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USE OF ARTIFICIAL NEURAL NETWORKS IN PREDICTING PARTICLEBOARD QUALITY PARAMETERS[1]

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ABSTRACT – This study aims to assess Artificial Neural Networks (ANN) in predicting particleboard quality based on its physical and mechanical properties. Particleboards were manufactured using eucalyptus (*Eucalyptus grandis*) and bonded with urea-formaldehyde and phenol-formaldehyde resins. To characterize quality, physical (density and water absorption and thickness swelling after 24-hour immersion) and mechanical (static bending strength and internal bond) properties were assessed. For predictions, adhesive type and particleboard density were adopted as ANN input variables. Networks of multilayer Perceptron (MLP) were adopted, training 100 networks for each assessed parameter. The results pointed out ANN as effective in predicting quality parameters of particleboards. With this technique, all the assessed properties presented models with adjustments higher than 0.90.

Keywords: Artificial intelligence; Particleboards; Physico-mechanical properties.

EMPREGABILIDADE DE REDES NEURAIS ARTIFICIAIS (RNA) NA PREDIÇÃO DA QUALIDADE DE PAINÉIS AGLOMERADOS

RESUMO – O presente trabalho tem como objetivo avaliar a empregabilidade de Redes Neurais Artificiais (RNA) na predição da qualidade de painéis aglomerados, baseando-se na análise de suas propriedades físicas e mecânicas. Desta forma, foram produzidos painéis aglomerados com partículas de ***Eucalyptus grandis*** *e colados com dois tipos diferentes de resinas - ureia-formaldeído e fenol-formaldeído. Para caracterizar a qualidade dos painéis, foram avaliadas as propriedades físicas (densidade, absorção de água após 24 horas de imersão e inchamento em espessura após 24 horas de imersão) e mecânicas (resistência a flexão estática e ligação interna). Como variáveis de entradas das RNA, foram adotados o tipo de adesivo e a densidade dos painéis, visando predizer as demais variáveis avaliadas. Foram adotadas Redes do tipo Perceptrons de múltiplas camadas, sendo treinadas 100 redes para cada um dos parâmetros avaliados. Os resultados obtidos indicaram ser o uso de RNA uma ferramenta eficiente na predição da qualidade de painéis aglomerados. Todas as propriedades avaliadas com uso desta técnica no presente estudo apresentaram modelos com ajustes superiores a 0,90.*

Palavras-chave: Inteligência artificial; Painéis de partículas; Propriedades físico-mecânicas.

1. INTRODUCTION

As for timber, density is one of the most influencing parameters in particulate compounds used for particleboard manufacturing. This variable should be defined at the time of manufacturing, especially by considering its applicability. This value has a significant relation to particleboard physical and mechanical properties. The higher the specific weight is, the higher the mechanical strength of particleboards will be. In contrast, more densified particleboards generally show less dimensional stability, which can be related to the release of compressive strain (MELO; DEL MENEZZI, 2010).

Another important component in particleboard manufacturing is adhesive, which presents significant technical and economic implications for wooden products since costs can reach up to half of the product total price (CARNEIRO et al., 2004). Urea-formaldehyde-based adhesives are widely used in particleboard industry, due to their low cost, the fast reaction in hot press machines and easy handling (ROFFAEL; SCHNEIDER, 1983). On the other hand, the growing demand for renewable materials have gradually promoted the use of vegetal tannin-based adhesives, which can be found in the wood (core), bark, roots, flowers, fruits and seeds of some tree species (HILLIG et al., 2002; CARNEIRO et al., 2004). In addition to economic and environmental implications, using adhesive has also a close relationship with particleboard quality and, as for the density, being a parameter established before the particleboard manufacturing and its choice takes into account mainly the use that will be attributed to the compound (MELO et al., 2010a; MELO et al., 2010b). Thus, aiming to predict particleboard quality using preselected variables, density and adhesive type are crucial parameters in the validation of any estimate.

These data can be used in establishing models to estimate the main qualitative parameters of particleboards. Among the modelling tools, the use of ANN has gained great importance in recent years due to its effectiveness and possibility of grouping different information at the same model. In forestry, this technique has already been used mainly in timber volume estimation in forest plantations (DIAMANTOPOULOU, 2005; SILVA et al., 2009; LEITE et al., 2011; BINOTI et al., 2013). However, studies that assess the feasibility of this tool for predicting the quality of wood products are still scarce. Studies carried out by Cook et al. (1991), Fernádez et al. (2008), Esteban et al. (2009) and Gürüler et al. (2015) have demonstrated feasibility for the application of this technique in predicting particleboard quality. In this sense, ANN can be used as a tool for predicting the quality of wood-based products even before its manufacturing.

