Predicting Effects of Selected Impregnation Processes on the Observed Bending Strength of Wood, with Use of Data Mining Models

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Wood materials have been used in many products such as furniture, stairs, windows, and doors for centuries. There are differences in methods used to adapt wood to ambient conditions. Impregnation is a widely used method of wood preservation. In terms of efficiency, it is critical to optimize the parameters for impregnation. Data mining techniques reduce most of the cost and operational challenges with accurate prediction in the wood industry. In this study, three data-mining algorithms were applied to predict bending strength in impregnated wood materials (*Pinus sylvestris* L. and *Millettia laurentii*). Models were created from real experimental data to examine the relationship between bending strength, diffusion time, vacuum duration, and wood type, based on decision trees (DT), random forest (RF), and Gaussian process (GP) algorithms. The highest bending strength was achieved with wenge (*Millettia laurentii*) wood in 10 bar vacuum and the diffusion condition during 25 min. The results showed that all algorithms are suitable for predicting bending strength. The goodness of fit for the testing phase was determined as 0.994, 0.986, and 0.989 in the DT, RF, and GP algorithms, respectively. Moreover, the importance of attributes was determined in the algorithms.

Keywords: Wood material; Bending strength; Mechanical properties; Data mining; Optimization

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INTRODUCTION

The chemical modification of wood has received much attention since the mid-twentieth century. Usually, chemical modification in solid wood is made for dimensional stability and biological resistance. Despite many studies in the literature, there have been only limited studies of industrial applications (Gérardin 2016). This is mainly due to the application difficulties of wood preservation processes such as acylation and the emergence of environmental, economic, and technical problems in the transition from laboratory to industry. Factors such as wood type, impregnation agent, impregnation time, temperature, vacuum, diffusion, solvent, concentration ratio, and retention ratio affect the mechanical properties of wood (Rowell 2009). Simsek *et al.* (2010) carried out mechanical and decay tests of beech wood (*Fagus orientalis* L.) and Scots pine wood (*Pinus sylvestris* L.) treated with environmentally friendly boron compounds. They reported that all the different concentrations of boron compounds applied decreased the bending strength compared with the control sample. In a similar study, Adanur *et al.* (2017) stated that different proportions of boron compounds decrease the bending resistance and increase the screw holding strength. In another study, Tan *et al.* (2017) examined static bending resistance and dynamic bending resistance properties of pine and beech wood using 1%, 3%, and 5% barite. The static bending strength values of pine and beech woods increased by 55% and 83% in 3% and 5% concentrations compared with control samples, respectively.

Technological developments necessitate interdisciplinary interaction. In the light of the available information, making new decisions and making predictions are important. Many complex real-world problems have been solved by data mining (Predic *et al.* 2018; Zhang *et al.* 2019). It is an automated analysis of data sets to expose relationships that are both understandable and useful (Hand and Mannila 2001; Wei and Watkins 2011). Data mining tasks can be classified as description or prediction. The purpose of the prediction is to find a model to estimate the values of future events (Rémy *et al.* 2018). Data mining techniques are often more powerful, flexible, and effective than statistical techniques for information discovery (Kantardzic 2011). Decision tree (DT), random forest (RF), and Gaussian process (GP) algorithms are widely used for predicting. These algorithms are easy to interpret and fast to calculate (Höppner *et al.* 2020). In data science, the DT is defined as a classification procedure. This classification algorithm recursively partitions a data set into smaller subdivisions based on a set of tests defined at each branch in the tree (Pu *et al.* 2018). RF is an ensemble method in machine learning that involves construction (growing) of multiple decision trees *via* bootstrap aggregation (Shaikhina *et al.* 2019). The RF algorithm is based on decision trees and combined with aggregation and bootstrap ideas. The RF algorithm maintains low bias on the training dataset by creating a collection of unpruned decision trees (Nadi and Moradi 2019). GP based on statistical learning theorem is a machine learning method. It is mainly used to calculate the covariance between the data points used in the model. It is suitable for high dimensional complex regression problems (Zhang *et al.* 2019).

Data analysis techniques provide useful information in wood science. It is important to understand how production components affect each other to solve problems in the wood industry. Very little research has been done on the prediction of the mechanical performance of wood materials. Tiryaki and Hamzacebi (2014) studied the bending strength of the heat-treated wood as predicted by artificial neural networks (ANNs), which successfully predicted bending resistance. Atoyebi *et al.* (2018) used ANNs to examine the physical and mechanical properties of particleboards and the impact of various factors on production. The study showed that ANNs have great potential in predicting the mechanical properties of particleboards.

In this paper, the RF, GP, and DT models were created to estimate the bending strength of impregnated wood. The relationships between wood type, vacuum time, and diffusion time were examined with these models.

EXPERIMENTAL

Material and Method

Material

Imported Scots pine and wenge logs were used. First, the logs were cut into battens. The cut slats were cut radially, and all samples were obtained from sapwood. Barite ($BaSO_4$) was obtained from Gülmer Mining (Bilecik, Turkey) in powder form. Scots pine is native and coniferous wenge is foreign and leafy tree species. The reason for choosing these tree species was to be able to compare the leafy and coniferous and native and foreign tree species.

