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ORIGINAL

Performance evaluation of multiple adaptive regression splines, teaching–learning based optimization and conventional regression techniques in predicting mechanical properties of impregnated wood

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Abstract

Understanding the mechanical behaviour of impregnated wood is crucial in making a preliminary decision on the usability of such woods for structural purposes. In this paper, by considering concentration (1, 3 and 5%), pressure (1, 1.5 and 2 atm.), and time (30, 60, 90 and 120 min), an experimental study was performed, and the mechanical behaviour of impregnated wood was determined as a result of the experimental process. Multiple adaptive regression splines (MARS), teaching–learning based optimization (TLBO) algorithms and conventional regression analysis (CRA) were applied to different regression functions by using experimentally obtained data. The functions were checked against each other to detect the best equation for each parameter and to assess performances of MARS, TLBO and CRA methods in the prediction of mechanical properties. The experimental results showed that higher values of mechanical properties were obtained when lower concentration, pressure and time were chosen. Overall, all the functions successfully predicted the mechanical properties. However, the MARS and TLBO provided better accuracy in predicting the mechanical properties. The modeling results indicated that the MARS and TLBO are promising new methods in predicting the mechanical properties of impregnated wood. With the use of these methods, the mechanical behavior of impregnated wood could be determined with high levels of accuracy. Thus, the proposed methods may facilitate a preliminary decision concerning the usability of such woods for areas where the mechanical properties are important. Finally, the employment of MARS and TLBO algorithms by practitioners in the wood industry is encouraged and recommended for future studies.

1 Introduction

Solid wood is a natural engineering material with superior mechanical, processing and aesthetic properties. These characteristics allow wood to be used as a substitute for many materials such as iron, plastic, and concrete etc. (Hashemi et al. 2010). However, as wood is subjected to biological organisms, water, light and fire, its useful life can be severely reduced (Yıldız et al. 2004). All these problems can be partially prevented by impregnating the wood with a preservative (Tomak et al. 2011). Therefore, wood products are impregnated with various preservatives prior to usage and thus their service life increases (Behzad et al. 2012).

The preservative treatment improves most of its features making the wood dimensionally more stable (Shanu et al. 2015). However, wood strength or mechanical properties undergo major changes when subjected to preservative treatment (Winandy 1995). It was reported that strength properties are the main criteria in selecting wood material for a particular task (Yıldız et al. 2004), and they are important for

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designing wood constructions. Hence, when treated wood is used in constructions, it is crucial to be aware of the alterations that its mechanical properties can undergo as a result of this treatment (Villasante et al. 2013).

The change in the mechanical behavior of wood treated with preservatives under different conditions has been partially studied so far. From the conducted studies, it is understood that comprehensive experiments need to be conducted to detect the impacts of treatment variables on the wood mechanical behavior. However, such a laborious process is both time-consuming and costly. Hence, modeling methods capable of predicting complex relationships between process variables and the mechanical properties of wood may be useful. In this way, the desired values of the mechanical properties can be predicted within a short period of time with a high accuracy rate; finally, it is possible to reduce the time and cost for experimental activities. In this regard, the present study deals with the development of prediction models for compression strength parallel to grain (CSPG), modulus of rupture (MOR) and modulus of elasticity (MOE) based on a laboratory database by multiple adaptive regression splines (MARS), teaching–learning based optimization (TLBO) and conventional regression analysis (CRA) methods.

MARS, an innovative and promising modeling tool, has been used as a flexible and fast method for making predictions (Friedman 1991). The main advantages of MARS lie in its capacity to capture the intrinsic complicated relationship in high-dimensional data patterns, produce simple and easier-to-interpret models and predict the contributions of the input variables (Zhang and Goh 2016). Recently, the MARS technique has been applied to many different fields of science and engineering, except for wood science, with successful results. For instance, Samui (2013) predicted elastic modulus of jointed rock mass by MARS. Cheng and Cao (2014) used this method to predict shear strength in reinforced-concrete deep beams. MARS has also been used in drought forecasting (Deo et al. 2017). The studies indicated that MARS has a great potential to solve problems in different fields of science and engineering.

Another novel and robust optimization algorithm called TLBO and CRA can be used to find the optimum coefficients for different regression functions. Although the TLBO is a new algorithm, it has been tested on a large number of problems in a variety of fields, including clustering (Amiri 2012), scheduling (Roy 2013), planing (Xia et al. 2014), prediction (Uzlu et al. 2014; Bayram et al. 2015), designing (Rao and More 2015), classification (Chen et al. 2015) and various engineering optimization problems (Pawar and Rao 2013; Lin et al. 2015). These applications proved the effectiveness and efficiency of the TLBO algorithm.

A comprehensive literature survey revealed that the effects of various process variables on the mechanical properties of wood impregnated under different conditions have been partially investigated experimentally. However, it was seen that a model for modeling a change in the mechanical behavior of impregnated wood has not yet been established in the literature. Besides, to the authors' knowledge, there are no studies that compare MARS, TLBO and CRA methods for modeling any wood properties in wood science. Thus, the main purposes of the present study were (a) to investigate how preservative treatment affects wood mechanical properties; (b) to develop equations by MARS, TLBO and CRA models for the first time as predictive tools for the prediction of MOR, MOE and CSPG of wood impregnated under different conditions and thus to obtain satisfactory results within quite a short period of time with low error rates; (c) to make a comparison between the developed MARS, TLBO and CRA; and (d) to make a decision on which method is better to employ to predict the investigated wood properties.

2 Methodology

2.1 Multivariate adaptive regression splines (MARS)

MARS, a rapid and flexible nonparametric method, was first presented by Friedman (1991). This method does not make a prior assumption regarding functional relationships between dependent and independent variables (Zhang and Goh 2016). Instead, it uses a divide and conquer strategy to detect the relationship among the variables. This strategy includes the division of the training data set into a number of piecewise linear segments called splines. The end points of splines are knots and the piecewise curves between two knots are known as basis functions (Suman et al. 2016), making MARS advantageous and flexible over other statistical methods for problems with a greater number of variables (Das and Suman 2015).

The construction of a MARS model involves two stages: a forward process followed by a backward process. The forward process selects iteratively the best pairs of basis functions that improve the model. This excessive forward stepwise selection process of basis functions may generate a complex and overfitted model that has a poor predictive ability for new data. To improve the predictive ability of the model, the backward process eliminates the ineffective basis functions from the model (Samui 2013; Khuntia et al. 2015).

MARS is built on basis functions, defined by the following formulations:

$$|x-t|_{+} = \max(0, x-t) = \begin{cases} x-t & f\ x>t \\ 0 & otherwise \end{cases} \tag{1}$$

$$|t-x|_{+} = \max(0, t-x) = \begin{cases} t-x & if\ x<t \\ 0 & otherwise \end{cases} \tag{2}$$

where t represents the "knots." The formulations serve as the basis function that predicts the function Y (Dey and Das 2016). The general MARS model equation can be defined as follows:

$$y = \beta_0 + \sum_{m=1}^{M} \beta_m \times bf_m(x) \quad (3)$$

where y is the output variable, M is the number of basis functions included in the model, β_0 is the constant term, $bf_m(x)$ is the mth basis function that may be a single spline function or an interaction of two or more spline functions, β_m is the coefficient of the mth basis function (Khuntia et al. 2015).