Binoti et al. (2013) emphasized that ANN consists of simple processing units (artificial neurons), which are connected to each other to perform certain tasks. According to Haykin (2001), ANN has shown superior performance when compared to regression models due to several factors, including robust structure, being distributed parallel into layers; tolerance to outliers; efficient learning, allowing generalizations and enabling to solve complex problems; possibility of modeling varied and distinct variables with their nonlinear relationships; possibility of using categorical variables, in addition to those numerical.

Thus, this study aims to assess the use of Artificial Neural Networks (ANN) to predict particleboard quality, using as input variables the density (quantitative variable) and adhesive type (categorical variable), and as output variables the particleboard physical and mechanical properties.

2. METHODOLOGY

2.1. Particleboard manufacturing

Particleboards were produced with pre-established nominal specific weights of 0.60, 0.70 and 0.80 g cm^{-3}, with four units for each density level. The boards were made of wood particles obtained from *Eucalyptus grandis* W. Hill ex Maiden retained between 3 and 1 mm meshes. Selected particles were conditioned in an oven at 60 °C during 24 hours, reaching about 3% moisture.

Particleboard manufacturing was performed using 8% of adhesive and 1% of paraffin. Adhesives used during the process were urea-formaldehyde and tannin-formaldehyde resins. Definitive pressing was performed in a hydraulic press at 180 °C, press closing time of 40 seconds, a pressure of 30 kgf/cm^2 and time of 8 minutes. Twenty-four particleboards with dimensions of 50 × 50 × 0.95 cm were manufactured, four of them for each treatment considering the pre-established nominal density and adhesives used.

2.2. Particleboard quality assessment

The manufactured particleboards were placed in an acclimatized chamber (20 °C and 65% relative humidity) to constant mass. For quality assessment, physical (water absorption and thickness swelling after 24-hour immersion) and mechanical (static bending strength and internal bond) tests were performed adopting the recommendations of the American Society for Testing and Materials–ASTM D 1037 (1999). From each particleboard, four samples were taken for mechanical tests and four samples for physical tests, determining their apparent density.

2.3. ANN adjustments

For ANN adjustment, the numerical variables were normalized linearly within a range of 0 to 1, and categorical variables were normalized using N-of-1 trials, in which every time that one category is 1, the others are assumed to be 0 (HEATON, 2010). Input layer consisted of two neurons, with one neuron for quantitative variable (density) and the other for qualitative variable (adhesive), depending on the response/ output variable. As output was used different physical (absorption and swelling) and mechanical (bending strength and internal bond) properties.

A hidden layer comprised the networks. According to Esquerre (2002), most often, networks require at least one hidden layer to solve nonlinearly separable problems. Intelligent Problem Solver (IPS) tool of Statistica 7.0 (STATSOFT, 2007) optimized the number of neurons in this layer, for each variable. The activation function used was sigmoidal.

Sigmoid activation function is the most common in the development of artificial neural networks, being infinitely differentiable if compared to the others; besides, a well-built network architecture can approach any continuous function with precision (VULGAR, 2014), as through the mathematical equation:

$$\varphi(v) = \frac{1}{1 + \exp^{\beta u}}$$

Wherein: φ is the sigmoid activation function, β is the estimate of the parameter that determines the slope of the sigmoidal function, and u is the function activation potential.

In the algorithm used, weights were based on information from the present data, inserting for each weight an individual update value. Initially, weights of all networks were generated randomly (HEATON, 2010); then, the individual update value progressed during the learning process based on the error function; the training continues until the error rate be shortened to an acceptable range or until the maximum number of seasons or cycles be reached (SHIBLEE et al., 2010). The estimates of particleboard quality (water absorption, thickness swelling, static bending strength and internal bond) were simulated with the possible combinations of the quantitative (density) and qualitative (adhesive) variables, totalling three combinations for each response variable.

