ARTIFICIAL INTELLIGENCE AND COLORIMETRY AS A COMBINED NON-DESTRUCTIVE METHOD TO PREDICT PROPERTIES OF HEAT-TREATED WOOD

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Colorimetric evaluation is practical, accurate and fast. Starting from the generally established fact that a heat treatment changes the wood properties, the present paper aimed to predict the properties of heat-treated wood by using colorimetry and artificial neural networks (ANNs). *Eucalyptus grandis* and *Pinus caribaea* wood samples were heat-treated to evaluate their color, as well as physical and mechanical properties. The relationship between the wood color and its physical and mechanical properties was evaluated through multilayer perceptron (MLP) neural network. The heat treatment darkened the wood, increased its dimensional stability and reduced its mechanical resistance. Artificial neural networks based on colorimetric and temperature parameters were efficient in modeling the wood properties, with better results to predict its physical parameters. The coefficient of determination (R^2) of the models was high and the root mean squared error (RMSE%) low – with homogeneous distribution. The findings suggest that colorimetry is adequate as a non-destructive tool to evaluate heat-treated wood.

Keywords: artificial neural networks, color changes, *Eucalyptus grandis*, *Pinus caribaea*

INTRODUCTION

The dark color of wood increases its commercial value, especially in the case of tropical wood species. Considering the high demand for raw wood material and the increasingly scarce supply, wood from forest plantations can be used, but with limitations caused by light color and lower quality.[1] Heat treatment adds value to wood from planted species, as it darkens the wood color, making it similar to that of high economic value wood, while also improving dimensional stability and resistance to xylophagous organisms.[1,5] However, modelling before this process and quality control need further studies.[2-4]

The heat treatment can make wood from planted forests viable for more demanding markets. This process consists of the application of heat between 120 and 250 °C,[6,7] for different periods of time,[8] at different pH[9] and atmospheric pressure,[10] without chemicals or waste generation, and, therefore, with reduced environmental impact.

It is known that the heat treatment changes the cell wall structure and chemical composition of the wood.[11–13] The heat applied destroys the cellulose and hemicelluloses of the wood,[14,15] compounds with high water absorption, and responsible for the volumetric variation of wood according to the environmental conditions. On the other hand, the heat treatment improves the physical properties of wood,[16,17] although the destruction of structural components of the cell wall can reduce its mechanical strength.[18,19] The balance between the gains in physical properties and a minimal reduction in mechanical strength of the wood is one of the main challenges in heat treatment, making it necessary to develop methods for process control. Heat-treated wood properties can be predicted with parameters such as mass loss, density, equilibrium moisture content or process variables, such as temperature and time.[3,4]

Colorimetric evaluation, used for aesthetic purposes,[20,21] is a fast and accurate method that can be used as a non-destructive tool to assess wood quality. The development of accurate and fast practices to evaluate heat-treated wood, based on colorimetry, can improve the process control and expand the application of this treatment.[22]

Artificial neural networks are used in several areas of science, such as medicine,[23] geosciences[24] and engineering,[25] including wood technology.[26,27] The combination of colorimetry with modern modeling methods, such as artificial neural networks, can help in predicting the quality of heat-treated wood.

The objective of this study was to model the physical and mechanical characteristics of *Eucalyptus grandis* and *Pinus caribaea* heat-treated wood based on colorimetric parameters using artificial neural networks.

EXPERIMENTAL

Characterization of the area evaluated

Samples were collected in a cultivated forest on red oxisol in Viçosa, Minas Gerais state, Brazil (42º 53' W longitude and 20º 45' S latitude). The climate of this region, according to the Köppen classification, is subtropical in altitude, with average maximum and minimum temperatures of 26.1 °C and 14.0 °C, respectively. Rainfall is concentrated from October to March, with an average annual rainfall of 1,300 mm.[28]

Sample preparation

Five 16-year-old *Eucalyptus grandis* and five 19-year-old *Pinus caribaea* trees were harvested in the inner region of the plantations, with height and diameter similar to the population average. After harvesting, a central plank was removed from the DAP region (1.3 meters high). Samples of 2 × 2 × 3 cm and 2 × 2 × 30 cm were obtained from these boards to evaluate the wood physical, mechanical and colorimetric properties.