2.2 Teaching–learning based optimization (TLBO) algorithm

The TLBO is a new meta-heuristic optimization algorithm based on the natural phenomenon of teaching and learning. This algorithm has been first developed by Rao et al. (2011). It is capable of presenting global solutions for nonlinear functions with a high level of consistency. The TLBO algorithm is based on the effect of the influence of a teacher on the outcome of learners in a class. Hence, the quality of a teacher affects directly the outcome of the learners (Rao et al. 2011).

The TLBO has some advantages over other population-based techniques, including genetic algorithm, artificial bee colony, particle swarm optimization and ant colony optimization. One of the most important advantages of the TLBO is that it does not require any parameters setting for the working of the algorithm, making the implementation of TLBO simpler (Rao et al. 2012).

Two common control parameters of the TLBO are the number of students (population size) and stopping criteria (maximum number of iteration). The population consists of an even number of students. The students consist of a series of design variables (X*i*). The acquisition of an initial population can be expressed as follows (Uzlu et al. 2014):

```
for i=1:Pn
    for    j=1:ng
        randomly select any X between Xmin and Xmax
        student(i,j)=X
    end for
end for
```

where P_n is population size, ng is the number of group if the design variables are categorized, X_{min} and X_{max} are the minimum and maximum values of the design variables of the regression functions.

In TLBO algorithm, a new population is obtained as a result of two basic stages known as "teacher phase" and "learning phase" (Dede 2013). In the teacher phase, the student, with minimum objective function f in the entire population, is found and mimicked as a teacher. Other students in the current population are modified as the neighborhood of the teacher (Uzlu et al. 2014). This process is conducted by the following equations:

$$student_i = \left[X_{i,1} \ X_{i,2} \ \cdots \ X_{i,D_n} \right], \quad i = 1, 2, \ldots, P_n, \quad (4)$$

$$mean = \left[mean(X_1) \ mean(X_2) \ \cdots \ mean(X_{DN}) \right], \quad (5)$$

$$student_{new\_t} = student_i + r * (teacher - TF * mean) \quad (6)$$

where DN is the number of design variables, Pn is the population size, r is a random number varying [0,1] and TF is a teaching factor (1 or 2). In this study, X_i is the unknown coefficient of a regression function:

$$TF = round(1 + rand * (2 - 1)) \quad (7)$$

The size of r must be equal to the size of the student for the scalar multiplication given in Eq (7). If the objective function of the modified student is less than the objective function of the current student, then the modified student is replaced with the current student; otherwise, it is preserved. The teaching phase is carried out in the hope that the level of students will be updated to the level of teachers (Togan 2013; Dede 2013; Uzlu et al. 2014).

In the learning phase, the modified students increase their knowledge by interacting with each other based on the teaching–learning procedure (Uzlu et al. 2014). This interaction is implemented as follows:

```
for i=1:Pn
randomly select studentj, i ≠ j
if f(studenti)< f(studentj)
difference = studenti-studentj
else
difference= studentj-studenti
end if
studentnew_i=studenti+r.*difference
    if f(studentnew_i)<f(studenti)
    studenti=studentnew_i
    end if
end for
```

If its objective function does not improve, then the new student obtained in the student and teaching phases is not taken into account. The learning and teaching phases are continued until the termination criterion is reached (Uzlu et al. 2014). At the end of the last iteration, the student whose objective function is minimum is the best solution (Dede 2013).

3 Model development applications

In this stage, the values of mechanical properties, which were obtained from the experimental study carried out under different conditions, were used as data for different modeling tools. The equations for three output parameters were created by using 36 experimental data, and the best equations were determined based on minimum error and maximum coefficient of determination, for each output parameter. Each model was trained with 27 data (75% of all data) and was subsequently tested with nine experimental data (25% of all data) to measure the model performances.

Following the data splitting process, firstly the MARS method was employed to obtain the equations that give the closest values to the actual values of the MOR, MOE and CSPG.

Then, four different regression functions (Eqs. 8–11) were considered for the TLBO and CRA techniques. These functions are linear function, power function, exponential function and quadratic function. The TLBO algorithm and the CRA technique were used to optimize unknown coefficients (w_i) of independent variables (x_i). Linear, exponential, quadratic, and power functions can be formulated as follows:

$$y_{linear} = w_0 + w_1x_1 + w_2x_2 + w_3x_3 + \cdots + w_nx_n \tag{8}$$

$$y_{power} = w_0 x_1^{w_1} x_2^{w_2} x_3^{w_3} x_4^{w_4} \cdots x_n^{b_n} \tag{9}$$

$$y_{exponential} = w_0 + \exp(w_1 + w_2x_1 + w_3x_2 + w_4x_3 + w_5x_4 + \cdots + w_{n+1}x_n) \tag{10}$$

$$y_{quadratic} = w_0 + w_1x_1 + w_2x_2 + w_3x_3 + w_4x_1x_2 + w_5x_1x_3 + w_6x_2x_3 + w_7x_1^2 + w_8x_2^2 + w_9x_3^2 \tag{11}$$

Because the values of the model variables are in different ranges, the optimization of the coefficients may become difficult. In other words, some values may be too big and some too small. Thus, a normalization operation for the data is generally needed (Uzlu et al. 2014). For this purpose, each group of inputs and outputs is normalized into range [0.1,0.9] in the TLBO algorithm. The normalization operation is performed with Eq. (12):

$$\text{Normalised value} = \left[\frac{\text{raw value} - \text{minimum value}}{\text{maximum value} - \text{minimum value}}\right] \times (0.9 - 0.1) + 0.1. \tag{12}$$

In the prediction of the MOR, MOE and CSPG, the purpose is to find the fittest model to the actual or experimental values. In this regard, the mean absolute percentage error (MAPE), the root means square error (RMSE) and the coefficient of determination (R^2) statistical parameters were adopted as essential tools in evaluating the fitting accuracy and predictive ability of the MARS, TLBO and CRA. The highest values of the R^2, the lowest values of the RMSE and MAPE mean better performance of the developed models (Uluer et al. 2009). The MAPE, RMSE and R^2 are calculated as follows:

$$\text{MAPE} = \frac{1}{N}\left(\sum_{i=1}^{N}\left[\left|\frac{t_i - td_i}{t_i}\right|\right]\right) \times 100 \tag{13}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(t_i - td_i)^2}{\sum_{i=1}^{N}(t_i - \bar{t})^2} \tag{14}$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(t_i - td_i\right)^2} \tag{15}$$

where t_i is the actual value, $\bar{t}$ is the average of predicted values, td_i is the predicted value, and N is the total number of samples.

