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Prediction of standard particleboard mechanical properties utilizing an artificial neural network and subsequent comparison with a multivariate regression model

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Abstract

The physical properties (specific gravity, moisture content, thickness swelling and water absorption) and mechanical properties (internal bond strength, bending strength and modulus of elasticity) were determined on 93 Spanish-manufactured standard particleboards of different thicknesses selected randomly at the end of the production process. The testing methods of the corresponding European standards (EN) were used, except in the case of the thickness swelling and absorption tests, for which the Spanish UNE standard was used. The thickness and the values obtained for the physical properties were entered into an artificial neural network in order to predict the mechanical properties of the board. The fit was compared with the usual multivariate regression models. The use of a neural network made it possible to obtain the values of bending strength, modulus of elasticity and internal bond strength of the boards utilizing the known data, not only of thickness, moisture content and specific gravity, but also of thickness swelling and water absorption. The neural network proposed is much better adapted to the observed values than any of the multivariate regression models obtained.

Key words: wood-based panels, physico-mechanical properties, ANN, regression fit, predictive model.

Resumen

Predicción de propiedades mecánicas del tablero de partículas estándar mediante una red neuronal artificial y comparación con un modelo de regresión multivariante

Se han determinado las propiedades físicas (densidad, humedad, hinchazón en espesor y absorción de agua) y mecánicas (tracción perpendicular a las caras, resistencia a flexión y módulo de elasticidad) de 93 tableros de partículas estándar de diferentes espesores, de fabricación española, elegidos aleatoriamente a la salida del proceso de producción, utilizando los métodos de ensayo recogidos en las normas EN correspondientes, excepto en los ensayos de hinchazón y absorción que se ha utilizado norma UNE (española). El espesor y los valores obtenidos de las propiedades físicas han sido introducidos en una red neuronal artificial (RNA) para predecir las propiedades mecánicas del tablero. El ajuste se ha comparado con los habituales modelos de regresión multivariante. La utilización de una red neuronal ha permitido obtener los valores de resistencia a flexión, módulo de elasticidad y resistencia a la tracción perpendicular a las caras de los tableros de partículas a través de los datos conocidos, no sólo de espesor, humedad y densidad sino también de hinchazón en espesor y absorción de agua. La red neuronal propuesta tiene una adecuación a los valores experimentales muy superior a cualquiera de los modelos de regresión multivariante obtenidos.

Palabras clave: tableros derivados de la madera, propiedades físico-mecánicas, RNA, ajuste por regresión, modelo predictivo.

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Introduction

Annual consumption of particleboard in Spain and Portugal stands at around 3.8 million cubic meters. It is a material primarily used in carpentry, furniture and construction.

Studies to determine the physical and mechanical properties of particleboard began in Spain right from the time the industry was established in the mid 1960s (García Esteban *et al.,* 2002).

The physico-mechanical properties of particleboard are an indication of quality and suitability in relation to the proposed use of the board. In most cases the testing methods listed in the specific standards for determining these properties require sophisticated equipment and, in general, long periods of time. In fact, results are normally obtained several hours or even several days after the manufacture of the board, which means there is some delay in detecting problems in the final product (Cook *et al.,* 2000).

This is why obtaining models capable of predicting properties such as bending strength and internal bond strength through the use of other properties which are quicker and easier to determine, such as moisture content, specific gravity, swelling and absorption, can be an extremely useful instrument in the production control process. The references consulted showed studies that relate the strength properties to the specific gravity and moisture content of the board, both of particle and fibreboard, with positive results in all cases (Halligan and Schniewind, 1974; Mc Nat, 1974; Vital *et al.,* 1974; Kelly, 1977; Hayashi *et al.,* 2003; Wong *et al.,* 2003; Cai *et al.,* 2004; Nemli *et al.,* 2007). However, in addition to specific gravity and moisture content, the present study included thickness swelling and water absorption to determine the prediction of internal bond strength (IB), bending strength (MOR) and modulus of elasticity (MOE).

In order to establish the model an artificial neural network (ANN) was developed. Although such models have existed for some sixty years, they were not fully developed until recent times, with the appearance of more powerful computers.

Artificial neural networks can be regarded as a complex group of interconnected non-linear functions (transfer functions or neurons) capable of self-adjusting using known input and output data. It could be said that these networks are multiple regression models in which the algorithm allowing a solution to be reached is unknown, or where the enormous complexity of the algorithm makes it impossible to use (Pérez and Martín, 2003).

Neural networks consist of three layers: an input layer, a hidden layer and an output layer. The input layer receives the initial values of the variables; the output layer shows the results of the network for the input values; and the hidden layer performs the operations designed to obtain an output. The input layer must have as many neurons as there are input variables, and the output layer must have as many neurons as the outputs produced by the network. However, there is no rule to enable it to be decided beforehand how many neurons should make up the hidden layer or whether the hidden layer needs to be made up of more than one sublayer (Isasi and Galván, 2004), which means that the only way to ascertain this is by means of a process of trial and error. Neural networks are usually represented as $[n_1\ n_{2,1}\ n_{2,2} \ldots\ n_{2,m}\ n_3]$, where n_1 is the number of neurons in the input layer, $n_{2,i}$ the number in the hidden layers and n_3 the number in the output layer (Fig. 1).