The supervised learning method of neural networks was used and adopted for ANN two groups of values: a group of input values and another with output values. Thus, for the training was considered the optimization of network parameters (synaptic weights) to emit responses to the input data as expected and, similarly, extrapolate this behaviour to other input data not foreseen in the training. This process was repeated until the error between the output patterns generated by the network reached the minimum value (HAYKIN, 2001).

2.4. ANN training

One-hundred multilayer perceptron neural networks were trained, commonly known as MLP (Multilayer Perceptron) for each response variable. It should be noted that in this type of network there are at least three different layers. Its reputation is because it can be adapted to the generalization of forms, layouts, and patterns, as well as its approach capacity as a function of its countless resources and domain to describe events (SERPEN; GAO, 2014).

Several methods determine the time at which neural network training should be finished. According to Chen et al. (2014), the exaggerated number of cycles can lead the network to lose its generalization power (overfitting); on the other hand, with a small number of cycles, the network cannot reach its best performance (under-fitting). However, to eliminate these problems, a mean squared error (MSE) lower than 1% or a further increase in MSE was used as stopping criteria for the training algorithm, as suggested by Chen et al. (2014). Thus, the training was finished when one of these criteria has been reached. Based on this analysis, one of the networks was chosen to estimate the physical and mechanical characteristics of particleboard. Artificial neural networks were adjusted by Statistica 7.0 software (STATSOFT, 2007).

2.5. ANN validation

Based on the above mentioned, different ANN configurations could be developed and trained for prediction physical and mechanical characteristics of the particleboards depending on their density and adhesive types (urea and tannin). However, to validate the different network configurations, as well as their performance in predicting the physico-mechanical characteristics of particleboards, 38 out of the 48 sampling units were randomly selected (80%), which were part of the adjustments, and 10 (20 %), which were used for the validation. The criteria used to validate the adjustments were the chi-square test (χ^2), standard error of the estimate expressed as a percentage (S_{yx}%), and aggregate difference (Da). These 10 sampling units were not part of the adjustments database, which is in accordance with Zucchini (2000), who states that the sample for validation should be independent and meet the modelling principles, as recommended by Gujarati and Porter (2011). In this case, 10 to 30% of the samples that are part of the database should be used for model validation.

3. RESULTS

3.1. Description of results

Average, minimum and maximum values obtained for the different physical and mechanical properties assessed in the particleboards, as well as their dispersion measures, are shown in Table 1. The results showed a certain variability since the input variables used in the study (density and adhesive type) could provide different responses for the assessed properties. The correlation between predicting variables for particleboard quality (density) and the other assessed parameters was significant.

3.2. Network architecture

In general, four networks were selected, each of them for each assessed property. The ANN architecture produced was formed of an input, a hidden and an output layer. The input layer was formed by two neurons, one of them a quantitative variable (density) and the other a qualitative variable (adhesive type). In the hidden layer, the number of neurons was determined by the Intelligent Problem Solver (IPS) tool (STATSOFT, 2007), which showed a different number of neurons according to the assessed property. For the parameters static bending strength and water absorption, the adopted model presented four neurons in the hidden layer. On the other hand, for the parameters thickness swelling and internal bond, the adopted model presented six neurons in the hidden layer (Figure 1). This difference can be attributed to the difficulty level of models in predicting the different properties. In this case, the higher the number of neurons is, the higher the model difficulty in predicting the assessed parameters.

Adjusted Networks

Accurate estimates of the physical and mechanical properties for particleboards could be calculated by using the different ANN selected. The observed adjustments had a coefficient of determination (R^2) ranging from 0.931 to 0.975, with a standard error of estimate (S_{yx}) ranging from 3.53 to 6.05% (Table 1). The performance of a particleboard is closely related to several parameters that compose its manufacturing process, such as density, quantity, and adhesive quality, pressing techniques, size and shape of the particles, the moisture content of the mattress, etc. (IWAKIRI, 2005). Among these parameters, stands out the density (MELO; DEL MENEZZI, 2010) and the adhesive used (MELO et al., 2010a; MELO et al., 2010b). Thus, this technique along with experimental data can effectively join the studied parameters; provide predictability to particleboards regarding their future performance, even before the manufacturing process.

The comparison between the data obtained experimentally and those estimated by the Artificial Neural Networks (ANN), as well as the graphical analysis of the residuals for the different physical and mechanical properties for particleboards, is shown in Figure 2. For the different properties assessed, the adjusted models presented efficacy for predicting these parameters.