Setting the best parameters is one of the most important implementation steps of the TLBO algorithm because a change in any algorithm parameter affects significantly the performance of the algorithm (Uzlu et al. 2014). In this study, the parameters of the TLBO algorithm were adjusted to the same values for linear, power, exponantial and quadratic models: the number of maximum iteration = 50,000 and the size of population = 50. Besides, unknown coefficients of regression equations were optimized in the range of [−5, 5]. After setting the parameters, thirty independent runs were performed by TLBO algorithm for each regression equation.

4 Experimental

4.1 Preparation of wood samples

European larch (*Larix decidua*) was used as wood material in carrying out the experiments. The samples were selected as defect free from normally grown woods from Artvin city of Turkey. The experimental samples were obtained from the sapwood part of the trunk of a Larix tree. Air-dried samples of Larix were prepared for impregnation treatment with dimensions of 20 (radial) × 20 (tangential) × 360 (longitudinal) mm^3 for MOR and MOE tests, 20 (radial) × 20 (tangential) × 30 (longitudinal) mm^3 for CSPG tests.

4.2 Impregnation chemical and method

In the present study, boric acid was used to impregnate the wood samples. It is a well-known preservative chemical for the wood preservation industry. This agent is recognized as a cheap, easily applicable, biologically active, flame retardant and environmentally safe preservative (Baysal and Yalinkilic 2005).

The wood samples were treated with aqueous solution of boric acid according to ASTM D 1413 (1976) standard test method. Samples were exposed to varying pressures (1, 1.5 and 2 atm.) for varying durations (30, 60, 90 and 120 min) at concentrations of 1, 3 and 5%. After the impregnation process, the test specimens were conditioned at 20 ± 2 °C and 65 ± 3% relative humidity in a conditioning room until they reached constant mass. The average data of the samples of each condition was used in statistical analysis.

4.3 Mechanical properties

The CSPG tests were performed according to TS 2595 (1977) standard. Prior to the tests, the wood samples were conditioned at 20 °C and 65% relative humidity for 6 weeks. Five replicates were made for each experimental variation in performing the MOR, MOE and CSPG tests. The MOR and MOE of the samples were determined according to TS 2474 (1976). The MOR, MOE and CSPG tests were conducted using a universal testing machine.

5 Results and discussion

5.1 Evaluation of experimental results

Table 1 shows the experimental values of the mechanical properties of the wood samples subjected to preservative treatment under different conditions.

An analysis of variance (ANOVA) was applied to all the data measured. The results of ANOVA showed that the experimental variables (concentration, pressure and time) have an important impact on the mechanical properties of wood with a significance level of 1%. In the following, significant differences between the groups were detected individually for mechanical properties based on concentration, pressure and time by Duncan's multiple mean comparison test. The results of the Duncan test indicated that the mean values of the mechanical properties depending on the concentration and pressure consist of three different groups, while the time consists of four different groups. The results of Duncan's mean comparison test are shown in Fig. 1 by letters. In the comparison graphs, the MOR values were divided by 1000 for ease of drawing.

It is necessary to emphasize that the combined effects of the concentration, pressure and time parameters reduced considerably the mechanical properties (Table 1), while individual effects of these parameters (Fig. 1) on the mechanical properties were lower than their combined effect.

Moreover, the results of ANOVA and Duncan's mean comparison test revealed that there are significant differences between the strength values of wood in terms of different levels of the experimental variables. In terms of the concentration results, the mean of strength values in low concentration was higher compared to the values obtained in intermediate and high concentration. In other words, an increase in the concentration rate generally exhibited a negative effect on strength values of the samples. With respect to the impregnation pressure, it is possible to see in Fig. 1 that an increase in the level of the pressure applied in the impregnation process reduced the strength values of the samples. Similar to the effect of concentration and pressure, an increase in the duration of preservative treatment led to a decrease in the strength values of the samples. In brief, the results of statistical analyses indicated that concentration, pressure and duration differences in the impregnation process are important factors affecting the mechanical properties of Larix wood.

In the literature, several researchers studied the influence of experimental variables such as concentration, pressure and time on mechanical properties. Toker et al. (2009) reported that the MOR and MOE of wood samples impregneted at high concentrations were lower than that of the samples impregnated at low concentrations. Ozciftci et al. (2011) reported that there were no statistically significant differences in the MOR and MOE of wood subjected to different impregnation durations. Değirmentepe et al. (2015) noted that the MOR, MOE and CSPG of treated beech samples reduced with increasing the concentration of impregnation agent. Similarly, Simsek and Baysal (2015) investigated the MOE of borate-treated beech. The results of their study showed that, generally, higher levels of concentration resulted in lower MOE. In another study, Tan et al. (2017) investigated the effects of impregnation with barite ($BaSO_4$) on the physical and mechanical properties of Scotch pine (*Pinus sylvestris* L.) and Oriental beech (*Fagus orientalis* L.). The results showed that the mechanical properties increased generally with increasing concentration of barite.

Table 1 Mean values of the mechanical properties of wood samples

Concentration (%)	Pressure (atm.)	Time (min)	MOR (N/mm^2)		MOE (N/mm^2)		CSPG (N/mm^2)	
			Mean	SD	Mean	SD	Mean	SD
1	**1**	**30**	**80.72**	**1.883**	**9828**	**191.494**	**45.33**	**0.724**
1	1	60	78.12	3.421	9826	184.472	44.62	0.843
1	1	90	76.54	2.736	9544	350.899	43.46	1.443
1	1	120	73.08	4.945	9126	161.338	41.61	0.608
1	1.5	30	77.92	1.994	9356	402.157	44.52	1.049
1	**1.5**	**60**	**76.02**	**3.821**	**8954**	**161.028**	**43.20**	**1.135**
1	1.5	90	70.38	4.091	8844	145.362	40.89	0.469
1	1.5	120	66.94	3.798	8662	167.839	40.08	0.754
1	2	30	69.60	2.763	8884	192.710	42.66	0.662
1	2	60	68.22	4.326	8616	191.128	41.78	0.988
1	**2**	**90**	**65.14**	**1.246**	**8306**	**82.946**	**40.15**	**0.819**
1	2	120	64.28	1.899	8260	199.750	39.32	0.574
3	1	30	68.72	2.544	8772	121.532	40.28	0.487
3	**1**	**60**	**65.32**	**4.125**	**8676**	**178.410**	**39.25**	**1.012**
3	1	90	56.84	1.808	8442	214.639	38.79	0.815
3	1	120	57.16	1.464	8374	185.957	37.89	0.633
3	1.5	30	58.96	2.850	8444	178.690	38.25	0.629
3	1.5	60	58.22	3.549	8146	137.949	38.06	0.589
3	**1.5**	**90**	**55.72**	**4.371**	**7872**	**105.451**	**36.93**	**0.845**
3	1.5	120	51.46	1.573	7698	136.821	36.63	0.758
3	2	30	55.52	1.616	7714	199.198	36.86	0.710
3	2	60	51.72	2.628	7408	108.949	35.82	0.680
3	2	90	49.46	1.585	7232	82.280	35.36	0.932
3	**2**	**120**	**47.90**	**2.618**	**6928**	**196.774**	**34.99**	**0.874**
5	1	30	48.10	3.499	7334	62.690	35.91	0.439
5	1	60	46.72	0.653	7236	92.087	34.45	0.672
5	**1**	**90**	**46.34**	**1.201**	**6904**	**101.143**	**33.71**	**0.587**
5	1	120	46.34	1.078	6686	110.815	33.32	0.439
5	1.5	30	47.62	2.738	6864	249.860	33.50	0.424
5	1.5	60	47.02	3.548	6368	373.189	32.80	0.561
5	1.5	90	43.74	1.389	5972	192.276	32.49	0.518
5	**1.5**	**120**	**43.46**	**1.928**	**5640**	**184.255**	**32.23**	**0.834**
5	**2**	**30**	**46.44**	**2.623**	**5736**	**184.472**	**31.73**	**0.894**
5	2	60	44.16	2.296	5426	150.930	30.26	0.316
5	2	90	41.72	1.569	5108	87.006	29.57	0.701
5	2	120	38.98	2.318	4978	121.120	27.84	2.228