The samples were dried at 100 °C to anhydrous condition and heat-treated at 125, 150, 175, 200 and 225 °C, with a heating rate of 10 °C/min and a residence period at maximum temperature of five hours.

Physical and mechanical tests

The physical evaluation (dry mass and dry volume) of the wood was carried out on 2 × 2 × 3 cm samples obtained immediately after the heat treatment. These samples were placed in a climatic chamber at 23 °C and 50% relative humidity until the stabilization of their mass.

Equilibrium moisture was calculated using the equation:

$$UEH = \left[\left(\frac{Mu - Ms}{Ms}\right) \times 100\right] \quad (1)$$

where UEH is hygroscopic equilibrium moisture, Mu is the mass of the sample after being placed in the environment with 23 °C and 50% relative humidity, and Ms is the dry mass of the sample.

The samples were immersed in water until the wood samples reached their maximum volume. The volumetric swelling was obtained with the equation:

$$VS = \left[\left(\frac{Vf - Vi}{Vi}\right) \times 100\right] \quad (2)$$

where VS is the volumetric swelling (%), Vi – the anhydrous volume of the sample, and Vf – the saturated volume of the sample.

The moduli of elasticity (MOE) and rupture (MOR) were determined in 2 × 2 × 30 cm samples according to the American Society for Testing and Materials.[29]

Colorimetric evaluation

Colorimetric analysis was performed on the longitudinal surface of the 2 × 2 × 3 cm and 2 × 2 × 30 cm samples, using a Konica Minolta CM-2500D spectrophotometer. The parameters lightness (L), red-green coordinate or red matrix (a*) and blue-yellow coordinate or yellow matrix (b*) were evaluated according to the CIELAB 1976 color system. Saturation and ink angle were not included in the models, as these parameters are directly correlated with the red (a*) and yellow (b*) matrix.

Statistical analysis

The data of physical, mechanical and colorimetric properties were submitted to variance homogeneity (Bartlett's test at 5% significance) and normality (Shapiro-Wilk test at 5% significance) tests and to the analysis of variance. The contrast between the treatments means was determined using the Tukey test at 5% significance level.

Artificial neural networks (ANNs)

The theory lying at the basis of ANNs has been discussed in the published literature.[30,31] The Multi-Layer Perception (MLP) is the ANNs type used in the present study to predict the heat-treated wood properties (Fig. 1). The ANNs was established with 70% (84 samples) of the data for its training and 30% (36 samples) for its validation per species.

The training of the ANNs by architecture was k-n-1_o, where k stands for the variables L, a*, b* considered as network inputs, n is the number of neurons in the hidden layer (six per species); 1 is one neuron in the output layer to predict the value of dependent variables in the training individual (EMC, VS, MOE or MOR) (Fig. 2). The exponential activation and the identity activation functions were applied in the hidden layer and in the output layer.

Performance evaluation

The validity of the artificial neural network prediction models was assessed with R2 and RMSE%. The one giving the highest value of the coefficient of determination (R^2) (Eq. 3) and the lowest root-mean-square error in percentage (RMSE%) (Eq. 4) and with a regular and good residual distribution graphic was the most appropriate:

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}\right] \quad (3)$$

$$RMSE\% = \frac{\sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}}{\bar{y}} \times 100 \quad (4)$$

where y_i is the observed value, $\hat{y}_i$ is the estimated value; $\bar{y}$ is the average of the observed values; n is number of observations.

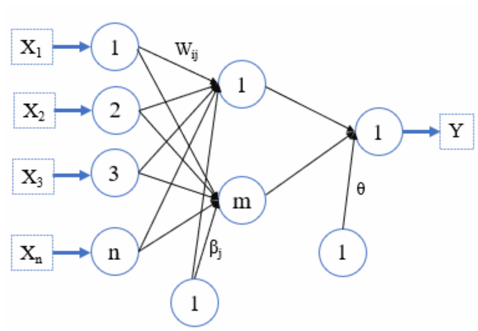


Figure 1: Multi-Layer Perception structure (MLP) to predict the physical and mechanical properties of the heat-treated *Eucalyptus grandis* and *Pinus caribaea* wood samples