Preparation of Impregnation Solution

The impregnation solution was prepared with 1% barite on a heated magnetic stirrer. The solution was prepared at 220 °C for 30 min and allowed to stand at room temperature (25 °C) for 24 h.

Impregnation Method

Impregnation was carried out as described in ASTM D 1413 (1976). Before the impregnation, all samples were coded and weighed with a 0.01 mm precision analytical balance. The samples were oven-dried at 103 ± 2 °C. Fully dry samples were impregnated with four different vacuum times (10, 20, 30, 40 min) and pressurization times (diffusion) (25, 35, 45, 55 min) in the impregnation boiler. Since vacuum and diffusion time are important variables that affect the impregnation of wood species, these two parameters were especially chosen. Another reason for choosing these parameters is to determine the effect of different vacuum and diffusion times on the bending strength. Impregnation conditions were carried out according to Taghiyari *et al.* (2013); 600 mm-Hg vacuum was applied as a pressure of 0.6 MPa. A total of 320 samples were prepared, including two tree species (2), different vacuum times (4), diffusion times (4), and 10 samples for each variation ($2 \times 4 \times 4 \times 5 = 160$).

Bending Strength

Wood test samples and bending tests were prepared according to TS 2470 (1976) and TS 2474 (1976), respectively. Five samples were prepared from each variation from two different tree species, four different vacuum times, four different diffusion times, for a total of 160 ($5 \times 2 \times 4 \times 4$) samples subjected to static bending resistance.

Data Collection

The experimental data used in this study were the measurements obtained by the bending tests of the wood material impregnated under different conditions. The data set consisted of 160 records. There were three attributes (wood type, vacuum time, and diffusion time) that feature in mechanical property prediction and one attribute serves as the output (bending strength). Table 1 contains a summary of the values of the numeric attributes from the training data set.

Table 1. Data Summary of the Values of the Numeric Attributes

Attribute name	Attribute type	Attribute description
Wood Type	Nominal	Wood type impregnated (Wenge, Scots pine)
Vacuum Time	Numeric	Vacuum time applied in impregnation process (10, 20, 30, 40 Min)
Diffusion Time	Numeric	Diffusion time applied in impregnation process (25, 35, 45, 55 Min)
Bending Strength	Numeric	Bending strength of impregnated wood (N/mm^2)

Models

Three algorithm models were selected to prediction bending strength of impregnated wood: decision trees (DT), random forest (RF), and Gaussian process (GP). These models were based on establishing the relationship between independent and dependent variables using training methods. In this study, 70% of all data were used for training and 30% for testing purposes. All models were developed with RapidMiner Studio Version 9.3 software (Boston, USA), which has been used in many studies (Phark *et al.* 2018; Cuesta *et al.* 2019). RapidMiner Studio consists of operators and each operator has a task. Operators are added end-to-end to prepare the process workflow. Several parameters have to be set when using algorithms as predictive modelling in this software. To find the best parameters, the optimize parameters (Grid) operator was used. Thus, the best parameters were determined for each model separately as shown in Fig. 1; the optimal parameters for all models are listed in Table 2.