Bold values: testing data, the other values: training data

5.2 Evaluation of modeling results

5.2.1 MARS modeling results

Table 2 presents basis functions of the MARS models.

As seen in Table 2, MARS models to predict MOR, MOE and CSPG involve a total of 7, 10 and 8 basis functions, respectively. The MARS equations of MOR, MOE and CSPG can be generated as a function of concentration (%), pressure (atm.) and time (min). The MOR, MOE and CSPG values can easily be predicted by Eqs. 16–18:

$$y_{MOR} = 82.0062 - 8.16405\mathrm{BF1} - 16.5678\mathrm{BF2} - 0.100029\mathrm{BF3} + 0.0253479\mathrm{BF4} + 3.0136\mathrm{BF6} + 2.97692\mathrm{BF9} \tag{16}$$

$$y_{MOE} = 10229.3 - 709.799\mathrm{BF1} - 1456.3\mathrm{BF2} - 6.61649\mathrm{BF3} - 398.516\mathrm{BF6} - 2.59654\mathrm{BF8} + 3.69407\mathrm{BF12} + 5.04349\mathrm{BF14} \tag{17}$$

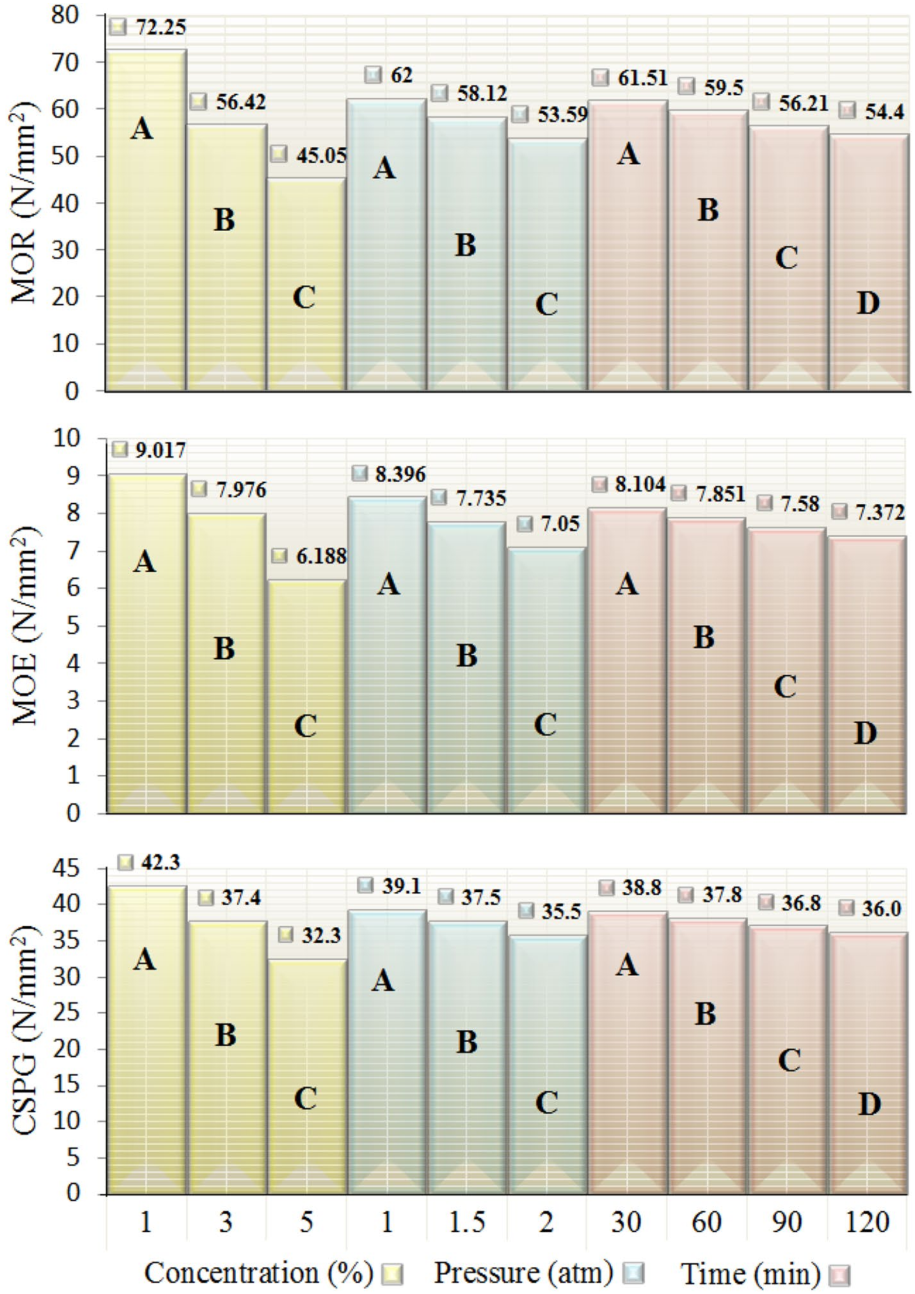

Fig. 1 Results of Duncan's mean comparison test. (The letters A, B, C, D define homogeneity groups)

$$y_{CSPG} = 46.2359 - 2.98568\text{BF1} - 0.0512078\text{BF3} - 3.53293\text{BF4} + 0.014079\text{BF5} - 0.0173743\text{BF6} + 0.029051\text{BF8} - 0.0143467\text{BF10} + 0.567494\text{BF16} \tag{18}$$

One major advantage of the MARS algorithm is that the relative importance of each input variable can also be detected on a scale of 0–100. This allows us to detect the contributions of different inputs to model outputs (Sharda et al. 2006). In this study, the relative importance of each input variable on the MOR, MOE and CSPG is indicated in Fig. 2.

The results indicate that the MOR, MOE and CSPG of impregnated wood samples are mostly influenced by concentration (%),followed by pressure (atm), and time (min).

5.2.2 TLBO algorithm and CRA results

In this section, the MOR, MOE and CSPG of impregnated wood were predicted by means of TLBO algorithm and CRA techniques. In both methods, quadratic, exponential, linear, and power functions are selected as regression functions. The best-fit coefficients obtained for the regression functions in both TLBO algorithm and CRA are presented in Table 3.