These networks are based on biological neural networks. They are capable of learning by using a series of examples, without the need to know beforehand the relations which may exist between the variables involved in the process, by adjusting the weight of the relations between the variables in order to then predict a coherent result when new data unknown to the network is entered.

This method has been widely used in the field of wood, in the prediction of thermal conductivity of wood through its chemical composition (Avramidis and Iliadis, 2005a), in obtaining hygroscopic equilibrium points (Avramidis and Iliadis, 2005b), in the classification of wood species using ultrasound (Jordan *et al.,* 1998), in the classification of wood defects (Drake and Packianather, 1998; Ramírez and Chacón, 2005), in the structural classification of wood using non destructive methods (Mier *et al.,* 2005), in obtaining the values of internal bond of particleboard by using the manufacturing parameters (Cook *et al.,* 1991; Cook and Whittaker, 1992; Cook and Whittaker; 1993; Cook and Chiu, 1997) and for anatomical distinction between species of the same genus by using their biometry (García Fernández *et al.,* 2007).

The aim of this study was to develop an artificial neural network in order to obtain three mechanical properties - internal bond strength, MOR and MOE - of particleboard of different thicknesses manufactured in Spain, utilizing thickness and four physical properties - specific gravity, moisture content, thickness swelling and water absorption. In addition, this predictive

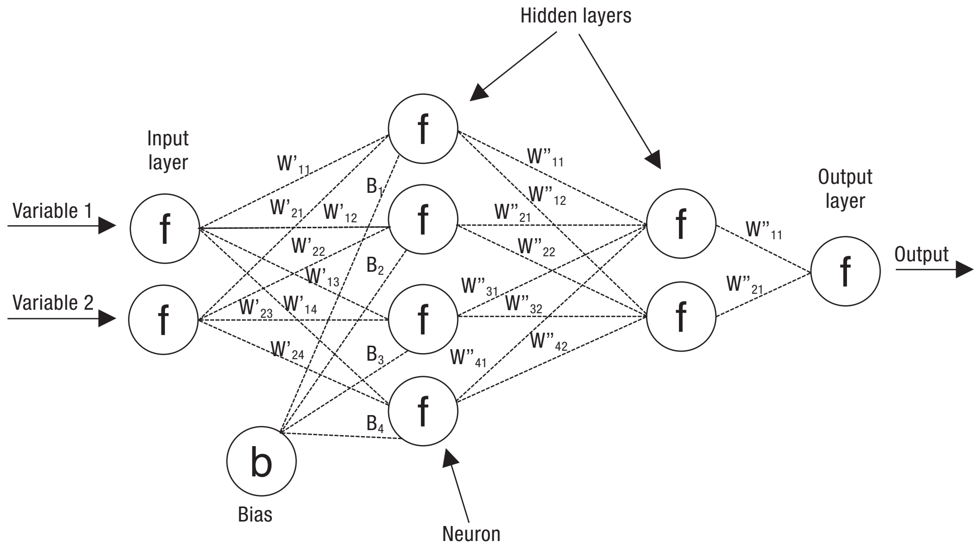

Figure 1. General artificial neural network architecture [2 4 2 1].

neural model was compared with the usual multivariate regression models.

Material and Methods

The study used 93 Spanish-manufactured standard particleboards classified as P2 by the UNE-EN 312 (AENOR, 2004) standard, of different thicknesses and with measurements of 2,440 × 1,220 mm. The boards were made up of pine wood (*Pinus pinaster* Aiton, *Pinus radiata* D. Don), eucalyptus wood at less than 10% (Eucaliptus globulus Labill), and urea-formaldehyde adhesive. The following physical and mechanical properties of the boards were determined: thickness swelling and water absorption (UNE 56713) (AENOR, 1971), moisture content (UNE-EN 322) (AENOR, 1994c), specific gravity (UNE-EN 323) (AENOR, 1994d), internal bond strength of the board (UNE-EN 319) (AENOR, 1994b), and MOR and MOE (UNE-EN 310) (AENOR, 1994a). In the case of ascertaining the swelling and absorption of the board, the Spanish rather than the European standard was used, as the Spanish standard requires a shorter testing time of two hours as opposed to the 24 hours specified in the European standard.

For the preparation of the test pieces, their measurements and the expression of the test results, the UNE-EN 325 (AENOR, 1994e) and UNE-EN 326-1 (AENOR, 1995) standards were used. The test pieces were conditioned in a conditioning chamber at 20 ± 2°C and 65 ± 5% relative humidity until constant weight was reached, in accordance with the testing standard used.

The laboratory has been accredited since 2000 for the associated tests by the Entidad Nacional de Acreditación (ENAC) —Spanish National Accreditation Body— in accordance with the UNE-EN ISO/IEC 17025:2005 standard «General requirements for the competence of testing and calibration laboratories».

The following equipment was used to determine the physical properties: a COBOS C-600-SX scale with a range of 0-600 g and a 0.01 g scale division; a MITUTOYO Digimatic digital calliper with a range of 0-300 mm and a 0.01 mm scale division; and MITUTOYO IDF 1,050 dial gauges with a range of 0-50 mm and 0.01 mm scale division. For the mechanical tests a MICROTEST universal testing machine was used, with a load cell of 5,000 N, class 0.5%.

A multivariate regression model was obtained using thickness, specific gravity, moisture content, thickness swelling and water absorption as independent variables, while the internal bond strength, MOR and MOE were established as dependent variables in order to show that the independent variables have an influence on the proposed model and to obtain regression coefficients with which to subsequently compare the neural network obtained.