Network validation

For a more detailed analysis and validation of the networks, in Table 2 are presented other statistical criteria (chi-square test, χ^2; standard error of the estimate expressed as a percentage, S_{yx}%; and aggregate

Table 1 – Average, maximum and minimum, standard deviation and coefficient of variation for the properties evaluated for the particleboards; Architecture of Neural Networks, input variables, network specifications (neuron number and number of layers), statistical adjustment and precision.
Tabela 1 – *Média, valor máximo e mínimo, desvio padrão e coeficiente de variação para as propriedades avaliadas nos painéis aglomerados; Arquitetura das RNA, variáveis de entrada no procedimento, especificações das redes (número de neurônio e número de camadas), estatística de ajuste e precisão.*

Observed Values for Evaluated Panels					
	Density (g/cm^3)	Absorption (%)	Swelling (%)	S. Bending (kgf/cm^2)	I. Bond (kgf/cm^2)
Minimum	0,59	24,12	16,11	108,15	1,47
Average	0,66	35,15	26,31	148,02	1,96
Maximum	0,78	47,28	39,47	196,48	2,73
Standard Desviation	0,03	6,03	5,84	26,93	0,35
CV (%)	5,20	22,91	16,63	18,20	16,63
Corr. Density	1,00	-0,49*	0,35*	0,72*	0,56*

RNA Architecture and Statistics Precision							
Rede	Variables		Neurons by layer			Adjustment	
			Input	Hidden	Output	R^2	S_{yx} (%)
Static Bending	Density	Adhesive	2	4	1	0,975	3,53
Internal Bond			2	6	1	0,948	5,35
Swelling			2	6	1	0,931	6,05
Absorption			2	4	1	0,961	5,15

R^2, determination coefficient; Syx(%), standard error of estimate; *Significant at 95% probability.

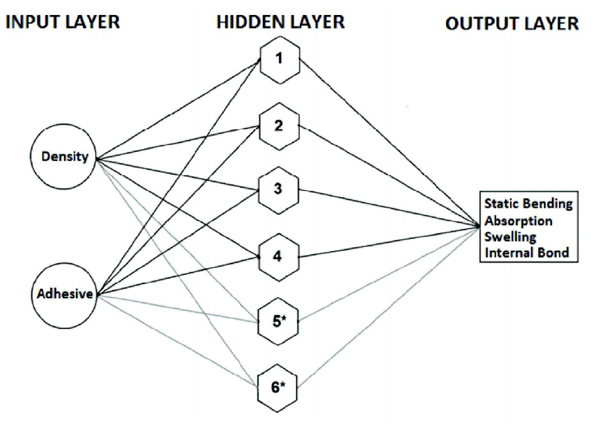

Figure 1 – Architecture of Artificial Neural Networks created to predict the properties of particleboards.
Figura 1 – *Arquitetura das Redes Neurais Artificiais criadas para predição das propriedades dos painéis aglomerados.*

difference, Da) regarding the network behaviour in relation to the validation sample. The calculated values of χ^2, faced with the table values, were not significant at 95% probability, accepting the null hypothesis that all the selected ANN are valid and reliable to predict the physical and mechanical properties of particleboards using density (g/cm^3) and adhesives (urea-formaldehyde and tannin-formaldehyde) as predictor variables.

In general, the different ANN previously selected during the adjustment to predict physical and mechanical data of particleboards showed the same behaviour for the standard error of the estimate (S_{yx}) values, corroborating Serpen and Gao (2014). These authors mention the efficiency of ANN in learning and generalization of data and forms, being possible to extract patterns of the determined database and reapply them in others accurately.

An aggregate difference (Da) can also be a statistic used for adjusting and selecting models, being the difference between the sum of observed values and the sum of estimated values, thus, being an efficient indicator of under or overestimation. In this study was adopted the presentation of Da expressed as a percentage to better visualize it.

The ANN developed to predict particleboard-bending information presented a positive value (0.42%), which characterizes an average underestimation of this property. The other ANN developed to predict the data of water absorption (“0.10%), internal bond (“0.71%) and thickness swelling (“0.45%) returned negative values and thus presented overestimation. However, the neural networks are clearly adaptable in predicting such physical and mechanical properties of particleboards, in which the aggregate difference values were very low (between ± 0.71%).