Table 2 Basis functions of MARS models for MOR, MOE and CSPG

Basis functions	MOR (N/mm^2)	MOE (N/mm^2)	CSPG (N/mm^2)
BF1	max (0, $X_1 - 1$)	max (0, $X_1 - 1$)	max (0, $X_1 - 1$)
BF2	max (0, $X_2 - 1$)	max (0, $X_2 - 1$)	–
BF3	max (0, $X_3 - 30$)	max (0, $X_3 - 30$	max (0, $X_3 - 30$)
BF4	max (0, $X_1 - 3$) × BF3	max (0, $X_1 - 3$)	max (0, $X_2 - 1$)
BF5	–	–	max (0, $X_3 - 30$) × BF1
BF6	max (0, $X_1 - 1$) × BF2	max (0, $X_2 - 1$) × BF4	max (0, $X_2 - 1.5$) × BF5
BF7	–	–	–
BF8	max (0, $3 - X_1$)	max (0, $3 - X_1$) × BF3	max (0, $X_2 - 1.5$) × BF3
BF9	max (0, $X_2 - 1$) × BF8	–	–
BF10	–	max (0, $90 - X_3$)	max (0, $X_1 - 3$) × BF3
BF11	–	max (0, $X_1 - 1$) × BF10	–
BF12	–	max (0, $X_2 - 1$) × BF11	–
BF13	–	–	–
BF14	–	max (0, $X_2 - 1$) × BF3	–
BF15	–	–	–
BF16	–	–	max (0, $X_1 - 3$)

X_1 concentration (%), X_2 pressure (atm.), X_3 time (min)

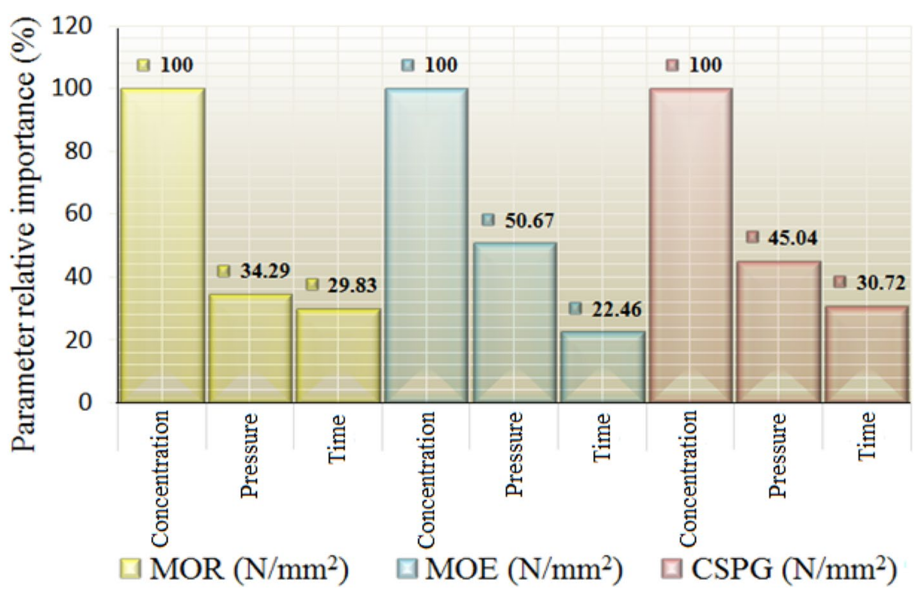

Fig. 2 Relative importance of the input variables on mechanical properties in the MARS models

5.2.3 Comparing MARS modeling results with results of TLBO and CRA models

In order to evaluate the capability of the MARS models to predict the MOR, MOE and CSPG of impregnated wood, their outcomes were compared with those of TLBO and CRA models. Comparisons were made based on the MAPE, RMSE and R^2, as shown in Table 4, where the most acceptable results for each of the MOR, MOE and CSPG are marked in bold.

It is possible to see from Table 4 that the results of all the models are generally saticfactory in predicting the MOR, MOR and CSPG. On the other hand, it is also clear from Table 4 that the best results were mostly obtained from the MARS algorithm for both training and testing data sets, especially for the MOR and CSPG. Further, it is necessary to express that the best results for the MOE for the testing phase were obtained from the quadratic function optimized by the TLBO. In other words, although the TLBO and CRA gave highly good predictions, especially for quadratic function, the MARS gave more accurate results, except for the MOE prediction in the testing phase. It is worth mentioning that the MARS also yielded highly acceptable results for the MOE. However, quadratic function optimized by TLBO algorithm presented slightly more accurate results as compared with the actual values of the MOE. Once the error

Table 3 Coefficients obtained from TLBO and CRA

Dependent variables	Method used	Coefficients									
		$y_{quadratic} = w_0 + w_1 x_1 + w_2 x_2 + w_3 x_3 + w_4 x_1 x_2 + w_5 x_1 x_3 + w_6 x_2 x_3 + w_7 x_1^2 + w_8 x_2^2 + w_9 x_3^2$									
		w_0	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9
MOR	CRA-quadratic	114.5961	−14.0360	−14.1187	−0.2032	1.7055	0.0125	0.0190	0.6137	−0.2703	0.0004
MOE	CRA-quadratic	10,641.4620	104.1443	−279.2464	−5.8688	−166.0878	−0.4706	−1.4929	−88.0261	−149.9620	0.0089
CSPG	CRA-quadratic	49.5126	−1.7918	−0.6484	−0.0248	−0.5466	0.0039	−0.0025	−0.0344	−0.4302	−0.0001
MOR	TLBO-quadratic	1.1288	−1.1206	−0.3204	−0.3584	0.2042	0.1350	0.0511	0.2940	−0.0082	0.0893
MOE	TLBO-quadratic	0.9455	−0.1139	−0.1346	−0.1314	−0.1712	−0.0437	−0.0346	−0.3630	−0.0386	0.0185
CSPG	TLBO-quadratic	0.9749	−0.5105	−0.0984	−0.1487	−0.1563	0.0995	−0.0160	−0.0394	−0.0307	−0.0601
$y_{exp\,onential} = w_0 + \exp(w_1 + w_2 x_1 + w_3 x_2 + w_4 x_3)$											
MOR	CRA-exponential	17.6689	4.6409	−0.1749	−0.2133	−0.0020	–	–	–	–	–
MOE	CRA-exponential	−187,086.5793	12.2049	−0.0037	−0.0070	−0.00005	–	–	–	–	–
CSPG	CRA-exponential	−552.2695	6.4060	−0.0043	−0.0062	−0.00006	–	–	–	–	–
MOR	TLBO-exponential	−0.3059	0.3729	−0.8779	−0.2678	−0.2284	–	–	–	–	–
MOE	TLBO-exponential	−2.4541	1.2769	−0.1975	−0.0960	−0.0564	–	–	–	–	–
CSPG	TLBO-exponential	−1.5986	0.9828	−0.2769	−0.0948	−0.0882	–	–	–	–	–
$y_{power} = w_0 x_1^{w_1} x_2^{w_2} x_3^{w_3}$											
MOR	CRA-power	115.8102	−0.2762	−0.2081	−0.0934	–	–	–	–	–	–
MOE	CRA-power	14,188.2247	−0.2005	−0.24055	−0.0828	–	–	–	–	–	–
CSPG	CRA-power	58.9455	−0.1552	−0.1365	−0.0654	–	–	–	–	–	–
MOR	TLBO-power	0.1979	−0.4479	−0.1436	−0.1369	–	–	–	–	–	–
MOE	TLBO-power	0.2983	−0.3016	−0.1497	−0.1151	–	–	–	–	–	–
CSPG	TLBO-power	0.2796	−0.3294	−0.1200	−0.1292	–	–	–	–	–	–
$y_{linear} = w_0 + w_1 x_1 + w_2 x_2 + w_3 x_3$											
MOR	CRA-Linear	95.6334	−6.8078	−8.0403	−0.0734	–	–	–	–	–	–
MOE	CRA-Linear	12,629.5289	−713.9491	−1363.3520	−9.2695	–	–	–	–	–	–
CSPG	CRA-Linear	52.9871	−2.52531	−3.66341	−0.0352	–	–	–	–	–	–
MOR	TLBO-Linear	0.9594	−0.6524	−0.1926	−0.1582	–	–	–	–	–	–
MOE	TLBO-Linear	1.0778	−0.5888	−0.2811	−0.1720	–	–	–	–	–	–
CSPG	TLBO-Linear	1.0157	−0.5775	−0.2095	−0.1810	–	–	–	–	–	–