The equations based on the models proposed by Halligan and Schniewind (1974) [Eq. 1-6] were used for the regression model:

$$IB = a_1 \cdot T + a_2 \cdot MC + a_3 \cdot SG + a_4 \cdot TS + a_5 \cdot WA + c \qquad [1]$$

$$MOR = a_1 \cdot T + a_2 \cdot MC + a_3 \cdot SG + a_4 \cdot TS + a_5 \cdot WA + c \quad [2]$$

$$MOE = a_1 \cdot T + a_2 \cdot MC + a_3 \cdot SG + a_4 \cdot TS + a_5 \cdot WA + c \quad [3]$$

$$\begin{aligned} IB = {} & a_1 \cdot T + a_2 \cdot MC + a_3 \cdot SG + a_4 \cdot TS + a_5 \cdot WA + \\ & + a_6 \cdot T^2 + a_7 \cdot MC^2 + a_8 \cdot SG^2 + a_9 \cdot TS^2 + a_{10} \cdot WA^2 + c \end{aligned} \quad [4]$$

$$\begin{aligned} MOR = {} & a_1 \cdot T + a_2 \cdot MC + a_3 \cdot SG + a_4 \cdot TS + a_5 \cdot WA + \\ & + a_6 \cdot T^2 + a_7 \cdot MC^2 + a_8 \cdot SG^2 + a_9 \cdot TS^2 + a_{10} \cdot WA^2 + c \end{aligned} \quad [5]$$

$$\begin{aligned} MOE = {} & a_1 \cdot T + a_2 \cdot MC + a_3 \cdot SG + a_4 \cdot TS + a_5 \cdot WA + \\ & + a_6 \cdot T^2 + a_7 \cdot MC^2 + a_8 \cdot SG^2 + a_9 \cdot TS^2 + a_{10} \cdot WA^2 + c \end{aligned} \quad [6]$$

IB = internal bond strength
T = thickness
MC = moisture content
SG = specific gravity
TS = thickness swelling
WA = water absorption.

The characterization of the network is based on the definition of the type of network and the transfer functions. For the network a feedforward multilayer percepton was used, trained by means of the backpropagation algorithm, one of the most commonly used algorithms in the references consulted (Krauss *et al.,* 1997; Drake and Packianather, 1998; Myhara and Sablani, 2001; Panchariya *et al.,* 2002; Nordmark, 2002; Avramidis and Iliadis, 2005a; Hernández-Pérez *et al.,* 2004; Diamantopoulou, 2005; Singh *et al.,* 2007; Peng *et al.,* 2007).

The transfer function used was a variant of the hyperbolic tangent (Myhara and Sablani, 2001; Hernández-Pérez *et al.,* 2004; Diamantopoulou, 2005), more specifically the hyperbolic tangent sigmoid transfer function (tansig) (Krauss *et al.,* 1997; Demuth *et al.,* 2002) [Eq. 7], which achieves the output much faster and is mathematically equivalent, improving the functioning of the network (Demuth *et al.,* 2002).

$$f(x) = \frac{2}{1 + e^{(-2x)}} - 1 \quad [7]$$

f(x) = output value of the neuron
x = input value of the neuron

As the output values of the transfer function are in the range of (–1, 1) the input and output data were normalized before the network was trained, by means of the equation [8] (Krauss *et al.,* 1997; Demuth *et al.,* 2002; Peng *et al.,* 2007).

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad [8]$$

X' = value after normalization of vector X
X_{min} and X_{max} = maximum and minimum values of vector X

The network training method was carried out by means of supervised learning (Hagan *et al.,* 1996; Haykin, 1999; Pérez and Martín, 2003; Isasi and Galván, 2004), for which purpose the results were divided into two groups selected at random and without repetition: the training group (80 boards, 88% of the total) and the testing group (13 boards, 12% of the total), in very similar percentages to those used by Cook and Chiu (1997). For the training the resilient backpropagation algorithm was used (Demuth *et al.,* 2002; Singh *et al.,* 2007), which improves the results of the learning in the case of sigmoid transfer functions (Demuth *et al.,* 2002). A very common problem in network training is overfitting, which is most obvious in the increase of the error in the testing group coupled with a progressive decrease in the error of the training group (Haykin, 1999; Isasi and Galván, 2004). To avoid this, an early-stopping method was used, as described in Demuth *et al.* (2002). For this purpose, every 5,000 epochs the regression coefficients between the value obtained and the expected value in the testing group were obtained (De Veaux and Ungar, 1996). The training ceases as soon as an increase in the error of the testing group is detected.