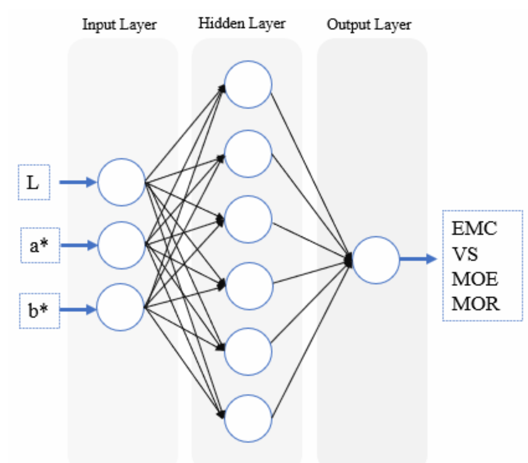


Figure 2: Artificial neural networks (ANN) architectures used to predict dependent variables: equilibrium moisture content (EMC), volumetric swelling (VS), modulus of elasticity (MOE) and modulus of rupture MOR of the *Eucalyptus grandis* and *Pinus caribaea* heat-treated wood

RESULTS AND DISCUSSION

Quality of heat-treated wood

The heat treatment darkened the *Eucalyptus grandis* and *Pinus caribaea* wood samples. The red and yellow matrix decreased for *E. grandis* wood and increased, followed by a decrease, for *P. caribaea*, as the temperature increased. As expected, the heat treatment improved the wood physical properties by reducing the equilibrium moisture content and volumetric swelling, but worsened the mechanical properties, reducing the modulus of elasticity and rupture (Table 1).

The increase in the heat treatment temperature darkened the wood, the reduction in the lightness was of 54% in the samples treated at 225 °C for both species, thus it would increase their market value. The reduction in lightness of the *Eucalyptus* samples occurred up to 200 °C and that of the *Pinus* up to 225 °C, with the most pronounced reduction for both species – between 150 and 200 °C. This reduction in lightness can be explained by the formation of compounds derived from the degradation of hemicelluloses into low molecular weight sugars, which absorb visible light.[32] The reduction in wood lightness with the heat treatment has also been reported for *Cunninghamia lanceolate*,[33] *Pinus radiata*[34] and *Eucalyptus pellita*[35] wood. The reduction of the red and yellow coordinates in *E. grandis* and *P. caribaea* wood, after being subjected to high temperatures, is associated to the degradation of polar extractives between 130 and 250 °C,[6,36] similarly to this work.

The reduction in the equilibrium moisture content, up to 45 and 44% lower in the *Pinus* and *Eucalyptus* heat-treated wood, respectively, is due to the chemical changes occurring during the heating treatment. This includes the degradation of hemicelluloses and cellulose,[11] reducing the number of hydrophilic sites and, consequently, the water adsorption capacity of the samples.[17] This also explains the reduction in the volumetric swelling of the samples, with a drop of 40 and 56% for *Pinus* and *Eucalyptus*, respectively. The improvement of physical properties shows the potential of the heat-treated wood to be used in environments with high humidity variation.

The reduction with more than 25 and 59% in the moduli of elasticity and rupture of *Pinus* and *Eucalyptus* heat-treated wood samples can be explained by the degradation of chemical components with a structural function, such as cellulose.[14,37] In addition, temperature degrades other anatomical components related to wood strength, such as tracheids in softwood and fibers in hardwood.[13,16] The reduction in mechanical strength can restrict the use of heat-treated wood, especially in applications where it is subject to load stress.

Table 1
Lightness (L), green-red coordinate (a*), blue-yellow coordinate (b*), equilibrium moisture content (EMC), volumetric swelling (VS), mechanical resistance (MOE) and modulus of rupture (MOR) of *Eucalyptus grandis* and *Pinus caribaea* heat-treated wood