X_1 concentration (%), X_2 pressure (atm.), X_3 time (min)

Table 4 The results of evaluation criteria for models

Predicted parameters	Equation type	Training			Testing		
		RMSE	MAPE	R^2	RMSE	MAPE	R^2
MOR	MARS	**1.2291**	**1.7110**	**0.9892**	**1.5691**	**2.2820**	**0.9918**
MOR	CRA-quadratic	1.4141	2.0448	0.9857	2.0459	2.7388	0.9803
MOR	CRA-exponential	1.4840	2.0743	0.9842	2.0673	2.8401	0.9792
MOR	CRA-power	2.4122	3.1477	0.9584	3.2793	3.9630	0.9421
MOR	CRA-linear	2.2046	3.5152	0.9652	2.3484	3.7534	0.9746
MOR	TLBO-quadratic	1.4140	2.0442	0.9856	2.0452	2.7385	0.9803
MOR	TLBO-exponential	1.4843	2.0743	0.9842	2.0710	2.8432	0.9791
MOR	TLBO-power	3.4455	5.1735	0.9158	5.1058	6.6927	0.8580
MOR	TLBO-linear	2.2046	3.5152	0.9652	2.3477	3.7536	0.9746
MOE	MARS	**84.9220**	**0.9320**	**0.9958**	230.5602	2.6599	0.9873
MOE	CRA-quadratic	97.4407	1.0404	0.9945	106.8346	1.0609	0.9964
MOE	CRA-exponential	227.4312	2.7677	0.9701	276.0831	3.2233	0.9664
MOE	CRA-power	492.2857	5.8756	0.8604	579.4813	6.9367	0.8352
MOE	CRA-linear	223.7757	2.7216	0.9711	271.3771	3.1771	0.9674
MOE	TLBO-quadratic	97.4410	1.0404	0.9945	**106.6800**	**1.0597**	**0.9964**
MOE	TLBO-exponential	268.8535	3.2461	0.9595	335.3821	3.6376	0.9572
MOE	TLBO-power	616.4547	7.3893	0.7827	738.2767	8.3780	0.7399
MOE	TLBO-linear	223.7757	2.7216	0.9711	271.4227	3.1773	0.9674
CSPG	MARS	**0.2276**	**0.5230**	**0.9974**	**0.4819**	**1.1168**	**0.9928**
CSPG	CRA-quadratic	0.3848	0.8260	0.9926	0.6902	1.6051	0.9856
CSPG	CRA-exponential	0.5693	1.3383	0.9837	0.6970	1.4642	0.9867
CSPG	CRA-power	1.2184	2.8176	0.9255	1.3338	3.1077	0.9280
CSPG	CRA-linear	0.5641	1.3211	0.9840	0.6980	1.4545	0.9865
CSPG	TLBO-quadratic	0.3848	0.8250	0.9926	0.6906	1.6053	0.9856
CSPG	TLBO-exponential	0.6618	1.5559	0.9784	0.7577	1.6101	0.9867
CSPG	TLBO-power	1.6690	3.8087	0.8612	1.9415	4.4148	0.8454
CSPG	TLBO-linear	0.5641	1.3211	0.9840	0.6976	1.4537	0.9865

values for different function types were evaluated, it was seen that the quadratic function among all function types yielded the best outcome for TLBO and CRA in all the data set. Bayram et al. (2015) reported that this is because the quadratic function creates new independent variables by using available independent variables.

Moreover, when the TLBO and CRA results were evaluated in itself depending on the function types, it became clear that the TLBO could not perform any significant improvement compared to the CRA except for the quadratic function. In other words, it was shown that the results of two techniques are very close to each other. On the other hand, the TLBO yielded a slightly better result for the testing set compared to the CRA in the prediction of the MOE and this result is the best one among all models for the MOE.

The best modeling approach for the MOR prediction was found to be the MARS. The MOR values could be predicted with a MAPE of 2.2820% and RMSE of 1.5691 by the MARS model. Similarly, MARS modeling gave the lowest errors with a MAPE of 1.1168% and RMSE of 0.4819 in predicting the CSPG. With respect to the MOE prediction, the best results were obtained from the quadratic function optimized by TLBO, with a MAPE of 1.0597% and RMSE of 106.6800.

Another important criterion for the evaluation of the model performance is the determination coefficient (R^2). R^2, which ranges from 0 to 1, shows the degree of the relationship or similarity between actual and predicted values. In other words, it summarizes the explanatory power of the established model (Bas and Boyacı 2007). It gives a very good fit when its value is close to 1, whereas it yields a poor fit when its value is close to 0 (Kecebas et al. 2012). In this study, the results of the R^2 for the best models of MOR, MOE and CSPG were found to be 0.9918 (MARS), 0.9964 (TLBO quadratic) and 0.9928 (MARS), respectively. It is possible to say that the low values for MAPE and the high values for R^2 are an indication of the good performance of the established models. It is also concluded that the results of the models are quite satisfactory in predicting the mechanical properties of the impregnated wood.

