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Artificial neural networks in variable process control: application in particleboard manufacture

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Abstract

Artificial neural networks are an efficient tool for modelling production control processes using data from the actual production as well as simulated or design of experiments data. In this study two artificial neural networks were combined with the control process charts and it was checked whether the data obtained by the networks were valid for variable process control in particleboard manufacture.

The networks made it possible to obtain the mean and standard deviation of the internal bond strength of the particleboard within acceptable margins using known data of thickness, density, moisture content, swelling and absorption. The networks obtained met the acceptance criteria for test values from non-standard test methods, as well as the criteria for using these values in statistical process control.

Key words: Artificial neural networks (ANN), statistical process control (SPC), internal bond strength, wood based panels.

Resumen

Redes neuronales artificiales en el control de procesos por variables: aplicación en la fabricación de tableros de partículas

Las redes neuronales artificiales son una herramienta eficaz para el modelado de los procesos de control de producción, tanto partiendo de datos de la propia producción como de datos simulados o procedentes de diseños de experimentos. En este estudio se han combinado dos redes neuronales artificiales con los gráficos de control de procesos y se ha comprobado si los datos obtenidos con ellas eran válidos para el control de producción por variables en la fabricación de tableros de partículas.

Las redes han permitido obtener valores de la media y la desviación típica de la cohesión interna del tablero de partículas dentro de unos márgenes aceptables a partir de datos conocidos de espesor, densidad, contenido de humedad, hinchazón y absorción. Las redes obtenidas han cumplido con los requisitos de aceptación de valores de ensayo por métodos alternativos al normalizado y con los requisitos impuestos para su utilización en el control estadístico de procesos.

Palabras clave: Redes neuronales artificiales (RNA), control estadístico de procesos (CEP), resistencia a la tracción interna, tableros derivados de madera.

1. Introduction

The application of statistical methods to production quality control began in the early 1920s. The Bell Telephone Company was the first to apply statistical control charts and develop statistical acceptance sampling. However, it was not until the Second World War that the importance of these techniques was really taken into

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account. The need to improve and control the quality of manufactured products led several companies to adopt production control techniques. 1946 saw the creation of the American Society for Quality, which encouraged the use of quality improvement techniques for both products and services. However, these techniques were not applied in companies until the 1960s in Japan and the 1970s in Europe and America. The first companies to apply them were from the chemical manufacturing industry, in which the application of statistical techniques to quality control enabled processing problems to be eliminated and new products to be developed more efficiently. Since the 1980s there have been major developments in statistical quality control techniques in numerous companies, resulting in a considerable increase in competitiveness for the companies in which they were applied (Montgomery, 2004).

One of the main tools used in statistical process control (SPC) is the control chart, also known as the Shewhart control chart, which consists of a centre line and two lines drawn parallel to it. The centre line represents the place where the characteristic measured should ideally be located and the parallel lines represent the control limits of the characteristic (Fig. 1). The control limits are determined by statistical considerations. The use of control lines which group 99.7% of production data is very common when the production process is working correctly (Montgomery, 2004).

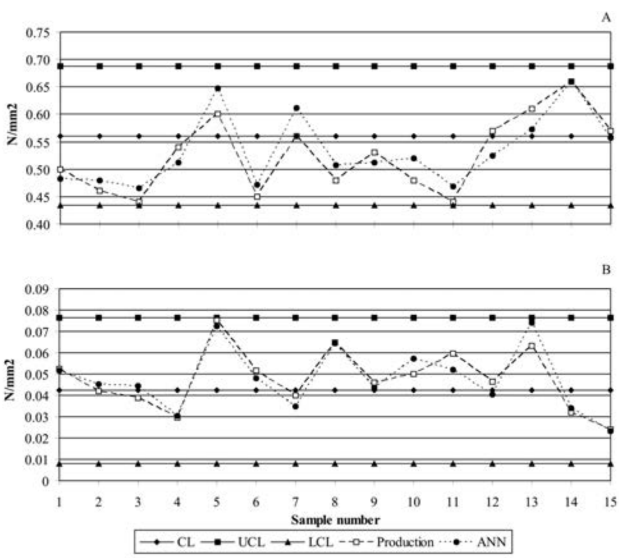

Figure 1. Control chart: (A) mean; (B) standard deviation. CL: centre line, UCL: upper control limit, LCL: lower control limit; Production: Observed data. ANN: data calculated by the artificial neural network.