The mean square error value (MSE) (Panchariya *et al.,* 2002; Kalogirou *et al.,* 2003) and the correlation coefficients R between the real and the expected value were used to assess the results of the learning process. The correlation coefficient R and the prediction error [Eq. 9] were used to assess the testing process, taking into account that for particleboard manufacturing processes the prediction of strength values with an error of 15% is regarded as acceptable, while an error of 20-30% is not (Cook and Chiu, 1997; Malinov *et al.,* 2001).

$$error\% = 100 \cdot \frac{\left(V_{pred} - V_{obs}\right)}{V_{obs}} \quad [9]$$

error % = prediction error
V_{pred} = predicted value by network
V_{obs} = observed value in testing

For accepting the correlation factor R, the UNE-EN 326-2 (AENOR, 2001) standard was taken into consi-

Table 1. Multivariate regression models

Equation	Parameters (95% confidence interval)	R^2	R	F	p-value	MSE
[10]	$a_1 = 2.03 \cdot 10^{-3}$ ($-4.88 \cdot 10^{-3}$, $8.03 \cdot 10^{-4}$) $a_2 = 3.55 \cdot 10^{-2}$ ($1.30 \cdot 10^{-2}$, $5.80 \cdot 10^{-2}$) $a_3 = 1.36 \cdot 10^{-3}$ ($7.47 \cdot 10^{-4}$, $1.97 \cdot 10^{-3}$) $a_4 = -1.36 \cdot 10^{-3}$ ($-2.66 \cdot 10^{-2}$, $7.98 \cdot 10^{-4}$) $a_5 = -1.38 \cdot 10^{-3}$ ($-4.75 \cdot 10^{-3}$,$1.99 \cdot 10^{-3}$) c = –0.54 (–1.13, 0.04)	0.48	0.70	16.17	$3.02 \cdot 10^{-11}$	$5.05 \cdot 10^{-3}$
[11]	$a_1 = 0.01$ (–0.14, 0.15) $a_2 = 0.79$ (–0.36, 1.95) $a_3 = 0.05$ (0.02, 0.08) $a_4 = 0.90$ (0.24, 1.56) $a_5 = -0.02$ (–0.19, 0.15) c = –31.94 (–61.76, –2.12)	0.26	0.51	6.13	$6.51 \cdot 10^{-5}$	13.34
[12]	$a_1 = 9.64$ (–3.39, 22.67) $a_2 = -10.44$ (–113.37, 92.49) $a_3 = 8.72$ (5.91, 11.52) $a_4 = 21.82$ (–37.25, 80.88) $a_5 = -0.39$ (–15.81, 15.03) c = –3,208.5 (–5,866.3, –550.6)	0.42	0.64	12.83	$2.40 \cdot 10^{-9}$	105,986.81
[13]	$a_1 = -0.01$ (–0.03, 0.01) $a_2 = -0.10$ (–0.31, 0.11) $a_3 = 6.12 \cdot 10^{-4}$ ($-1.34 \cdot 10^{-2}$, $1.46 \cdot 10^{-2}$) $a_4 = -0.01$ (–0.08, 0.05) $a_5 = -0.01$ (–0.02, 0.01) $a_6 = 2.01 \cdot 10^{-4}$ ($-1.52 \cdot 10^{-4}$, $5.53 \cdot 10^{-4}$) $a_7 = 6.08 \cdot 10^{-3}$ ($--3.56 \cdot 10^{-3}$, $1.57 \cdot 10^{-2}$) $a_8 = 3.52 \cdot 10^{-7}$ ($-1.02 \cdot 10^{-5}$, $1.10 \cdot 10^{-5}$) $a_9 = -3.86 \cdot 10^{-5}$ ($-5.85 \cdot 10^{-3}$, $5.78 \cdot 10^{-3}$) $a_{10} = 1.29 \cdot 10^{-4}$ ($-1.72 \cdot 10^{-4}$, $4.31 \cdot 10^{-4}$) c = 0.72 (–3.92, 5.36)	0.51	0.71	8.48	$2.46 \cdot 10^{-9}$	$4.79 \cdot 10^{-3}$
[14]	$a_1 = 0.50$ (–0.31, 1.31) $a_2 = 8.95$ (–0.84, 18.75) $a_3 = -0.55$ (–1.20, 0.11) $a_4 = = -5.63$ (–8.79, –2.47) $a_5 = 0.82$ (0.10, 1.54) $a_6 = -0.01$ (–0.03, 0.04) $a_7 = -0.43$ (–0.88, 0.02) $a_8 = 4.59 \cdot 10^{-4}$ ($-3.48 \cdot 10^{-5}$, $9.53 \cdot 10^{-4}$) $a_9 = 0.58$ (0.31, 0.86) $a_{10} = -0.01$ ($-2.73 \cdot 10^{-2}$, $7.88 \cdot 10^{-4}$) c = 124.45 (–91.70, 340.60)	0.42	0.65	6.03	$8.37 \cdot 10^{-7}$	10.40
[15]	$a_1 = 125.90$ (50.93, 200.87) $a_2 = -67.67$ (–974.65, 839.32) $a_3 = -57.48$ (–118.02, 3.07) $a_4 = -300.51$ (–593.18, –7.83) $a_5 = 49.22$ (–17.77, 116.20) $a_6 = -2.51$ (–4.03, –0.99) $a_7 = 5.07 \cdot 10^{-2}$ ($5.05 \cdot 10^{-3}$, $9.64 \cdot 10^{-2}$) $a_8 = 1.18$ (–40.43, 42.79) $a_9 = 30.01$ (4.92, 55.11) $a_{10} = -0.93$ (–2.23, 0.37) c = 17,713.95 (–2,294.86, 37,722.76)	0.52	0.72	8.74	$1.38 \cdot 10^{-4}$	89,105.48

deration. This standard specifies a value of the correlation coefficient of 0.70 for accepting the relation between the test values obtained by a standardized test and those obtained by an alternative method.