Species	T(°C)	L	a*	b*	EMC	VS	MOE	MOR
Eucalyptus grandis	100	$55.3^{3.1}$a	$18.3^{9.0}$a	$17.6^{8.3}$a	$10.8^{2.4}$a	$18.2^{4.3}$a	$4122^{11.6}$a	$122^{10.3}$a
	125	$46.3^{5.3}$b	$16.3^{7.6}$b	$14.7^{12.1}$b	$10.4^{2.5}$a	$17.3^{5.6}$a	$4079^{9.8}$a	$106^{12.8}$a
	150	$38.2^{6.9}$c	$11.8^{18.0}$c	$11.9^{13.5}$c	$9.6^{4.4}$b	$16.5^{6.4}$b	$4088^{11.2}$a	$91^{11.9}$b
	175	$32.9^{7.6}$d	$10.3^{15.0}$d	$9.4^{10.1}$d	$8.4^{2.8}$c	$15.0^{5.5}$c	$3883^{11.3}$a	$86^{12.8}$b
	200	$24.3^{4.5}$e	$4.2^{15.5}$e	$5.8^{11.3}$e	$6.2^{2.2}$d	$9.7^{6.1}$d	$3333^{14.6}$b	$52^{12.5}$c
	225	$24.9^{6.0}$e	$3.0^{14.1}$f	$3.8^{15.5}$f	$6.0^{2.7}$e	$7.9^{4.4}$e	$3051^{13.8}$b	$44^{14.1}$c
Pinus caribaea	100	$76.6^{3.2}$a	$9.1^{17.1}$c	$22.2^{4.8}$c	$11.7^{3.6}$a	$13.8^{7.9}$a	$2399^{14.0}$a	$69^{12.9}$a
	125	$71.2^{4.5}$b	$7.8^{14.4}$cd	$22.9^{6.9}$bc	$11.9^{2.3}$b	$12.6^{9.4}$ab	$2321^{12.4}$a	$59^{11.5}$ab
	150	$66.9^{7.8}$c	$10.4^{10.5}$b	$28.1^{8.7}$a	$10.4^{3.3}$c	$12.3^{8.8}$b	$2112^{15.3}$ab	$53^{16.9}$b
	175	$55.7^{6.5}$d	$11.8^{18.1}$ab	$24.5^{9.6}$ab	$9.3^{2.0}$d	$10.3^{9.5}$c	$2144^{13.1}$ab	$44^{16.3}$c
	200	$42.2^{8.1}$e	$12.5^{17.6}$a	$20.7^{15.8}$d	$7.8^{2.5}$e	$9.0^{9.8}$d	$1987^{13.8}$b	$32^{14.4}$d
	225	$31.7^{7.3}$f	$5.2^{22.2}$d	$12.4^{12.6}$e	$6.4^{4.0}$f	$8.3^{8.2}$e	$1783^{13.2}$c	$28^{14.5}$d

Means followed by the same letter, per column and species, do not differ by the Tukey test at 5%; Values in superscript represent the coefficient of variation, in percentage

Table 2
Inputs: lightness (L), green-red (a*) and blue-yellow (b*) coordinates, and outputs: equilibrium moisture content (EMC), volumetric swelling (VS), modulus of elasticity (MOE) and rupture (MOR), for each species studies, for training and validation of artificial neural networks (ANNs)