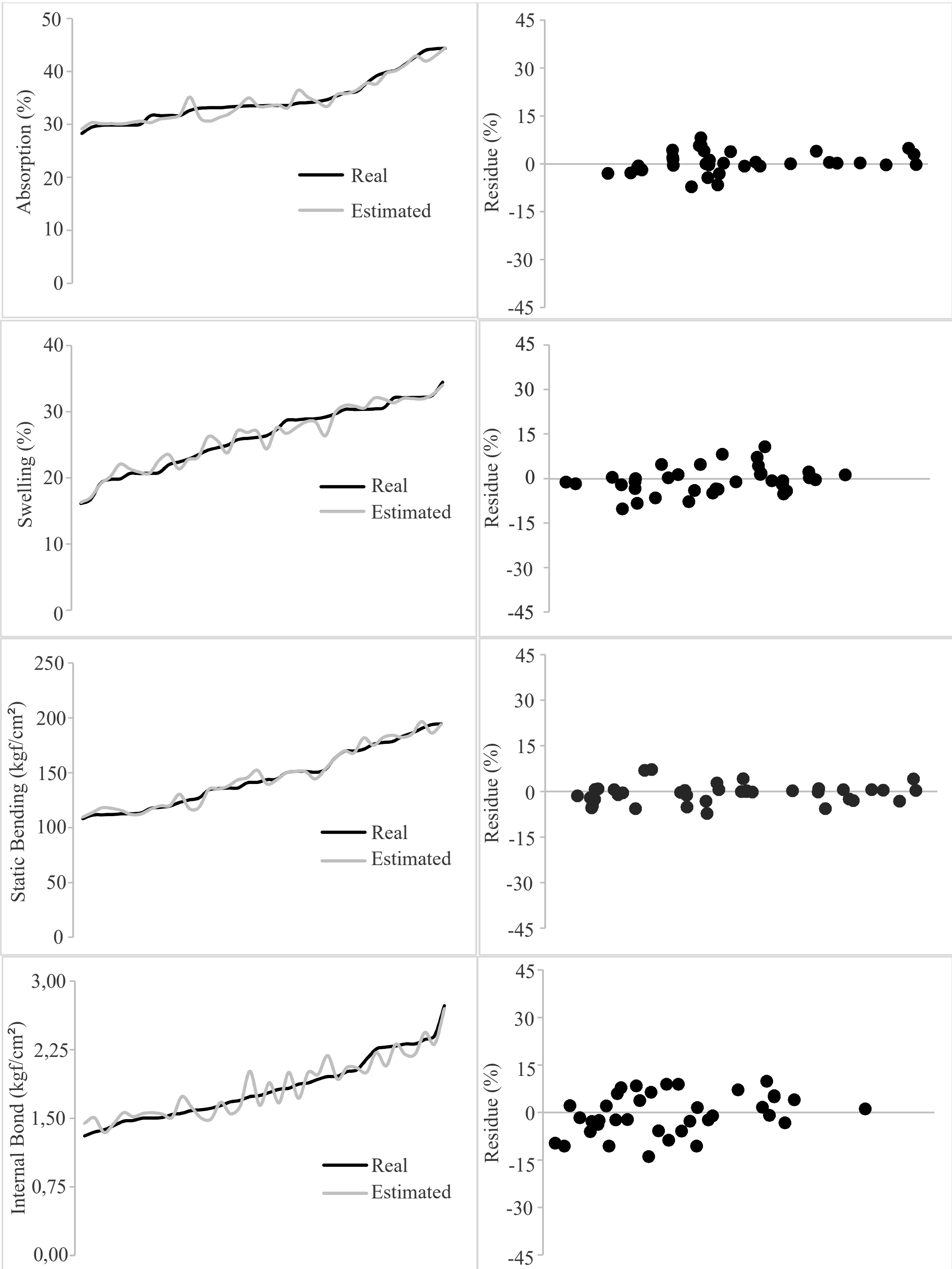

Figure 2 – Artificial Neural Networks selected - comparison between real and estimated values; and residue analysis - for the different physical and mechanical properties evaluated for particleboards.
Figura 2 – *Redes Neurais Artificias (RNA) selecionadas – comparação entre os valores reais e estimados; e análise de resíduos – para as diferentes propriedades físicas e mecânicas avaliadas para os painéis aglomerados.*