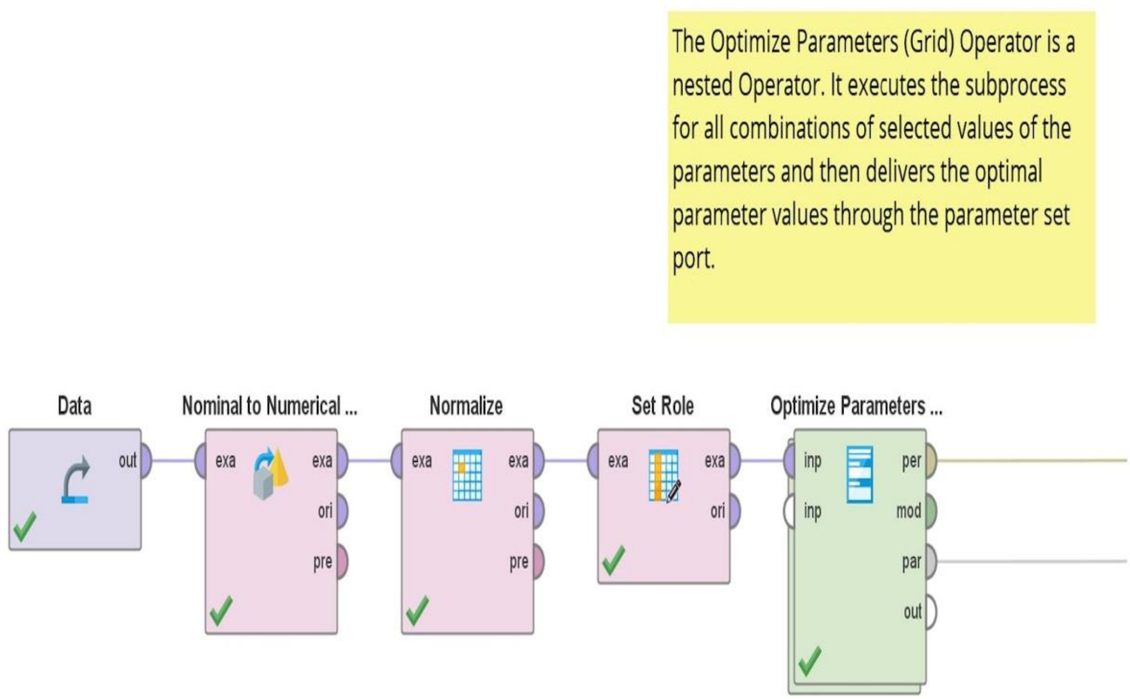

Fig. 1. The process workflow used to optimize the parameters of the models

Table 2. The Optimal Parameters for All Models

Decision Trees (DT)		**Random Forest (RF)**		**Gaussian Process (GS)**	
Criterion	Least square: An Attribute is selected for splitting, that minimizes the squared distance between the averages of values in the node with regards to the true value.	Criterion	Least square: An Attribute is selected for splitting, that minimizes the squared distance between the averages of values in the node with regards to the true value.	Kernel type	The type of the kernel function is selected through this parameter.
Maximal depth	60	Number of trees	70	Kernel length scale	3
		Maximal depth	100	Max basis vectors	80

After determining the optimal parameters, the process was created to compare the models. Figure 2 shows the process workflow used to compare models.

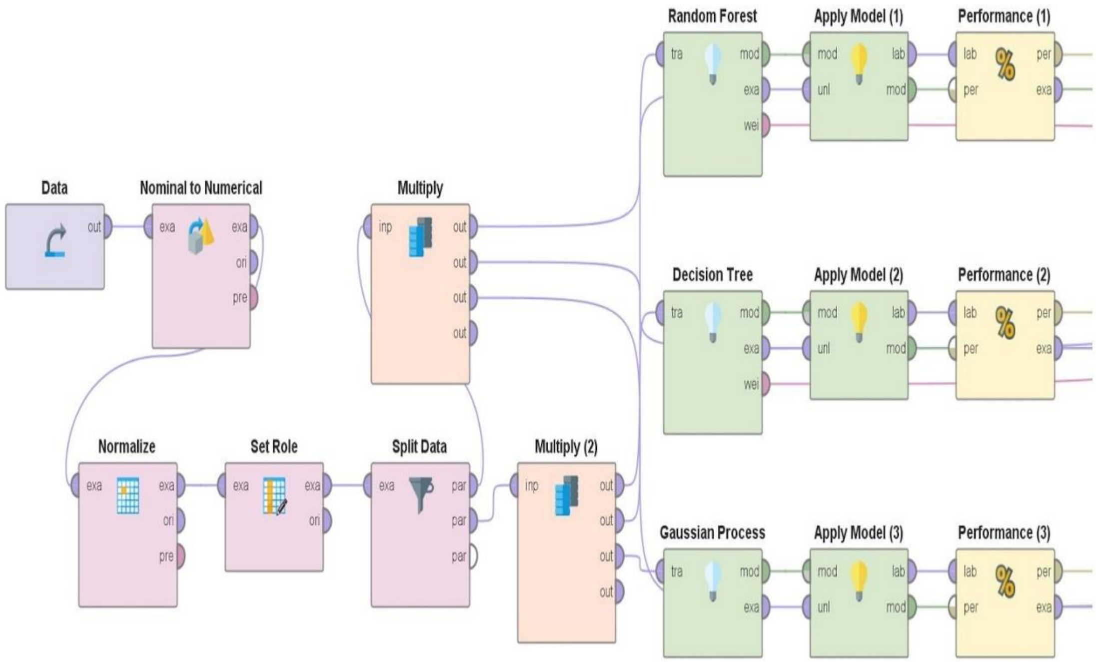

Fig. 2. The process workflow used to compare models

Simulations were created based on the models. The aim was to find the input values for the highest bending strength. Rapidminer software allows for preparing real-time simulations. Figure 3 shows the process workflow prepared for simulation.