In the particleboard industry, the mechanical properties of bending strength, modulus of elasticity and internal bond strength are used as the most appropriate parameters for determining board quality. However, determining these properties requires sophisticated testing equipment and a great deal of time for preparing and conditioning the test samples and conducting the testing, which means that if a problem occurred, it would only be detected once the board was manufactured (Morris et al., 1994; Cook et al., 2000). This is why, in terms of production control, it is very important to find a relation between easily measured data and the final properties.

Several studies exist which relate the composition or physical properties of the boards to their mechanical properties using regression models of varying complexity (Halligan and Schniewind, 1974; McNatt, 1974; Vital et al., 1974; Kelly, 1977; Hayashi et al., 2003; Wong et al., 2003; Cai et al., 2004; Nemli et al., 2007) or artificial neural networks (ANN) (Cook and Chiu, 1997; Cook et al., 1991; Cook and Whittaker, 1993; Cook et al., 2000; García Fernández et al., 2008b) for early detection of possible production problems.

ANNs are mathematical structures based on the functioning of a biological neural network, which are capable of solving problems using knowledge acquired through a series of examples (Pérez and Martín, 2003). These structures have a series of interconnected elements known as process elements or artificial neurons. The interconnections between the artificial neurons and the activation bias of each of the neurons are responsible for storing the knowledge of the network (Priore et al., 2002). Each neuron receives a series of entry signals (X_i) and produces a single output (S_j) (Fig. 2). In the case of feedforward networks, the inputs of a neuron are either the outputs of the elements interconnected with the neuron or the input variables.

The neurons that make up an ANN are organised in a series of layers. In general there are three layers in a network, two of which have external connections, while the third is an inner layer. The input layer receives the values from the initial variables, the hidden layer performs the operations designed to obtain certain characteristics from the dataset, and the output layer shows the network answer for a given input.

There is no procedure to define the number of neurons the ANN should have, which means that it can be difficult to choose a model, even for an experienced

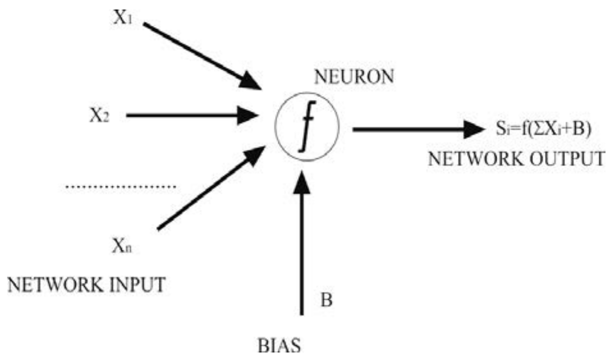

Figure 2. General structure of an artificial neuron.

user. In general, the ANN is obtained by a process of trial and error (Lin and Tseng, 2000). Structures with few neurons tend to be less sensitive to small changes in the process, while adding an excessive amount of neurons to the network does not greatly improve its results (Cheng, 1995).

ANNs have been applied to production control process modelling by several authors (Cook et al., 1991; West et al., 1999; Bissessur et al., 1999; Cook et al., 2000; Cook et al., 2001), using data from the actual production as well as simulated or design of experiments data (Sukthomya and Tannock, 2005).

They have also been used to complement SPC (Cheng, 1995; Guh et al., 1999; Chen and Wang, 2004; Guh, 2005; Chen et al., 2007; Cheng and Cheng, 2008; Abbasi, 2009), improving previously obtained results in all cases.

In general, ANNs are applied in industry both to production process modelling and to production monitoring and control (García Fernández et al., 2008a).

In this study two artificial neural networks were combined with control process charts in order to check if the data obtained with the networks were valid for variable process control in particleboard manufacture.

2. Materials and methods

2.1. Materials

148 particleboards of varying thickness, classified as P2 in accordance with the UNE-EN 312 standard (AENOR, 2004) and chosen at random from daily production, were used to calculate the ANNs to obtain the mean and standard deviation of the internal bond strength of the boards. For the SPC, 15 extra boards with a thickness of 16 mm were selected (statistical control group) (Table 1).

Physico-mechanical testing was carried out on all the boards in order to determine the swelling and absorption (UNE 56713) (AENOR, 1971), moisture content (UNE-EN 322) (AENOR, 1994c), density (UNE-EN 323) (AENOR, 1994d) and internal bond strength (UNE-EN 319) (AENOR, 1994b). In the case of swelling, the Spanish rather than the European standard was chosen (UNE-EN 317) (AENOR, 1994a), as it requires less testing time and also provides the measurement of the water absorbed by the samples.