For the calculations of the multivariate regression model Statistics Toolbox® ver. 4 was used, and for the creation of the artificial neural network the Neural Network Toolbox® ver. 4.0.2 was used. Both of these are part of the MATLAB® ver. 6.5.0. Release 13 programme.

Results and Discussion

In regression model building, there is little to be gained by separating data into parts for fitting and testing (Diamantopoulou 2005, Hirsch 1991). Therefore, for the fit of the regression model all the available data were used (Table 1).

The best determination coefficient, R^2, obtained is 0.52 for equation [15], which indicates that the models proposed are capable of explaining at best 52% of the values observed. These values are lower than those obtained by other authors (Halligan and Schniewind, 1974; Cai *et al.,* 2004). This may be due to the fact that the equations obtained by these authors were calculated using boards purposely manufactured for the studies under very controlled conditions, while the samples of the present study were taken from boards chosen at random from the production chain (Kelly, 1977).

However, the values obtained for the p-value indicate that it is highly unlikely that all the regression coefficients are zero (MathWorks Inc, 2002). It can therefore be stated that thickness, moisture content, specific gravity, thickness swelling and water absorption all have an influence on the result of the properties of internal bond strength, MOR and MOE. These results agree with those obtained by other authors (Halligan and Schniewind, 1974; Hayashi *et al.,* 2003; Nemli *et al.,* 2007).

In the neural network the values of moisture content, specific gravity, absorption and swelling and nominal thickness were used as input variables. Internal bond strength, MOR and MOE were used as output values.

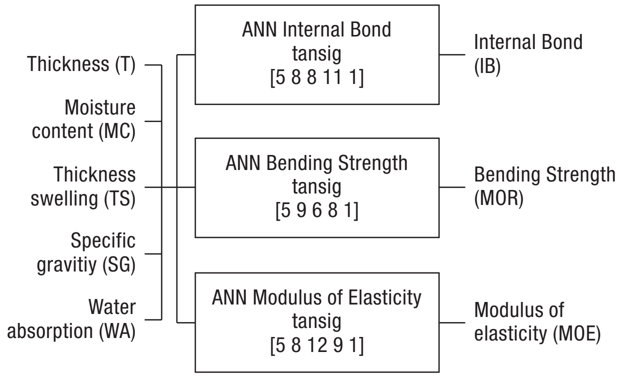

Figure 2. Architecture of the network used.

To obtain the mechanical properties through the physical properties three independent networks were designed, which is regarded as more efficient than a global network for the three mechanical properties (Sha and Edwards, 2007) (Fig. 2).

Although the amount of data available for the training was lower than necessary (222) (Sha, 2007) and the neural network proposed would not be completely mathematically defined, the purpose of the present study was not to determine all the parameters of the network, but rather to establish a group of parameters which would ensure a correct generalization by the network (Tompos *et al.,* 2007) and would satisfy the criterion specified in the UNE-EN 326-2 (AENOR, 2001) standard.

The results of the training process are shown in Table 2.

The R results are very similar to those in the references consulted, which range from 0.90 to 0.99 in the training process (Myhara *et al.,* 1998; Hernández-Pérez *et al.,* 2004; Peng *et al.,* 2007; Diamantopoulou, 2005; Avramidis and Iliadis, 2005a).

The graphs in Figure 3 show the correlations of the observed values versus the neural network predicted values in the training process.

For the testing, 13 randomly selected boards which had not previously been entered into the network were used (Table 3).

Table 2. Results of the training process

Subnetwork	Property	Network structure	R	Linear regression model	MSE
1	IB	[5 8 8 11 1]	0.997	$y = 0.99 \cdot x + 0.01$	$6.86 \cdot 10^{-4}$
2	MOR	[5 9 6 8 1]	0.989	$y = 0.98 \cdot x + 0.34$	$2.1 \cdot 10^{-3}$
3	MOE	[5 8 12 9 1]	1.0	$y = x + 8.15$	$1.34 \cdot 10^{-5}$

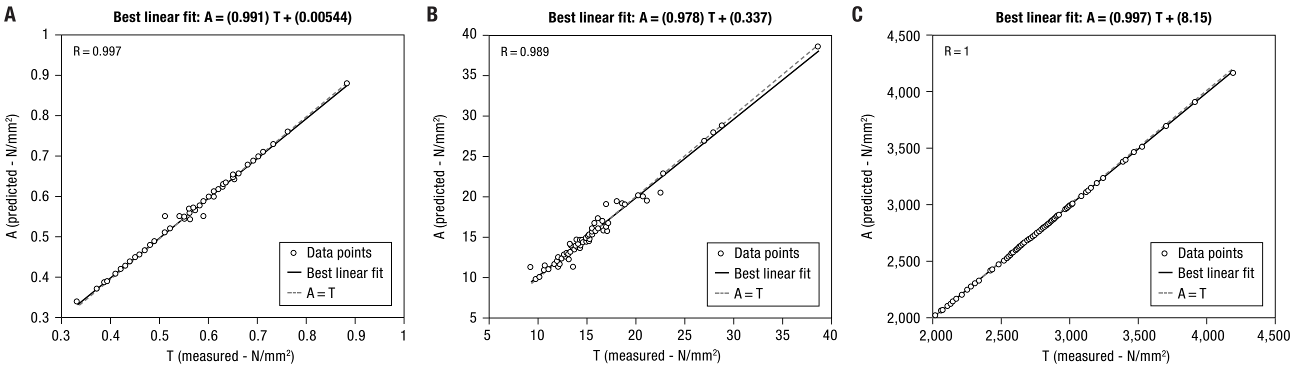

Figure 3. Correlation of observed values *vs.* neural network predicted values in the training process: internal bond strength (A) MOR (B) MOE (C).