Table 2 – Average, maximum and minimum attributes, real, estimated and statistics for the validation, for physical and mechanical properties of particleboards evaluated.
Tabela 2 – *Atributos médios, mínimos e máximos, reais, estimados e estatísticas para a validação, para as diferentes propriedades físicas e mecânicas avaliada para os painéis aglomerados.*

Variables	Minimum	Average	Maximum	S_{yx} (%)	Ad (%)	χ^2 cal.	χ^2 tab.
Bending Adjustment	112,68	158,04	197,58				
Bending Validation	111,92	157,38	197,85	3,10	0,42	0,435	
Bond Adjustment	1,48	1,77	2,41				
Bond Validation	1,51	1,79	2,38	5,58	-0,71	0,585	3,325
Swelling Adjustment	19,16	30,92	39,17				
Swelling Validation	19,06	31,07	39,22	5,15	-0,45	0,512	
Absorption Adjustment	31,65	40,90	48,15				
Absorption Validation	30,33	40,94	49,85	5,47	-0,10	0,557	

Syx(%), standard error of estimate; Ad(%), aggregate difference; χ^2 cal, chi-square calculated; χ^2 tab chi-square tabulated with 95% and 9 Freedom degree.

In addition, percentage residual values close to zero are desirable since it shows the ability of the models in estimating the variables of interest with accuracy. Thus, a more detailed graphical analysis of the residuals was used throughout the amplitude of the variables of interest of the validation data, as can be observed in Figure 3.

4. DISCUSSION

Particleboard density was an exceptional predictor of the assessed properties. Such behaviour consolidates the feasibility in using the particleboard density as an input variable in the model and confirms the behaviour suggested by several authors, including Hillig et al. (2002), Iwakiri (2005), and Melo and Del Menezzi (2010), who state that the density is a variable closely related to the particleboard properties.

Commercialization requirements suggested by the American National Standard – ANSI 208.1 (ASTM, 1993) set the maximum values for thickness swelling and static bending strength at 35% and 112 kgf/cm^2, respectively. Therefore, meeting or not these standards depend on the choice of input variables assessed in this study (density and adhesive type). Thus, the ANN use is one of the possible alternatives for predicting these parameters and meeting the minimum requirements established for the commercialization of these products.

Iwakiri (2005) points out that particleboard quality is related to the interaction of several factors, such as density and adhesive type used. As for timber, the density is one of the parameters that most influence particleboard quality. Commercial particleboards are produced with a density varying between 0.60 and 0.70 g/cm^3, with resistance directly related to this parameter. Another important component in particleboard manufacturing is the adhesive, with significant technical and economic implications of the use of wood-based products.

Mendas and Delali (2012) emphasize that the use of artificial intelligence has a great potential for a variety of application, especially in engineering and agriculture. However, Cartwright (2008) states that there must be a direct relation between the input parameters and a target response. For Gürüler et al. (2015), usually, the networks are produced to perform a non-linear mapping from a set of inputs and outputs interconnected. In these cases, ANN is developed aiming to achieve a performance of a typical biological system based on the interconnections of these elements, similarly to what happens with the biological neurons. Additionally, Jain and Martin (1998) report that ANN presents some advantages over the conventional techniques, such as the ability of generalization, parallelism and the possibility of learning.

Draper and Smith (1998) point out that even if the adjustment estimators are good indicators to be used in selecting the models, they cannot be used alone. According to these authors, the graphical analysis of residual is essential in choosing the equation since the error tendency can occur in a particular amplitude of class of the response variable, without being detected by the statistics that measures the accuracy. Therefore, when assessing the graphical distribution of residuals (Figure 2), we could note that all selected networks for the different physical and mechanical components of particleboards had satisfactory behaviour in relation