The prediction results closest to the actual values of the MOR, MOE and CSPG were calculated by employing

Table 5 Prediction results for the best models of MOR, MOE and CSPG

Concentration (%)	Pressure (atm.)	Time (min)	MOR (N/mm^2)		MOE (N/mm^2)		CSPG (N/mm^2)	
			MARS		TLBO-quadratic		MARS	
			Predicted	Error (%)	Predicted	Error (%)	Predicted	Error (%)
1	**1**	**30**	**82.006**	**−1.5934**	**9835.178**	**−0.0730**	**46.236**	**−1.9985**
1	1	60	79.005	−1.1333	9624.217	2.0536	44.700	−0.1785
1	1	90	76.005	0.6997	9429.073	1.2042	43.163	0.6824
1	1	120	73.004	0.1046	9249.863	−1.3573	41.627	−0.0413
1	1.5	30	76.699	1.5667	9402.771	−0.4999	44.469	0.1136
1	**1.5**	**60**	**73.698**	**3.0540**	**9169.198**	**−2.4034**	**42.933**	**0.6176**
1	1.5	90	70.698	−0.4511	8951.759	−1.2185	41.397	−1.2398
1	1.5	120	67.697	−1.1303	8750.155	−1.0177	39.861	0.5471
1	2	30	71.392	−2.5751	8895.274	−0.1269	42.703	−0.1007
1	2	60	68.391	−0.2512	8639.407	−0.2717	41.606	0.4157
1	**2**	**90**	**65.391**	**−0.3846**	**8399.535**	**−1.1261**	**40.510**	**−0.8958**
1	2	120	62.390	2.9408	8175.476	1.0233	39.413	−0.2365
3	1	30	65.678	4.4265	8978.951	−2.3592	40.265	0.0384
3	**1**	**60**	**62.677**	**4.0459**	**8739.302**	**−0.7296**	**39.573**	**−0.8231**
3	1	90	59.676	−4.9901	8516.260	−0.8797	38.882	−0.2360
3	1	120	56.676	0.8476	8308.816	0.7784	38.190	−0.7919
3	1.5	30	60.408	−2.4556	8380.344	0.7539	38.498	−0.6486
3	1.5	60	57.407	1.3966	8118.637	0.3359	37.807	0.6658
3	**1.5**	**90**	**54.406**	**2.3581**	**7872.574**	**−0.0073**	**37.115**	**−0.5012**
3	1.5	120	51.405	0.1065	7643.026	0.7141	36.424	0.5635
3	2	30	55.138	0.6889	7706.765	0.0938	36.732	0.3483
3	2	60	52.137	−0.8056	7422.663	−0.1979	35.959	−0.3866
3	2	90	49.136	0.6556	7154.496	1.0717	35.185	0.4940
3	**2**	**120**	**46.135**	**3.6850**	**6902.165**	**0.3729**	**34.412**	**1.6514**
5	1	30	49.350	−2.5988	7418.409	−1.1509	35.428	1.3418
5	1	60	47.870	−2.4615	7150.862	1.1766	34.721	−0.7855
5	**1**	**90**	**46.390**	**−0.1079**	**6898.638**	**0.0777**	**34.013**	**−0.8990**
5	1	120	44.910	3.0858	6663.571	0.3355	33.306	0.0435
5	1.5	30	47.093	1.1061	6653.719	3.0635	33.662	−0.4827
5	1.5	60	45.613	2.9917	6363.778	0.0663	32.954	−0.4700
5	1.5	90	44.133	−0.8992	6089.771	−1.9721	32.247	0.7492
5	**1.5**	**120**	**42.653**	**1.8562**	**5831.164**	**−3.3894**	**31.539**	**2.1439**
5	**2**	**30**	**44.837**	**3.4526**	**5813.898**	**−1.3581**	**31.895**	**−0.5208**
5	2	60	43.357	1.8193	5501.722	−1.3955	30.585	−1.0734
5	2	90	41.877	−0.3754	5205.321	−1.9053	29.274	0.9998
5	2	120	40.397	−3.6342	4924.854	1.0676	27.964	−0.4451

Bold values: testing data, the other values: training data

the best models. This was achieved by MARS models for MOR and CSPG. Among all the equations constructed for the MOE, the smallest error values were obtained from the equation of the quadratic function using the TLBO algorithm (Table 4). The prediction results and individual percentage errors for the best models of the MOR, MOE and CSPG are given in Table 5.

As seen in Table 5, the prediction results of MOR, MOE and CSPG by the best models were found to be very close to the actual values for almost all variations. Upon analysis of prediction results in Table 5, it is also possible to see that the maximum percentage errors of the best prediction models did not exceed 4.9901% for the MOR, 3.3894% for the MOE and 2.1439% for the CSPG. These results are highly satisfactory in predicting the investigated wood properties.

Figure 3 depicts the comparison graphs of the actual and the predicted results of the MOR, MOE and CSPG for testing data sets of the best models. Figure 3 clearly

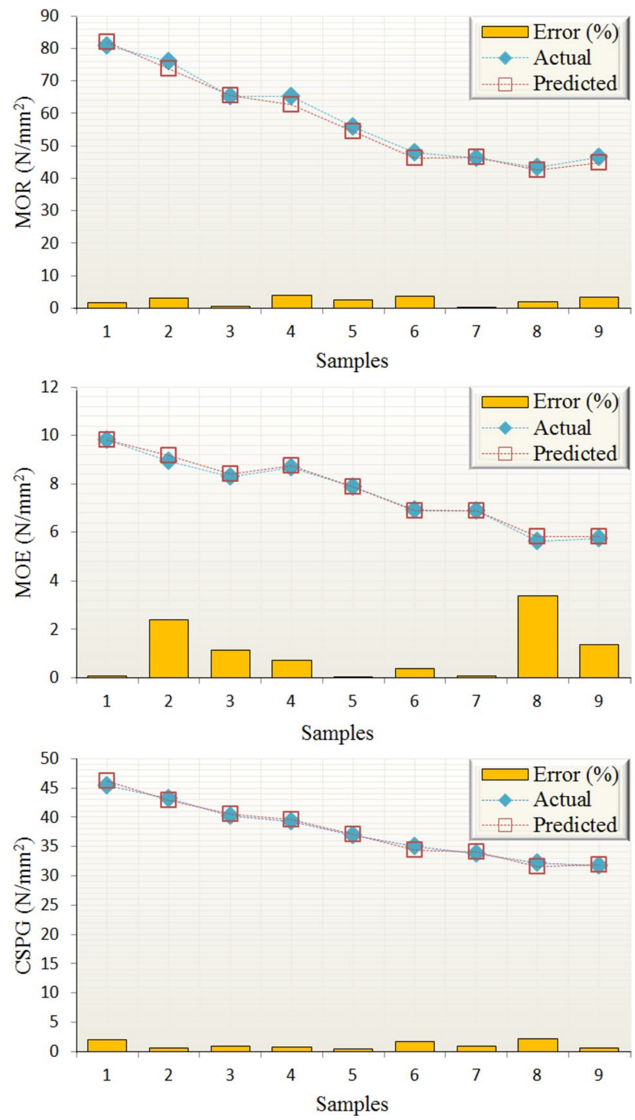

Fig. 3 Comparison of actual and model outputs of the best models for testing data

