites,” *Materials & Design* 32(7), 4062-4068. DOI: 10.1016/j.matdes.2011.03.020

Heng, S., and Suetsugi, T. (2013). "Using artificial neural network to estimate sediment load in ungauged catchments of the tonle sap river basin, Cambodia," *Journal of Water Resource and Protection* 5(2), 111-123. DOI: 10.4236/jwarp.2013.52013

Hyndman, R. J., and Athanasopoulos, G. (2014). *Forecasting: Principles and Practice*,

Online Open Access Textbooks, Published by otext.com.
Hyndman, R. J., and Koehler, A. B. (2006). "Another look at measures of forecast accuracy," *International Journal of Forecasting* 22, 679-688. DOI: 10.1016/j.ijforecast.2006.03.001
Kasal, A. (2008). "Effect of the number screws and screw size on moment capacity of furniture corner joints in case construction," *Forest Products Journal* 58(6), 36-44.
Kasal, A., Sener, S., Belgin, C. M., and Efe, H. (2006). "Bending strength of screwed corner joints with different materials," *G.U. Journal of Science* 19(3), 155-161.
Kasal, A., Smardzewski, J., Kuşkun, T., and Erdil, Y. Z. (2016). "Numerical analyses of various sizes of mortise and tenon furniture joints," *BioResources* 11(3), 6836-6853. DOI: 10.15376/biores.11.3.6836-6853
Kendall, M. G. (1938). "A new measure of rank correlation," *Biometrika* 30, 81-93.
Kmet, S., Sincak, P., and Stehlik, P. (2011). "Artificial neural network for creep behaviour predictions of a parallel-lay aramid rope under varying stresses," *Strain* 47(s2), 121-128. DOI: 10.1111/j.1475-1305.2010.00747.x
Kumar, K., and Thakur, G. S. M. (2012). "Advanced applications of neural networks and artificial intelligence: A review," *I.J. Information Technology and Computer Science* 6, 57-68. DOI: 10.5815/ijitcs.2012.06.08
Londhe, S. N., and Deo, M. C. (2003). "Wave tranquility studies using neural networks," *Marine Structure* 16, 419-436. DOI: 10.1016/j.marstruc.2003.09.001
Maleki, S., Kazemi Najafi, S., Ebrahimi, G., and Ghofrani, M. (2017). "Withdrawal resistance of screws in structural composite lumber made of poplar (*Populus deltoides*)," *Construction and Building Materials* 142, 499-505. DOI: 10.1016/j.conbuildmat.2017.03.039
Ozsahin, S. (2012). "The use of an artificial neural network for modeling the moisture absorption and thickness swelling of oriented strand board," *BioResources* 7(1), 1053-1067.
Rajendra, M., Jena, P. C., and Raheman, H. (2009). "Prediction of optimized pretreatment process parameters for biodiesel production using ANN and GA," *Fuel* 88(5), 868-875. DOI: 10.1016/j.fuel.2008.12.008
Saffari, M., Yasrebi, J., Sarikhani, F., Gazni, R., Moazallahi, M., Fathi, H., and Emadi, M. (2009). "Evaluation of artificial neural network models for prediction of spatial variability of some soil chemical properties," *Research Journal of Biological Sciences* 4(7), 815-820.
Sefeedpari, P., Sahahin, R., Akram, A., Chau, K. W., and Pishgar-Komleh, S. H. (2016). "Prophesying egg production based on energy consumption using multi-layered adaptive neural fuzzy inference system approach," *Computers and Electronics in Agriculture* 131, 10-19. DOI: 10.1016/j.compag.2016.11.004 0168-1699
Smardzewski, J., İmirzi, H. O., Lange, J., and Podskarbi, M. (2015). "Assessment method of bench joints made of wood-based composites," *Composite Structures* 123, 123-131. DOI: 10.1016/j.compstruct.2014.12.039
Smardzewski, J., Lewandowski, W., and İmirzi, H. O. (2014). "Elasticity modulus of cabinet furniture joints," *Materials & Design* 60, 260-266. DOI: 10.1016/j.matdes.2014.03.066
Smardzewski, J., and Majewski, A. (2013). "Strength and durability of furniture drawers and doors," *Materials & Design* 51, 61-66. DOI: 10.1016/j.matdes.2013.03.101
Spearman, C. (1904). "The proof and measurement of association between two things," *The American Journal of Psychology* 15, 72-101.

Taormina, R., Chau, K. W., and Sivakumar, B. (2015). "Neural network river forecasting through baseflow separation and binary-coded swarm optimization," *Journal of Hydrology* 529, 1788-1797. DOI: 10.1016/j.jhydrol.2015.08.008

Tiryaki, S., Bardak, S., and Aydın, A. (2016). "Modeling of wood bonding strength based on soaking temperature and soaking time by means of artificial neural networks," *International Journal of Intelligent Systems and Applications in Engineering* 4(Special Issue), 153-157.

Tiryaki, S., Bardak, S., and Bardak, T. (2015). "Experimental investigation and prediction of bonding strength of Oriental beech (*Fagus orientalis* Lipsky) bonded with polyvinyl acetate adhesive, " *Journal of Adhesion Science and Technology* 29(23), 2521-2536. DOI: 10.1080/01694243.2015.1072989

Tiryaki, S., and Hamzacebi, C. (2014). "Predicting modulus of rupture (MOR) and modulus of elasticity (MOE) of heat treated woods by artificial neural networks," *Measurement* 49, 266-274. DOI: 10.1016/j.measurement.2013.12.004

Tracey, J. A., Zhu, J., and Crooks, K. R. (2011). "Modeling and inference of animal movement using artificial neural networks," *Environmental and Ecological Statistics* 18(3), 393-410. DOI: 10.1007/s10651-010-0138-8

Verma, T. N., Nashine, P., Singh, D. V., Singh, T. S., and Panwar, D. (2017). "ANN: Prediction of an experimental heat transfer analysis of concentric tube heat exchanger with corrugated inner tubes," *Applied Thermal Engineering* 120(25), 219-227. DOI: 10.1016/j.applthermaleng.2017.03.126

Wang, W. C., Xu, D. M., and Chau, K. W. (2014). "Assessment of river water quality based on theory of variable fuzzy sets and fuzzy binary comparison method," *Water Resour Manage* 28, 4183-4200. DOI: 10.1007/s11269-014-0738-4

Wang, Y., and Lee, S. H. (2014). "Design and analysis on interference fit in the hardwood dowel-glued joint by finite element method," *Procedia Engineering* 79, 166-172. DOI: 10.1016/j.proeng.2014.06.326

Yadav, A. K., Malik, H., and Chandel, S. S. (2015). "Application of rapid miner in ANN based prediction of solar radiation for assessment of solar energy resource potential of 76 sites in Northwestern India," *Renewable and Sustainable Energy Reviews* 52, 1093-1106. DOI: 10.1016/j.rser.2015.07.156

Yuste, A. J., and Dorado, M. P. (2006). "A neural network approach to simulate biodiesel production from waste olive oil," *Energy & Fuels* 20(1), 399-402. DOI: 10.1021/ef050226t

Zhang, J., and Eckelman, C. A. (1993). "Rational design of multi-dowel corner joints in case construction," *Forest Products Journal* 43(11/12), 52-58.

Zhang, S., and Chau, K. W. (2009). "Dimension reduction using semi-supervised locally linear embedding for plant leaf classification," in: *Proceedings of Emerging Intelligent Computing Technology and Applications* 2009 *Conference* Ulsan, South Korea pp. 948-955.

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