The samples were prepared in accordance with the UNE-EN 326-1 standard (AENOR, 1995) and then conditioned at a temperature of 20±2ºC and relative humidity of 65±5% until constant weight was reached.

The physical properties were determined by means of a MITUTOYO Digimatic digital calliper with a 0-300 mm range and 0.01 mm scale division, a COBOS C-600-SX digital balance with a 0-600 g range and 0.01 g scale division, two MITUTOYO IDF 1050 digital dial gauges with a 0-50 mm range and 0.01 mm scale division, and an immersion tank with automatic temperature control. The internal bond test was carried out using a universal MICROTEST machine with a load cell of 5000N and Class 0.5%.

Table 1. Number of boards used in the ANN and SPC analysis

	Number of particles boards considered		Thickness	Results achieved
ANN	148		Variable	Mean and standard deviation
	110 (training group)	38 (testing group)		
SPC	15 mm		16 mm	Statistical control group

2.2. Artificial neural networks

In order to obtain the board internal bond strength value and its variability, it was decided to design two separate ANNs, in this way improving their performance (Sha and Edwards, 2007).

In both cases the input variables chosen were the board thickness and the means and standard deviations of the properties of moisture content, density, swelling and absorption (García Fernández et al., 2008b). The output variables were the mean and the standard deviation of the internal bond test.

The ANN model chosen was a multilayer perceptron trained by the backpropagation algorithm. This is the most commonly used model in the references consulted, both in the field of SPC and in particleboard production control (Cook et al., 1991; Cook and Whittaker, 1993; Cheng, 1995; Bissessur et al., 1999; Chen and Wang, 2004; Sukthomya and Tannock, 2005; Cheng and Cheng, 2008; García Fernández et al., 2008b).

The transfer function used was the hyperbolic tangent sigmoid (Eq. 1) (Garcia Fernández et al., 2008b), a variation of the hyperbolic tangent (Cheng, 1995; Chen and Wang, 2004; Cheng and Cheng, 2008). The two functions are mathematically equivalent but the hyperbolic tangent sigmoid function produces an output much more quickly, thereby improving the efficiency of the network (Demuth et al., 2002).

$$f(x) = \frac{2}{1+e^{(-2x)}} - 1 \tag{1}$$

f(x): Output value of the neuron, x: Input value of the neuron.

The transfer function chosen produces an output in the interval (-1, +1) and therefore the input data were normalised before they were used to train the network (Eq. 2) (Demuth et al., 2002; Cheng and Cheng, 2008; García Fernández et al., 2008b).

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{2}$$

X': Vector X after normalisation, X_{min} and X_{max}: Minimum and maximum values of vector X.

The learning method chosen was supervised learning (Hagan et al., 1996; Haykin, 1998; Pérez and Martín, 2003; Isasi and Galván, 2004). The initial group of 148 boards was therefore divided into two groups: the training group (110 boards, 74% of the total) and the testing group (38 boards, 26% of the total) (Table 1). These percentages are within the ranges used by other authors (Cook and Whittaker, 1993; Cook and Chiu, 1997; García Fernández et al., 2008b).

To avoid the problem of overfitting of the ANN, the early-stopping technique was used. Overfitting occurs during the network learning process and is a clear indication that the network is not extracting the knowledge from the initial data. The network is perfectly adapted to the training group but is not capable of generalising. When overfitting occurs, there is a decrease in the error (differences between the value predicted by the network and the test value observed) in the training group while in the testing group the error begins to increase (Hagan et al., 1996; Haykin, 1998; Malinov and Sha, 2003; Isasi and Galván, 2004). In order to avoid this, the errors were checked every 1000 epochs.

To assess the result of the ANN, the prediction error was obtained (Eq. 3) in addition to the correlation coefficient (R) between the predicted value and the observed value. A prediction error of 15% was regarded as acceptable for a production process and from 20 to 30% it was regarded as reject (Cook and Chiu, 1997; Malinov et al., 2001).

$$E\% = 100 \cdot \frac{\left(V_{pred} - V_{obs}\right)}{V_{obs}} \tag{3}$$

E%: Prediction error, V_{pred}: Value predicted by network, V_{obs}: Value observed in testing.

To assess R, the criteria used was that specified in the UNE-EN 326-2 standard (AENOR, 2001), where 0.70 is the acceptable value for the relation between the values obtained by a standard test method and those obtained by alternative methods.