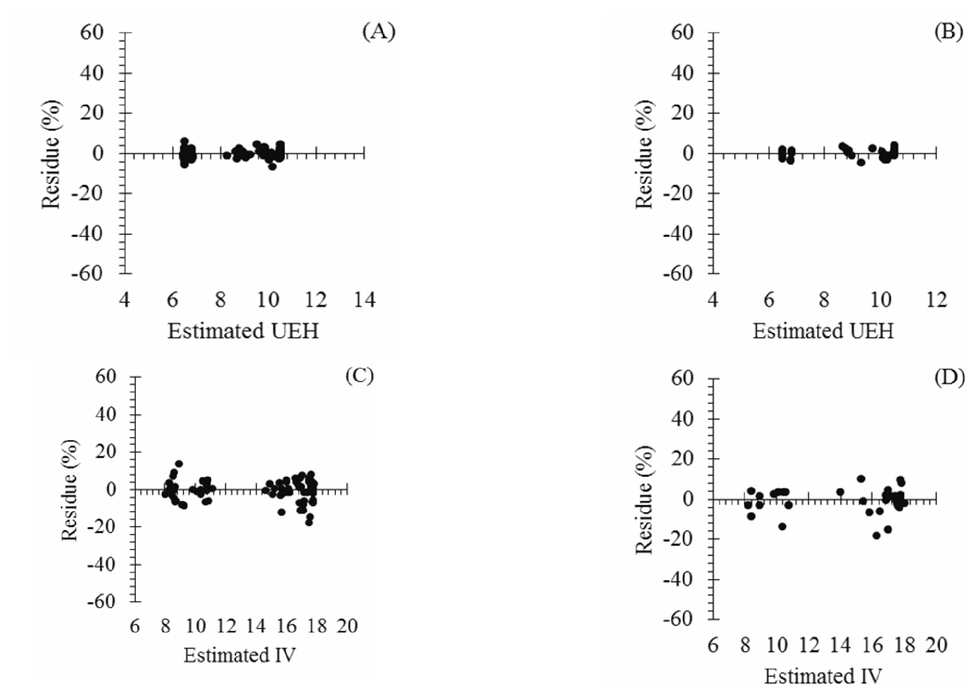
Species	Inputs	Output	Training		Validation	
			R²	RMSE%	R²	RMSE%
Eucalyptus grandis	L; a*; b*	EMC	0.989	2.0	0.988	2.1
		VS	0.952	5.6	0.945	6.0
		MOE	0.669	8.9	0.487	12.3
		MOR	0.900	9.8	0.810	14.2
Pinus caribaea	L; a*; b*	EMC	0.987	2.0	0.965	3.4
		VS	0.857	6.7	0.555	12.8
		MOE	0.643	10.4	0.293	15.4
		MOR	0.931	10.0	0.792	16.2

The prediction derived from the artificial neural networks for the *E. grandis* and *P. caribaea* heat-treated wood was satisfactory for the output variables, but with better results for the wood physical parameters, such as equilibrium moisture content and volumetric swelling, with greater determination coefficient (R2) and lowest square root-mean error in percentage (RMSE%) (Table 2).

Correlation coefficients greater than 0.945 and 0.555 for equilibrium moisture content and volumetric swelling, and 0.792 and 0.293 for modulus of rupture and elasticity, respectively, for training and validation reinforce the suitability of artificial neural networks for predicting physical and mechanical properties of heat-treated wood.[38]

The greater precision of these networks in predicting the physical parameters, compared to wood mechanics, is due to the smaller variation in the first group. Higher correlation coefficient values, to predict physical properties, with neural networks, in relation to the mechanics values of heat-treated wood, were also reported for density and equilibrium moisture of *Abies bornmülleriana* and *Carpinus betulus* (0.98),[38] in addition to modulus of elasticity and rupture in panels (0.73 and 0.66, respectively),[39] and fracture toughness in solid wood (0.62).[40]

The root mean squared error in percentage was lower for networks with higher correlation coefficients. The values of the root mean squared error for the physical parameters of the heat-treated wood (equilibrium moisture and volumetric swelling) were between 2 and 6.7, for the training, and between 2.1 and 12.8 for the validation, while those of the wood mechanical parameters – between 8.9 and 10.4, and 12.3 and 16.2 for training and validation, respectively. The coefficients of variation of the wood mechanical properties in the treatments were higher, between 9.8 and 16.9, than those of the wood physical parameters, between 2.4 and 9.8. This greater data variability reduced the quality of artificial neural networks, but with acceptable values for this evaluation type. The artificial neural networks, using the colorimetric variables, predicted the physical and mechanical parameters of the heat-treated wood with regular distribution of residues (Figs. 3 and 4). The homogeneous distribution of the errors without tendency to underestimate or overestimate the results of heat-treated wood properties from neural networks improves their quality. On the other hand, the physical and mechanical properties of the wood vary between individuals and parts of the same individual. These variations are greater for the mechanical properties, compared to the physical ones, which explains why the artificial neural networks predicted the modulus of rupture and elasticity with lower precision, compared to equilibrium moisture.[41] The distribution of errors, the coefficient of determination and the mean error show the potential of colorimetry and artificial neural networks as a combined non-destructive tool to evaluate heat-treated wood.