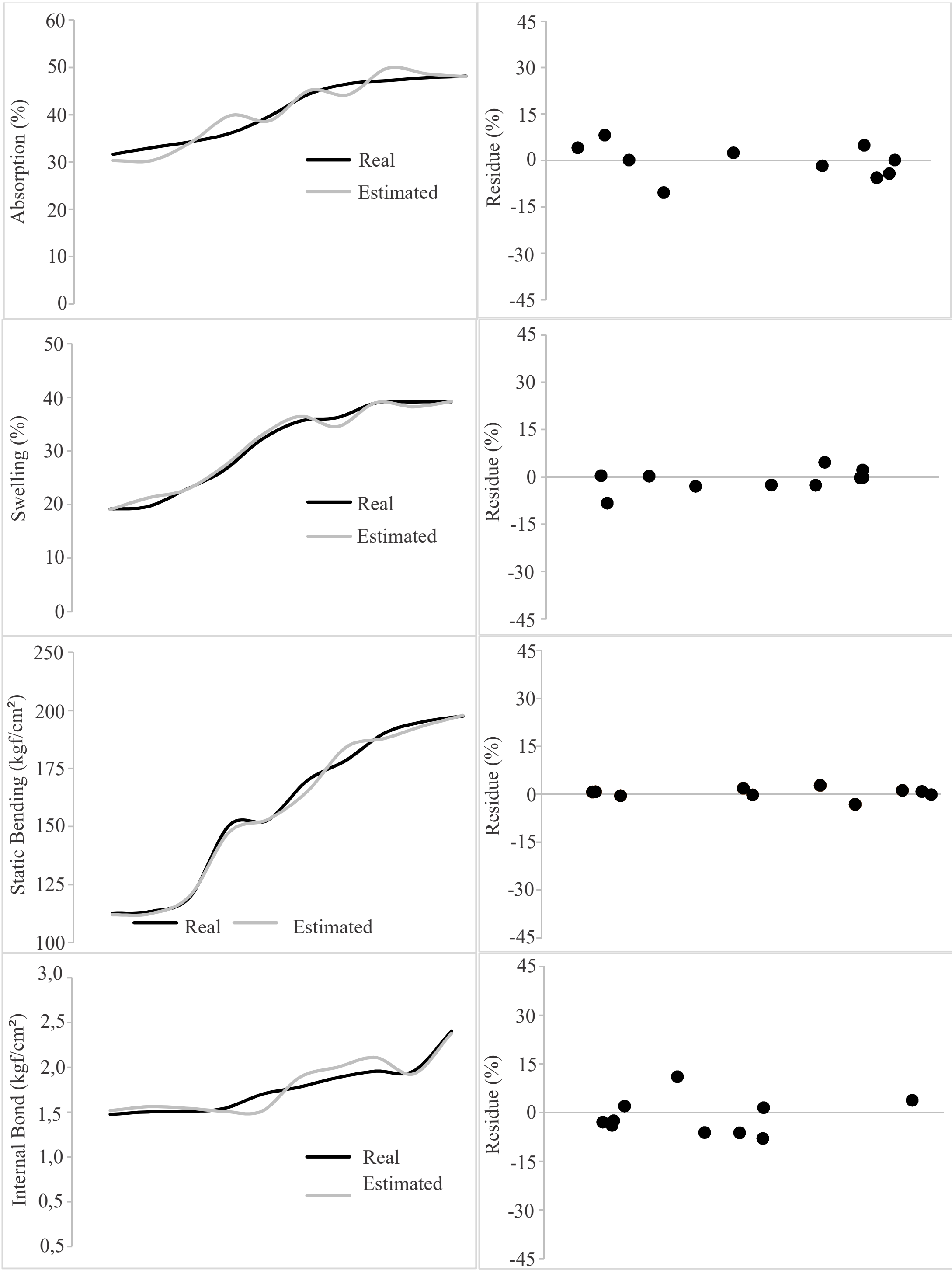

Figure 3 – Artificial Neural Networks validation - comparison between real and estimated values; and residue analysis - for the different physical and mechanical properties evaluated for particleboards.
Figura 3 – *Validação das Redes Neurais Artificias (RNA) – comparação entre os dados ajustados e estimados; e análise de resíduos – para as diferentes propriedades físicas e mecânicas avaliadas para os painéis aglomerados.*

to the residual dispersion, demonstrating the ANN effectiveness in predicting these properties.

5. CONCLUSIONS

The results obtained in this study indicate artificial neural networks (ANN) feasibility in predicting the main physical and mechanical properties of particleboards. The adjusted and validated models were able to estimate accurately these properties using as input variables the density and adhesive type used in the particleboard manufacturing.

These results are highly relevant as they influence positively in planning the production of these products. However, new studies involving the use of ANN for different raw materials and particleboard compositions, as well as different adhesives, should be developed to assist the decision-making regarding the choice of different production process aspects (type and size of particle, type and quantity of adhesive, density, time and pressure of pressing, etc.) known to influence particleboard quality.

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