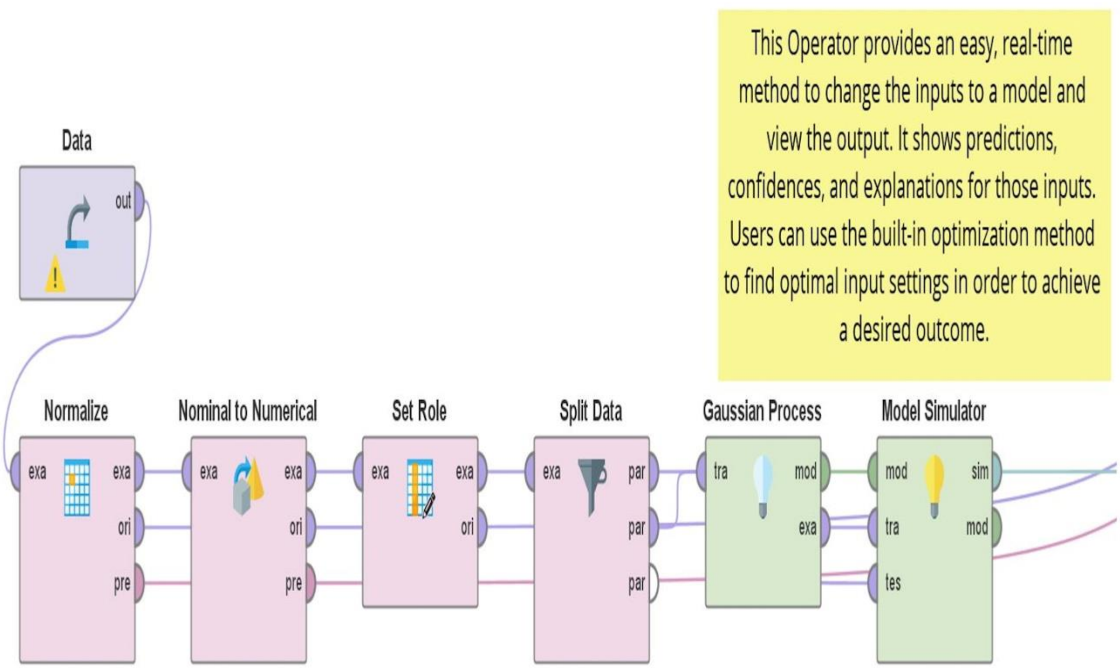

Fig. 3. The process workflow prepared for simulation

Finally, weights of attributes (wood type, vacuum time, and diffusion time) were determined with DT and RF algorithms. Thus, the most important feature for the prediction was found.

Model Evaluation

Goodness of fit (R^2), root mean square error (RMSE), and mean square error (MSE) were used to evaluate the estimation accuracy of each model, as follows,

$$R^2 = \left[\frac{\sum(Y_p - \overline{Y_p})(Y_o - \overline{Y_o})}{\sqrt{\sum(Y_p - \overline{Y_p})^2 (Y_o - \overline{Y_o})^2}}\right]^2 \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=0}^{n}\left(Y_o - Y_p\right)^2} \quad (2)$$

$$\text{MSE} = \text{RMSE}^2 \quad (3)$$

where Y_O and Y_P are the measured and predicted values, respectively, and the bar denotes the mean of the variable.

RESULTS AND DISCUSSION

Mechanical Properties

Wood type, vacuum time, and diffusion time affected the bending strength of impregnated wood material. Table 3 presents the bending strength depending on changes in the wood type, vacuum time, and diffusion time. Increasing vacuum and diffusion times caused decreases in bending strength of both Scots pine and wenge wood. Under the same conditions, the bending strength of wenge wood gave higher values than Scots pine.

Results of the Models

Three machine learning models were established using the experimental data. All models were trained and tested with the same data sets, and the predictive performance of models were compared. The estimated results of the three data mining models tested for wenge and Scots pine wood are given in Tables 4 and 5, respectively. For wenge wood, percentages of correct predictions were found as 99.55%, 99.37% and 99.38% for decision tree, random forests, and Gaussian process models, respectively. For Scots pine wood, percentages of correct predictions were found as 99.49%, 99.38%, and 99.46% for decision tree, random forests, and Gaussian process models, respectively.

Three different assessment criteria were used to evaluate all estimation models (DT, RF, GP). In the classification problem, these performance measures are widely used (Caballero *et al.* 2017; Shafaei *et al.* 2019). Various performance measures related to the DT, RF, and GS models are shown in Table 6.

MSE and RMSE are measures of error each. Therefore, low results are measures showing high performance in inverse proportion to performance (Wang and Xu 2004; Gultepe 2019).

Table 3. The Bending Strength Depending on Changes in the Wood Type, Vacuum Time, and Diffusion Time

				Bending Strength (N/mm^2)		
Wood Type	Vacuum Time (min)	Diffusion Time (min)	N	Mean	SD	HG
Scots pine	40	55	5	106.90	0.492	A
		45	5	107.48	0.444	A
		35	5	108.95	1.054	B
		25	5	110.80	0.847	C
	30	55	5	111.81	0.609	D
		45	5	112.60	0.724	D
		35	5	114.32	0.792	E
		25	5	115.67	0.577	F
	20	55	5	116.26	0.590	F
		45	5	117.46	0.473	G
		35	5	118.09	0.623	GH
		25	5	118.69	0.432	HI
	10	55	5	118.86	0.249	HI
		45	5	119.33	0.389	IJ
		35	5	119.89	0.463	JK
		25	5	120.65	0.406	K
Wenge	40	55	5	126.01	0.677	L
		45	5	126.59	0.568	LM
		35	5	126.98	0.633	MN
		25	5	127.64	0.547	N
	30	55	5	127.70	0.539	N
		45	5	128.70	0.644	O
		35	5	130.89	0.791	P
		25	5	131.80	0.875	Q
	20	55	5	132.76	0.594	R
		45	5	133.59	0.518	S
		35	5	134.73	0.607	T
		25	5	135.26	0.768	T
	10	55	5	135.52	0.465	T
		45	5	136.89	0.759	U
		35	5	138.71	0.803	V
		25	5	140.83	0.833	W