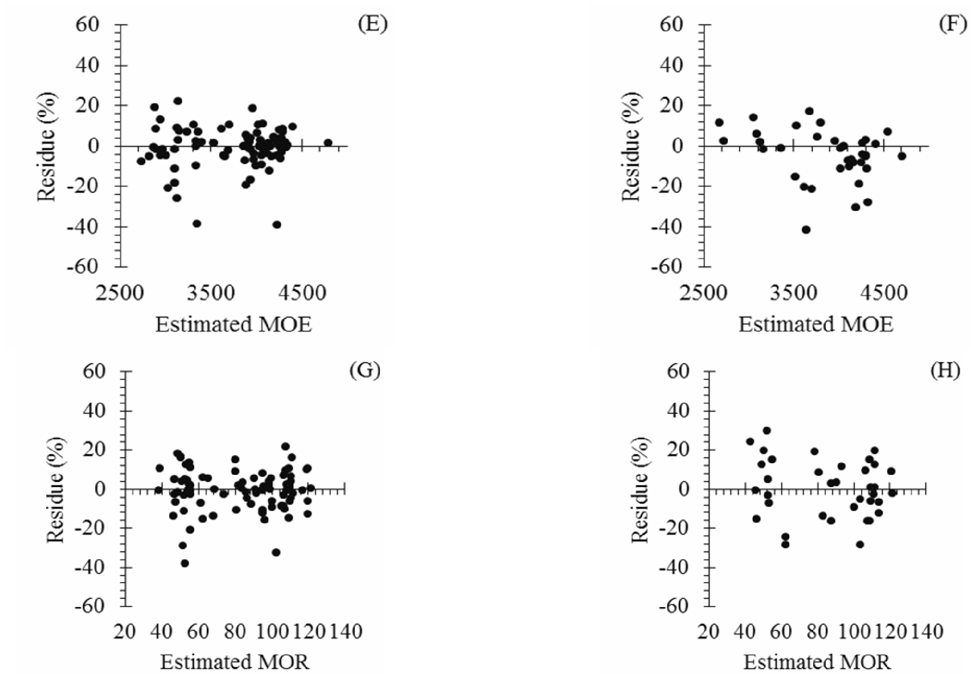
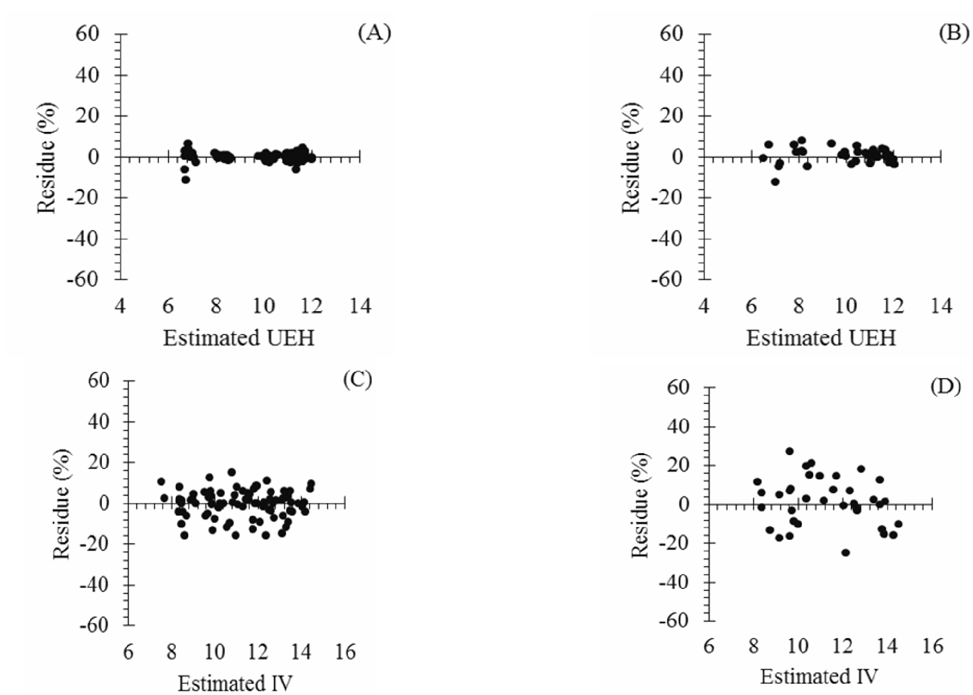