Figure 4 shows the correlations of the observed values versus the neural network predicted values in the testing process.

The values of the correlation coefficient, R, concur with the data obtained by Cook *et al.* (2000) for the values of internal bond strength and bending using the parameters of the manufacturing process, and are higher than the specifications of the UNE-EN 326-2 (AENOR, 2001) standard for acceptance of results obtained by a method other than the standardized method ($R \geq 0.70$).

The fit is satisfactory, as the average prediction error of the values obtained for the properties of internal bond strength, MOR and MOE are much lower than 15% (Table 3), which means that the neural network can be regarded as appropriate for obtaining information on mechanical properties (Cook and Chiu, 1997). The values of the regression coefficient are higher than those obtained in any of the multivariate models.

Table 3. Results of the testing process

Subnetwork	Property	R	Linear regression model	Average error (%)
1	IB	0.872	$y = 1.54\,x - 0.292$	14.65
2	MOR	0.867	$y = 2.14\,x - 15$	13.79
3	MOE	0.872	$y = 1.71\,x - 1.54 \cdot 10^{-3}$	12.20

Data

No.	Internal bond strength			MOR			MOE		
	Observed	**Predicted**	**Error (%)**	**Observed**	**Predicted**	**Error (%)**	**Observed**	**Predicted**	**Error (%)**
1	0.72	0.87	–17.65	12.7	17.8	–28.49	2,177	2,056.6	5.85
2	0.61	0.43	40.40	13.9	16.4	–15.15	2,513	3,039	–17.31
3	0.36	0.34	5.78	21.8	37.64	–42.07	2,865	2,919.6	–1.87
4	0.58	0.68	–14.96	12.9	13.4	–3.59	2,618	3,172.2	–17.47
5	0.72	0.86	–16.65	16.6	19.04	–12.79	3,158	3,280	–3.72
6	0.64	0.68	–6.96	16.4	17.44	–5.97	2,867	3,436.2	–16.56
7	0.47	0.35	32.56	15.1	14.84	1.77	2,878	3,164.3	–9.05
8	0.52	0.51	2.84	10.8	11.3	–4.03	2,081	2,050.2	1.5
9	0.54	0.60	–10.39	14.3	16.0	–10.49	2,947	4,158.1	–29.13
10	0.52	0.42	23.44	12.8	9.6	33.52	2,434	2,429.5	0.18
11	0.52	0.57	–8.06	16.8	18.06	–6.76	2,736	3,100.1	–11.74
12	0.59	0.62	–4.99	15.2	16.4	–7.10	3,008	3,772.7	–20.27
13	0.54	0.51	5.79	16.2	15.1	7.50	3,164	4,157.5	–23.90
		Mean	**14.65**		**Mean**	**13.79**		**Mean**	**12.20**

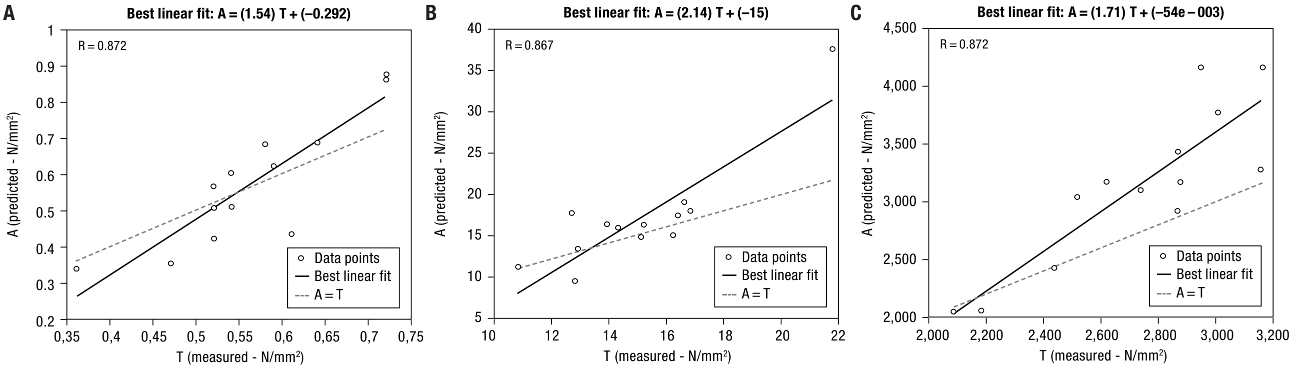

Figure 4. Correlation of observed values *vs.* neural network predicted values in the testing process: internal bond srength (A) MOR (B) MOE (C).

Conclusions

— The use of an artificial neural network allows the values of internal bond strength, MOR and MOE of particleboards to be obtained through the known data not only of thickness, moisture content and specific gravity, but also of thickness swelling and water absorption. The R values and the prediction error values concur with those previously obtained by other authors.

— The R value is higher than that required by the UNE-EN 326-2 (AENOR, 2001) standard for accepting the results obtained by methods other than the standardized method.