Notes: N: number of samples; 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 no statistical difference between the samples according to the Duncan's multiply range test at 95% confidence level

Table 4. The Estimated Wenge Results of the Three Data Mining Models for Testing Phase

Wood Type	Vacuum Time (Min)	Diffusion time (Min)	Experimental	DTP	DT Error (%)	RFP	RF Error (%)	GSP	GS Error (%)
Wenge	10	25	140.890	140.410	0.341	138.413	1.758	138.872	1.437
Wenge	10	25	142.030	140.410	1.141	138.413	2.547	138.872	2.249
Wenge	10	45	136.380	136.947	-0.416	136.571	-0.140	136.696	-0.231
Wenge	10	45	137.240	136.947	0.214	136.571	0.488	136.696	0.397
Wenge	10	55	135.140	135.663	-0.387	135.220	-0.059	134.536	0.445
Wenge	10	55	135.480	135.663	-0.135	135.220	0.192	134.536	0.696
Wenge	20	35	135.200	134.610	0.436	134.381	0.605	134.943	0.191
Wenge	20	45	132.940	133.748	-0.607	133.759	-0.616	133.969	-0.769
Wenge	20	55	132.690	132.653	0.028	132.896	-0.155	132.329	0.272
Wenge	20	55	133.130	132.653	0.358	132.896	0.176	132.329	0.604
Wenge	30	25	130.760	131.830	-0.818	131.209	-0.344	131.403	-0.488
Wenge	30	25	131.830	131.830	0.000	131.209	0.471	131.403	0.324
Wenge	30	25	132.770	131.830	0.708	131.209	1.176	131.403	1.037
Wenge	30	35	130.960	130.637	0.247	130.528	0.330	130.947	0.010
Wenge	30	35	131.580	130.637	0.717	130.528	0.800	130.947	0.484
Wenge	30	45	127.940	129.055	-0.872	129.310	-1.070	129.668	-1.339
Wenge	30	45	128.330	129.055	-0.565	129.310	-0.763	129.668	-1.037
Wenge	30	45	129.130	129.055	0.058	129.310	-0.139	129.668	-0.417
Wenge	30	55	127.170	127.870	-0.550	128.633	-1.151	127.964	-0.621
Wenge	30	55	127.230	127.870	-0.503	128.633	-1.103	127.964	-0.574
Wenge	30	55	128.340	127.870	0.366	128.633	-0.228	127.964	0.294
Wenge	40	25	127.110	127.553	-0.349	127.857	-0.588	126.749	0.283
Wenge	40	25	128.430	127.553	0.683	127.857	0.446	126.749	1.318
Wenge	40	35	127.180	126.933	0.195	127.377	-0.155	126.819	0.285
Wenge	40	45	126.130	126.360	-0.182	126.911	-0.619	126.119	0.009
Wenge	40	45	126.980	126.360	0.488	126.911	0.055	126.119	0.682
Wenge	40	45	127.120	126.360	0.598	126.911	0.165	126.119	0.792
Wenge	40	55	125.230	126.227	-0.796	126.889	-1.325	125.188	0.033
Wenge	40	55	126.140	126.227	-0.069	126.889	-0.594	125.188	0.754

Notes: DTP: Decision Trees Predicted; RFP: Random Forest Predicted; GSP: Gaussian Process Predicted; Error (%): Percentage Error Ratios

Table 5. The Estimated Scots Pine Results of the Three Data Mining Models for Testing Phase

Wood Type	Vacuum Time (Min)	Diffusion time (Min)	Experimental	DTP	DT Error (%)	RFP	RF Error (%)	GSP	GS Error (%)
Scots pine	10	35	119.400	120.157	-0.634	119.396	0.003	120.170	-0.641
Scots pine	10	35	119.600	120.157	-0.465	119.396	0.170	120.170	-0.475
Scots pine	10	55	118.940	118.737	0.171	118.442	0.418	118.179	0.641
Scots pine	10	55	119.130	118.737	0.330	118.442	0.577	118.179	0.801
Scots pine	20	25	118.000	118.800	-0.678	118.427	-0.362	118.660	-0.556
Scots pine	20	25	118.870	118.800	0.059	118.427	0.372	118.660	0.176
Scots pine	20	25	118.990	118.800	0.160	118.427	0.473	118.660	0.277
Scots pine	20	45	117.000	117.573	-0.489	117.653	-0.558	117.651	-0.553
Scots pine	20	55	115.600	116.613	-0.877	116.742	-0.988	116.397	-0.684
Scots pine	20	55	115.870	116.613	-0.642	116.742	-0.752	116.397	-0.452
Scots pine	30	25	116.370	115.493	0.754	114.591	1.529	115.360	0.875
Scots pine	30	35	113.900	114.025	-0.110	113.840	0.052	114.304	-0.354
Scots pine	30	35	114.550	114.025	0.458	113.840	0.620	114.304	0.216
Scots pine	30	35	115.080	114.025	0.917	113.840	1.077	114.304	0.681
Scots pine	30	45	111.830	112.795	-0.863	112.734	-0.808	112.960	-1.002
Scots pine	30	55	112.560	111.618	0.837	112.024	0.476	111.656	0.809
Scots pine	40	45	108.110	107.318	0.733	108.670	-0.518	107.559	0.513
Scots pine	40	55	106.850	106.908	-0.054	108.430	-1.479	106.806	0.041