Figure 3: Graphic distribution of residues for the artificial neural networks estimated using the training data [(A) – Equilibrium Moisture Content EMC; (C) – Volumetric Swelling VS; (E) – Modulus of Elasticity MOE; (G) – Modulus of Rupture MOR], and validation of the networks [(B) – Equilibrium Moisture Content EMC; (D) – Volumetric Swelling VS; (F) – Modulus of Elasticity MOE; (H) – Modulus of Rupture MOR] from the colorimetric variables (L; a*; b*) of heat-treated wood of *Eucalyptus grandis*



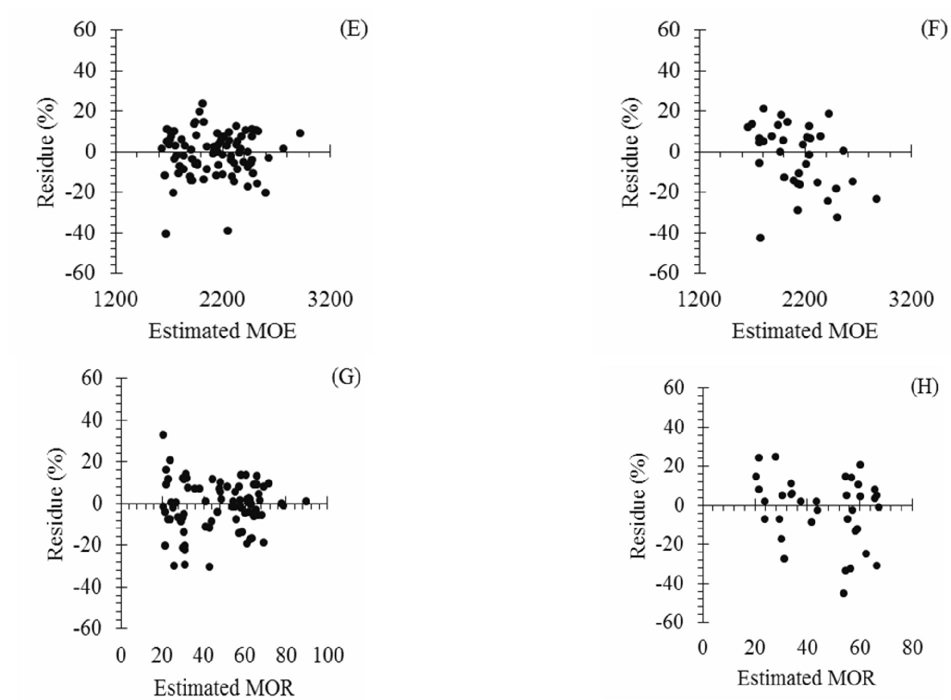


Figure 4: Graphic distribution of residues for the artificial neural networks estimated using the training data [(A) – Equilibrium Moisture Content EMC; (C) – Volumetric Swelling VS; (E) – Modulus of Elasticity MOE; (G) – Modulus of Rupture MOR], and validation of the networks [(B) – Equilibrium Moisture Content EMC; (D) – Volumetric Swelling VS; (F) – Modulus of Elasticity MOE; (H) – Modulus of Rupture MOR] from the colorimetric variables (L; a*; b*) of heat-treated wood of *Pinus caribaea*

CONCLUSION

The heat treatment reduced the lightness and mechanical strength of *Eucalyptus grandis* and *Pinus caribaea* wood samples, but improved their physical properties. The variation of physical characteristics, equilibrium moisture content and volumetric swelling of the wood was smaller between the samples subjected to the same treatment than that of mechanical properties, such as modulus of elasticity and rupture. Thus, the accuracy of the artificial neural networks used to predict the physical parameters of wood was higher, with correlation coefficients higher than 0.945 and 0.555 for the equilibrium moisture content and volumetric swelling, and 0.792 and 0.293 for the modulus of rupture and elasticity in training and validation, respectively. The distribution of errors was homogeneous and without homoscedasticity. To conclude, colorimetry can be used as a non-destructive tool with the potential to assess the quality of heat-treated wood.

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