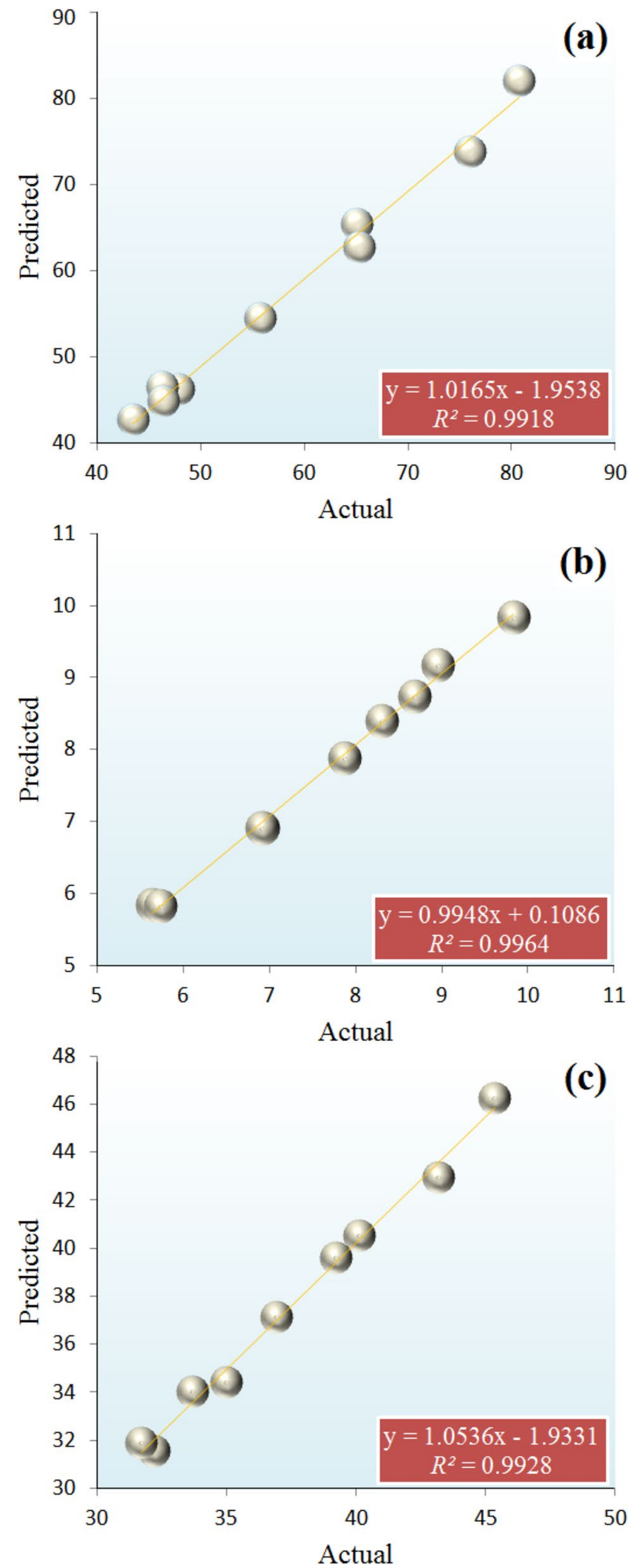

Fig. 4 Presentation of the fit between actual and predicted values of the MOR, MOE and CSPG for the best models (**a** MOR by the MARS model, **b** MOE by the TLBO-quadratic model, **c** CSPG by the MARS model)

demonstrates that the predicted values using the best models are nearly equal to the actual values, revealing the efficiency of the MARS and TLBO quadratic models to predict the MOR, MOE and CSPG.

As stated previously, the goodness-of-fit of prediction models was evaluated by means of R^2. Figure 4 presents a graphical presentation of the fit between the predicted and actual outputs of the MOR, MOE and CSPG for the proposed models.

As can be observed in Fig. 4, the actual and predicted values of MOR, MOE and CSPG indicated a high correlation in the testing data sets. In Fig. 4, the high values of R^2 confirm the excellent fit between the actual outputs and the prediction results. This is an important point that increases the reliability of the models.

Table 6 Some modeling studies conducted for predicting mechanical properties

Authors	Material	Prediction method	MOR (N/mm^2)	MOE (N/mm^2)	CSPG (N/mm^2)	IB (N/mm^2)	BS (N/mm^2)
Fernandez et al. (2008)	Particleboard	Artificial neural networks				▲	
		Multiple linear regression				▲	
Esteban et al. (2009)	Solid wood	Artificial neural networks		▲			
Yapıcı and Ulucan (2012)	Heat treated solid wood	Fuzzy logic	▲	▲			
Fernandez et al. (2012)	Plywood	Artificial neural networks	▲	▲			
Eslah et al. (2012)	Particleboard	Multiple linear regression	▲	▲		▲	
Tiryaki and Hamzacebi (2014)	Heat treated solid wood	Artificial neural networks	▲	▲			
Tiryaki et al. (2015)	Solid wood	Artificial neural networks					▲
Yang et al. (2015)	Heat treated solid wood	Artificial neural networks	▲	▲	▲		
This study	Impregnated solid wood	Multiple adaptive regression splines	▲	▲	▲		
		Teaching-learning based optimization	▲	▲	▲		
		Conventional regression analyses	▲	▲	▲		

IB internal bond strength, *BS* bonding strength

It is important to emphasize that there is limited information on the employment of the MARS, TLBO and CRA methods for predicting the MOR, MOE and CSPG of wood impregnated under different conditions. On the other hand, some researchers employed different tools in predicting some mechanical properties of wood and wood based materials. Table 6 lists some attempts regarding the prediction of mechanical properties in wood science.

As seen in Table 6, the majority of previous studies on the prediction of the mechanical properties include the use of neural networks and multiple linear regression methods. Therefore, this study will make an important contribution to the literature.

6 Conclusion

This study investigated the mechanical behaviour of wood impregnated with boric acid under different conditions. Furthermore, in this study, the ability of MARS, TLBO and CRA techniques in modeling MOR, MOE and CSPG based on the impregnation prosess variables, namely, concentration (%), pressure (atm), and time (min), was assessed. The main conclusions of the study are as follows.

(1) Experimental results revealed that the MOR, MOE and CSPG values decreased with an increase in the amount of the applied concentration, pressure and time.
(2) The comparison results demonstrated that the MARS algorithm generally gave better predictions than the TLBO and CRA, which shows that MARS is capable of capturing the relationships between the input variables and the dependent responses without making any specific assumption. Furthermore, the MOR, MOE and CSPG of treated samples are mostly influenced by concentration, followed by pressure, and time by the MARS models. This can serve as a useful information in planning future experimental designs or studies.
(3) A comparison of the results of TLBO and CRA showed that the best prediction results for the mechanical properties were obtained from the quadratic function compared to exponentiel, power and linear functions for both techniques.
(4) The results demonstrated that the MARS and the quadratic function optimized by the TLBO were the most successful approaches in predicting the MOR, MOR and CSPG. Therefore, the use of these promising algorithms in wood science is recommended for future studies.
(5) The modeling results are very close to the actual values of the mechanical properties. Satisfactory results can be thus predicted by employing the best models rather than performing experimental activities. As a result, the time, the consumption of experimental materials and design costs can be reduced to a minimum.

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