Notes: DTP: Decision Trees Predicted; RFP: Random Forest Predicted; GSP: Gaussian Process Predicted; Error (%): Percentage Error Ratios

Table 6. Various Performance Measures Related to the DT, RF, GS Models

Model	Testing phase			Training phase		
	R^2	RMSE	MSE	R^2	RMSE	MSE
DT	0.994	0.680	0.462	0.997	0.573	0.323
RF	0.986	1.028	1.057	0.993	0.885	0.783
GP	0.989	0.926	0.857	0.996	0.653	0,426

After determining the performance of the models, the simulation process was performed separately. Figure 4 shows the simulation screen for the decision tree model. The term simulation differs from the term modeling. Simulation can be defined as the representation of a process. The simulation process is done to achieve three goals. First, users better understand complex models such as deep learning. Second, users check whether the model is behaving as expected. Third, users find the most appropriate input settings to achieve the desired result.

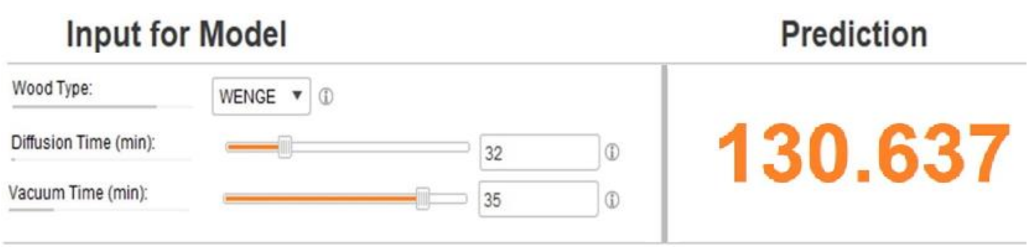

Fig. 4. Screenshot of simulation of decision tree model

Determination of Optimum Conditions

The values of the attributes for the highest bending strength were determined with all models. Table 7 shows the attributes and values for the highest bending strength.

All models determined similar input attributes (Diffusion time, Vacuum Time, and Wood Type) for the highest bending strength. Simulation results can be used to support decision-making in the impregnation process. The best parameters are determined according to the needs of the enterprises so that limited resources can be used more effectively.

Table 7. The Attributes and Values for the Highest Bending Strength

	DT	RF	GP
Highest Bending Strength (N/mm^2)	140.410	140.118	138.859
Diffusion time (min)	30	30	27
Vacuum Time (min)	14	14	11
Wood Type	Wenge	Wenge	Wenge

The weights of attributes were determined by decision trees and random forest algorithms. attributes and weight values, where each weight represents the feature importance for the given attribute (diffusion time, vacuum time, and wood type). Table 8 shows the weight of attributes for Decision Trees and Random Forest algorithms.

Table 8. The Weight of Attributes for Decision Trees and Random Forest Algorithms

Decision Tree		Random Forest	
Attribute	**Weight**	**Attribute**	**Weight**
Diffusion time (min)	0.912	Diffusion time (min)	0.593
Vacuum Time (min)	0.083	Vacuum Time (min)	0.376
Wood Type	0.005	Wood Type	0.030

Discussion

According to the bending strength tests performed in the study, the bending strength of wenge wood was 15% higher than that of Scots pine. In wenge and Scots pine woods, increasing the vacuum time from 10 min to 40 min resulted in a gradual decrease in bending strength values. Bending strength of Scots pine woods applied to vacuum for 40 min was 108.53 N/mm², and when the vacuum was reduced to 10 min, bending resistance increased by 10.2% to 119.68 N/mm². Under the same conditions, this increase in wenge wood was determined as 8.81%. The effect of diffusion time applied on bending strength showed the same effect in both tree species. Reducing the diffusion time from 55 min to 25 min resulted in a 2.6% increase in bending strength of the two wood species. In wenge wood species, the highest bending strength (140.83 N/mm²) was obtained in 10 min vacuum and 25 min diffusion conditions. The lowest bending resistance value was obtained under 40 min vacuum and 55 min diffusion conditions. The highest (120.65 N/mm²) and the lowest (106.90 N/mm²) bending strength values of Scots pine wood were obtained under the same conditions where the highest and lowest values obtained in the wenge wood. As a result, increasing diffusion and vacuum times decreases the bending strength values of the tree species used in the study, which was consistent with previous reports. Aydemir *et al.* (2016) impregnated Scots pine, ash and Iroko wood with boron compounds and reported that impregnated wood exhibited higher strength properties (MOR) than control samples.