— The network calculated is much better adapted to the observed values than any of the multivariate regression models obtained.

References

ASOCIACIÓN ESPAÑOLA DE NORMALIZACIÓN (AENOR), 1971. Tableros de partículas. Ensayos. Determinación de la hinchazón y de la absorción de agua por inmersión total. Standard UNE 56713. Madrid, España.

ASOCIACIÓN ESPAÑOLA DE NORMALIZACIÓN (AENOR), 1994a. Tableros derivados de la madera. Determinación del módulo de elasticidad en flexión y de la resistencia a la flexión. Standard UNE-EN 310. Madrid, España.

ASOCIACIÓN ESPAÑOLA DE NORMALIZACIÓN (AENOR), 1994b. Tableros de partículas y tableros de fibras. Determinación de la resistencia a la tracción perpendicular a las caras del tablero. Standard UNE-EN 319. Madrid, España.

ASOCIACIÓN ESPAÑOLA DE NORMALIZACIÓN (AENOR), 1994c. Tableros derivados de la madera. Determinación del contenido de humedad. Standard UNE-EN 322. Madrid, España.

ASOCIACIÓN ESPAÑOLA DE NORMALIZACIÓN (AENOR), 1994d. Tableros derivados de la madera. Determinación de la densidad. Standard UNE-EN 323. Madrid, España.

ASOCIACIÓN ESPAÑOLA DE NORMALIZACIÓN (AENOR), 1994e. Tableros derivados de la madera. Determinación de las dimensiones de las probetas. Standard UNE-EN 325. Madrid, España.

ASOCIACIÓN ESPAÑOLA DE NORMALIZACIÓN (AENOR), 1995. Tableros derivados de la madera. Muestreo e inspección. Parte 1: Muestreo y despiece de probetas y expresión de los resultados de ensayo. Standard UNE-EN 326-1. Madrid, España.

ASOCIACIÓN ESPAÑOLA DE NORMALIZACIÓN (AENOR), 2001. Tableros derivados de la madera. Muestreo, despiece e inspección. Parte 2: Control de la calidad en fábrica. Standard UNE-EN 326-2. Madrid, España.

ASOCIACIÓN ESPAÑOLA DE NORMALIZACIÓN (AENOR), 2004. Tablero de Partículas. Especificaciones. Standard UNE-EN 312. Madrid, España.

AVRAMIDIS S., ILIADIS L., 2005a. Predicting wood thermal conductivity using artificial neural networks. Wood Fiber Sci 37(4), 682-690.

AVRAMIDIS S., ILIADIS L., 2005b. Wood-water sorption isotherm prediction with artificial neural networks: a preliminary study. Holzforschung 59, 336-341.

CAI Z., WU Q., LEE J., HIZIROGLU S., 2004. Influence of board density, mat construction, and chip type on performance of particleboard made from eastern red cedar. Forest Prod. J 54(12), 226-232.

COOK D.F., CHIU C.C., 1997. Predicting the internal bond strength of particleboard, utilizing a radial basis function neural network. Eng Appl Artif Intell 10(2), 171-177.

COOK D.F., MASSEY J.G., SHANNON R.E., 1991. A neural network to predict particleboard manufacturing process parameters. For Sci 5, 1463-1478.

COOK D.F., RAGSDALE C.T., MAJOR R.L., 2000. Combining a neural network with a genetic algorithm for process parameter optimization. Eng Appl Artif Intell 13, 391-396.

COOK D.F., WHITTAKER A.D., 1992. Neural network models for prediction of process parameters in wood products manufacturing. 1st Industrial Engineering Research Conference, Chicago, 20-21 May. pp. 209-211.

COOK D.B. WHITTAKER, A.D., 1993. Neural-network process modelling of a continuous manufacturing operation. Eng Appl Artif Intell 6, 559-564.

DE VEAUX R.D., UNGAR L.G., 1996. A brief introduction to neural networks. [en línea]. Disponible en http://www.williams.edu/mathematics/rdeveaux/pubs.html [Consulta: 27 marzo 2008].

DEMUTH H., BEALE M., HAGAN M., 2002. Neural Network Toolbox user's guide, version 4. Natick: The Mathworks Inc, MA 01760, USA. 808 pp.

DIAMANTOPOULOU M.J., 2005. Artificial neural networks as an alternative tool in pine bark volume estimation. Comput Electron Agric 48, 235-244.

DRAKE P.R., PACKIANATHER M.S., 1998. A decision tree of neural networks for classifying images of wood veneer. Int J Adv Manuf Technol 14, 280-285.

GARCÍA ESTEBAN L., GUINDEO A., PERAZA C., DE PALACIOS P., 2002. La madera y su tecnología. En: Tableros de partículas y de fibras. Fundación Conde del Valle de Salazar-Mundi Prensa-AITIM, Madrid, España. pp. 117-157.

GARCÍA FERNÁNDEZ F., GARCÍA ESTEBAN L., DE PALACIOS DE PALACIOS P., GUINDEO CASASÚS A., 2007. Use of an artificial neural network to differentiate the wood of *Juniperus cedrus* Webb & Bertel and *Juniperus canariensis* Guyot. Pan-American IAWA Meeting 2007, San Luis Potosi, México, July 15-20.

HAGAN M.T., DEMUTH H.B., BEALE M., 1996. Neural network design. PWS Pub Co, Boston, USA. 732 pp.