According to the modelling performance results, the highest estimation accuracy was seen in DT (Table 6). Also, other models showed similar results to DT. All models are suitable for estimating the bending strength of impregnated wood material. In the literature, an R^2 value greater than 0.9 represents a very satisfactory model (Leachtenauer *et al.* 1997; Heng and Suetsugi 2013). The success of the models provides evidence of the benefits of data mining in the wood impregnation industry. The most successful model parameters are shown among the models considering that the MSE value approaches 0 (Gultepe 2019). When the MSE values are examined, it is seen that the model that gives the values closest to 0 is the decision tree. In addition, multiple regression model was created. In this way, the prediction performance of statistical analysis (multiple regression) and the data mining models (decision tree random forests and Gaussian process) were compared. The prediction performance of the multiple regression model (R^2 = 0.985, RMSE = 1.042, MSE = 1.086 for testing phase) was found to be somewhat lower than the decision tree model (R^2 = 0.994, RMSE = 0.680, MSE = 0.462 for testing phase), random forests model (R^2 = 0.986, RMSE = 1.028, MSE = 1.057 for testing phase) and Gaussian process model (R^2 = 0.989, RMSE = 0.926, MSE = 0.857 for testing phase).

According to the results obtained from the algorithms (Table 8), the most important factors are diffusion time, vacuum time, and wood species, respectively. Multi-attribute problems must be solved to identify the weights of attributes. Zavadskas *et al.* (2010) reported that data mining algorithms can be used for this purpose.

Future research should examine the performance of these data mining algorithms in the prediction of bending strength of impregnated wood material in more complex conditions. The anisotropic structure of wood offers sufficient options to create different conditions. Sapwood-heartwood ratio, early wood-late wood ratio, annual ring characteristics, density, and moisture content are some of them.

CONCLUSIONS

1. Experiments were performed by varying three impregnation parameters: the wood type, the diffusion time, and the vacuum time. The highest average bending strength obtained was 140.83 N/mm^2 at the 10 min vacuum time and 25 min diffusion time with wenge wood.
2. Bending strength of impregnated wood material was successfully estimated by data mining techniques. The use of data mining algorithms in the impregnation of wood can greatly increase productivity because prediction algorithms respond to the best inputs for each situation.
3. Three different prediction models (DT, RF, GP) were compared according to R^2, MSE, and RMSE performance measurements. The highest success in the estimations was observed in DT algorithm with 0.994 R^2 value for the testing phase. It was concluded that prediction algorithms can affect the optimization of the impregnation process positively.
4. The importance of the factors was defined as diffusion time, vacuum time, and wood type vacuum duration, respectively.

REFERENCES CITED

Adanur, H., Fidan, M. S., and Yaşar, Ş. Ş. (2017). "The technological properties of oriental beech (*Fagus orientalis* Lipsky) impregnated with boron compounds and natural materials," *BioResources* 12(1), 1647-1661. DOI: 10.15376/biores.12.1.1647-1661

ASTM-D 1413-99 (1976). "Standard test method of testing wood preservatives by laboratory soil block cultures, " ASTM International, West Conshohocken, USA.

Atoyebi, O. D., Awolusi, T. F., and Davies, I. E. (2018). "Artificial neural network evaluation of cement-bonded particle board produced from red iron wood (*Lophira alata*) sawdust and palm kernel shell residues," *Case Studies in Construction Materials* 9, e00185 (In press). DOI: 10.1016/j.cscm.2018.e00185

Aydemir, D., Civi, B., Alsan, M., Can, A., Sivrikaya, H., Gunduz, G., and Wang, A. (2016). "Mechanical, morphological and thermal properties of nano-boron nitride treated wood materials," *Maderas. Ciencia y tecnología* 18(1), 19-32. DOI: 10.4067/S0718-221X2016005000003

Caballero, D., Pérez-Palacios, T., Caro, A., Amigo, J. M., Dahl, A. B., ErsbØll, B. K., and Antequera, T. (2017). "Prediction of pork quality parameters by applying fractals and data mining on MRI," *Food Research International* 99, 739-747. DOI: 10.1016/j.foodres.2017.06.048

Cuesta, H. A., Coffman, D. L., Branas, C., and Murphy, H. M. (2019). "Using decision trees to understand the influence of individual-and neighborhood-level factors on urban diabetes and asthma," *Health & Place* 58, 102119. DOI: 10.1016/j.healthplace.2019.04.009

Gérardin, P. (2016). "New alternatives for wood preservation based on thermal and chemical modification of wood—A review," *Annals of Forest Science* 73(3), 559-570. DOI: 10.1007/s13595-015-0531-4

Gultepe, Y. (2019). "A comparative assessment on air pollution estimation by machine learning algorithms," *European Journal of Science and Technology* 16, 8-15. DOI: 10.31590/ejosat.530347

Hand, D. J. Mannıla, H., and Smyth, P. (2001). *Principles of Data Mining (Adaptive Computation and Machine Learning)*, MIT Press, Cambridge, MA, USA.

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

Höppner, S., Stripling, E., Baesens, B., and Verdonck, T. (2020). "Profit driven decision trees for churn prediction," *European Journal of Operational Research* 284(3), 920-933. DOI: 10.1016/j.ejor.2018.11.072

Kantardzic, M. (2011). *Data Mining: Concepts, Models, Methods, and Algorithms*, John Wiley & Sons, Hoboken, NJ, USA.

Leachtenauer, J. C., Malila, W., Irvine, J., Colburn, L., and Salvaggio, N. (1997). "General image-quality equation: GIQE," *Applied Optics* 36(32), 8322-8328. DOI: 10.1364/AO.36.008322

Nadi, A., and Moradi, H. (2019). "Increasing the views and reducing the depth in random forest," *Expert Systems with Applications* 138, 112801. DOI: 10.1016/j.eswa.2019.07.018

Phark, C., Kim, W., Yoon, Y. S., Shin, G., and Jung, S. (2018). "Prediction of issuance of emergency evacuation orders for chemical accidents using machine learning algorithm," *Journal of Loss Prevention in the Process Industries* 56, 162-169. DOI: 10.1016/j.jlp.2018.08.021

Predic, B., Ilic, M., Spalevic, P., Trajkovic, S., Jovic, S., and Stanic, A. (2018). "Data mining based tool for early prediction of possible fruit pathogen infection," *Computers and Electronics in Agriculture* 154, 314-319. DOI: 10.1016/j.compag.2018.09.023

Pu, Y., Apel, D. B., and Lingga, B. (2018). "Rockburst prediction in kimberlite using decision tree with incomplete data," *Journal of Sustainable Mining* 17(3), 158-165. DOI: 10.1016/j.jsm.2018.07.004

Rémy, N. M., Martial, T. T., and Clémentin, T. D. (2018). "The prediction of good physicians for prospective diagnosis using data mining," *Informatics in Medicine Unlocked* 12, 120-127. DOI: 10.1016/j.imu.2018.07.005

Rowell, R. M. (ed.) (2009). *Handbook of Wood Chemistry and Wood Composites*, Taylor & Francis, London.

Shafaei, S. M., Loghavi, M., Kamgar, S. (2019). "Feasibility of implementation of intelligent simulation configurations based on data mining methodologies for prediction of tractor wheel slip," *Information Processing in Agriculture* 6(2), 183-199. DOI: 10.1016/j.inpa.2018.10.004

Shaikhina, T., Lowe, D., Daga, S., Briggs, D., Higgins, R., and Khovanova, N. (2019). "Decision tree and random forest models for outcome prediction in antibody incompatible kidney transplantation," *Biomedical Signal Processing and Control* 52,

456-462. DOI: 10.1016/j.bspc.2017.01.012
Simsek, H., Baysal, E., and Peker, H. (2010). "Some mechanical properties and decay resistance of wood impregnated with environmentally-friendly borates," *Construction and Building Materials* 24(11), 2279-2284. DOI: 10.1016/j.conbuildmat.2010.04.028
Taghiyari, H. R., Enayati, A., and Gholamiyan, H. (2013). "Effects of nano-silver impregnation on brittleness, physical and mechanical properties of heat-treated hardwoods," *Wood Science and Technology* 47(3), 467-480. DOI: 10.1007/s00226-012-0506-7
Tan, H., Ulusoy, H., and Peker, H. (2017). "The effects of impregnation with barite (BaSO 4) on the physical and mechanical properties of wood materials," *Journal of Bartin Faculty of Forestry* 19(2), 160-165. DOI: 10.24011/barofd.346900
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
TS 2470 (1976). "Wood-sampling methods and general requirements for physical and mechanical tests," Turkish Standards Institution, Ankara, Turkey.
TS 2474 (1976). "Wood - Determination of ultimate strength in static bending," Turkish Standards Institution, Ankara, Turkey.
Wang, W., and Xu, Z. (2004). "A heuristic training for support vector regression," *Neurocomputing* 61, 259-275. DOI: 10.1016/j.neucom.2003.11.012
Wei, W., and Watkins Jr, D. W. (2011). "Data mining methods for hydroclimatic forecasting," *Advances in Water Resources* 34(11), 1390-1400. DOI: 10.1016/j.advwatres.2011.08.001
Zavadskas, E. K., Turskis, Z., Ustinovichius, L., and Shevchenko, G. (2010). "Attributes weights determining peculiarities in multiple attribute decision making methods," *Engineering Economics* 66(1), 32-43. DOI:
Zhang, M., Li, M., Shen, Y., Ren, Q., and Zhang, J. (2019). "Multiple mechanical properties prediction of hydraulic concrete in the form of combined damming by experimental data mining," *Construction and Building Materials* 207, 661-671. DOI: 10.1016/j.conbuildmat.2019.02.169

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