HALLIGAN A.F., SCHNIEWIND A.P., 1974. Prediction of particleboard mechanical properties at various moisture contents. Wood Sci Technol 8(1), 68-78.

HAYASHI K., OHMI M., TOMINAGA H., FAKUDA K., 2003. Effect of board density on bending properties and dimensional stabilities of MDF-reinforced corrugated particleboard. J Wood Sci 49, 398-404.

HAYKIN S., 1999. Neural networks: a comprehensive foundation. Prentice Hall, 2nd ed, New Jersey, USA. 842 pp.

HERNÁNDEZ-PÉREZ J.A., GARCÍA-ALVARADO M.A., TRYSTAM G., HEYD B., 2004. Neural networks for the heat and mass transfer prediction during drying of cassava and mango. Innovative Food Science and Emerging Technologies 5, 57-64.

HIRSCH R.P., 1991. Validation samples. Biometrics 47(3), 1193-1194.

ISASI P., GALVÁN I.M., 2004. Redes neuronales artificiales, un enfoque práctico. Pearson Educación, SA, Madrid, España. 229 pp.

JORDAN R., FEENEY F., NESBITT N., EVERTSEN J.A., 1998. Classification of wood species by neural network analysis of ultrasonic signals. Ultrasonic 36, 219-222.

KALOGIROU S., EFTEKHARI M., MARJANOVIC L., 2003 Predicting the pressure coefficients in a naturally ventilated test room using artificial neural networks. Build Environ 38, 399-407.

KELLY M.W., 1977. Critical literature review of relationships between processing parameters and physical properties of particleboard. Madison: USDA Forest Service Research Paper, FPL 10, Forest Products Laboratory, Wis 53705, USA. 70 pp.

KRAUSS G., KINDANGEN J.I., DEPECKER P., 1997 Using artificial neural networks to predict interior velocity coefficients. Build Environ 4, 295-303.

MALINOV S., SHA W., MCKEOWN J.J., 2001. Modelling the correlation between processing parameters and properties in titanium alloys using artificial neural network. Comput Mater Sci 21, 375-394.

MATHWORKS INC., 2002. Statistics toolbox user's guide, revised for version 4.1. Natick, MA 01760, USA.816 pp.

MCNATT J.D., 1974. Properties of particleboards at various humidity conditions. Madison: USDA Forest Service Research Paper, FPL 225, Forest Products Laboratory, Wis 53705, USA. 25 pp.

MIER R., GARCÍA DE CECA J.L., DÍEZ M.R., FERNÁNDEZ-GOLFÍN J.I., HERMOSO E., 2005. Aplicación de redes neuronales a la clasificación visual de madera estructural. Comparación con otros métodos de clasificación. IV Congreso Forestal Español, 26-30 Zaragoza.

MYHARA R.M., SABLANI S., 2001. Unification of fruit water sorption isotherm using artificial neural networks. Dry Technol 19(8), 1543-1554.

MYHARA R.M., SABLANI S., AL-ALAWI S.M., TAYLOR M.S., 1998. Water sorption isotherms of dates: modeling using GAB and artificial neural network approaches. Food Science and Technology - Lebensmittel- Wissenschaft & Technologie 31, 699-706.

NEMLI G., AYDIN I., ZEKOVIÇ E., 2007. Evaluation of some of the properties of particleboard as function of manufacturing parameters. Mater Des 28, 1169-1176.

NORDMARK U., 2002. Knot identification from CT images of young *Pinus sylvestris* sawlogs using artificial neural networks. Scand J Forest Res 17, 72-78.

PANCHARIYA P.C., POPOVIC D., SHARMA A.L., 2002. Desorption isotherm modeling of black tea using artificial neural networks. Dry Technol 20(2), 351-362.

PENG G., CHEN X., WU W., JIANG X., 2007. Modeling of water sorption isotherm for corn starch. J Food Eng 80, 562-567.

PÉREZ M.L., MARTÍN Q., 2003. Aplicaciones de las redes neuronales a la estadística. Cuadernos de Estadística. Ed La Muralla, SA, Madrid, España. 140 pp.

RAMÍREZ G., CHACÓN M.I., 2005. Clasificación de defectos en madera utilizando redes neuronales artificiales. Computación y Sistemas 9(1), 17-27.

SHA W., 2007. Comment on the issues of statistical modelling with particular reference to the use of artificial neural networks. Appl Catal A-Gen 324, 87-89.

SHA W., EDWARDS K.L., 2007. The use of artificial neural networks in materials science based research. Mater Des 6, 1747-1752.

SINGH T.N., SHINA S., SINGH V.K., 2007. Prediction of thermal conductivity of rock through physico-mechanical properties. Build Environ 42, 146-155.

TOMPOS A., MARGITFALVI J.L., TFIRST E., HÉBERGER K., 2007. Predictive performance of «highly complex» artificial neural networks. Appl Catal A-Gen 324, 90-93.

VITAL B.R., LEHMANN W.F., BOONE R.S., 1974. How species and board densities affect properties of exotic hardwood particleboards. Forest Prod J 24(12), 37-45.

WONG E.D., YANG P., ZHANG M., WANG Q., NAKAO T., LI K.F., KAWAI S., 2003. Analysis of the effects of density profile on the bending properties of particleboard using finite element method (FEM). Holz Als Roh-und Werkst 61, 66-72.