The ANNs were created using the Neural Network Toolbox® ver. 4.0.2 application, which is part of the MATLAB® Ver. 6.5.0. Release 13 programme.

2.3. Statistical quality control

In order to perform the SPC it was necessary to first check the networks obtained against the 15 extra 16 mm-thick boards chosen at random from the production line (Table 1). To assess the results, it was checked not only that the two conditions imposed on the networks were met, but also that the data obtained by the networks had the same classification of in control/out of control as the real data, in order to ensure acceptability of the numerical output of the network for the mean and the standard deviation as well as the production classification.

Particleboard production control is based on determining the quantitative values corresponding to the physico-mechanical properties of the boards, which are defined by the mean (m) and the standard deviation (σ). The control chart equations of the centre line and control limits can be expressed by equation (4) (Montgomery, 2004):

$$\begin{aligned} UCL &= \mu + L \cdot \sigma \\ CL &= \mu \\ LCL &= \mu - L \cdot \sigma \end{aligned} \tag{4}$$

UCL: upper control limit, CL: centre line, LCL: lower control limit; L: constant, μ: mean of some quality characteristic of interest, σ: standard deviation of some quality characteristic of interest.

L is the distance from the control limits to the centre line. Normally L=3 is used, which ensures a type I error probability of 0.0027; that is, only 27 test samples out of 10,000 would cause a false alarm (Montgomery, 2004).

In this study, control charts were prepared both for the mean and the standard deviation. As the best estimator of μ, the unbiased estimator of the grand mean was used (Eq. 5).

$$\overline{\overline{X}} = \frac{1}{m} \cdot \sum_{i=1}^{m} \overline{X}_i \tag{5}$$

$\overline{\overline{X}}$: Grand mean, $\overline{X}_i$: sample means, m: number of samples.

The sample standard deviation (*S*), which is not an unbiased estimator of σ, was used as the estimator of σ. In fact, *S* is an estimator of $c\cdot\sigma$, where *c* is a constant that depends on the number of data per sample (*n*) (Eq. 6), with the standard deviation of *S* being $\sigma\sqrt{1-c^2}$.

$$c \approx \frac{4(n-1)}{4n-3} \tag{6}$$

c: constant, n: number of data per sample.

If there is no known value for σ, it must be estimated using the average of the sample standard deviations (Eq. 7).

$$\overline{S} = \frac{1}{m} \cdot \sum_{i=1}^{m} S_i \tag{7}$$

$\overline{S}$: Mean of standard deviations, S_i: sample standard deviation, m: number of samples.

In this case, the control lines correspond to equation (8) for the mean and to equation (9) for the standard deviation.

$$\begin{aligned} UCL &= \overline{\overline{X}} + 3\frac{\overline{S}}{c\sqrt{n}} \\ CL &= \overline{\overline{X}} \\ LCL &= \overline{\overline{X}} - 3\frac{\overline{S}}{c\sqrt{n}} \end{aligned} \tag{8}$$

$\overline{\overline{X}}$: Grand mean, $\overline{S}$: Mean of standard deviations, c: constant, n: number of data per sample.

$$\begin{aligned} UCL &= \overline{S} + 3\frac{\overline{S}}{c}\sqrt{1-c^2} \\ CL &= \overline{S} \\ LCL &= \overline{S} - 3\frac{\overline{S}}{c}\sqrt{1-c^2} \end{aligned} \tag{9}$$

$\overline{S}$: Mean of standard deviations, c: constant.

Of the 148 boards selected for the calculation of the ANNs, 41 had a thickness of 16 mm, and these were used to obtain the estimators of the mean and standard deviation of the process to plot the Shewhart charts. Using these charts, the data of the 15 extra boards from the statistical control group were checked.

For the SPC calculations and charts the Microsoft® EXCEL 2003 spreadsheet was used.

3. Results and discussion

3.1. Artificial neural networks

The networks obtained for the mean and standard deviation of the internal bond strength of the boards consisted of a hidden layer made up of three sublayers of [10 8 1] neurons in the case of the mean and [20 15 11] neurons in the case of the standard deviation (Fig. 3).

Table 2 shows the result obtained in the training process for the mean and the standard deviation.

The amount of data available for the training process is less than the specified number for mathematically defining the networks obtained (Sha, 2007). However, the aim is not to define single networks in which all the parameters are perfectly defined, but rather to find net-

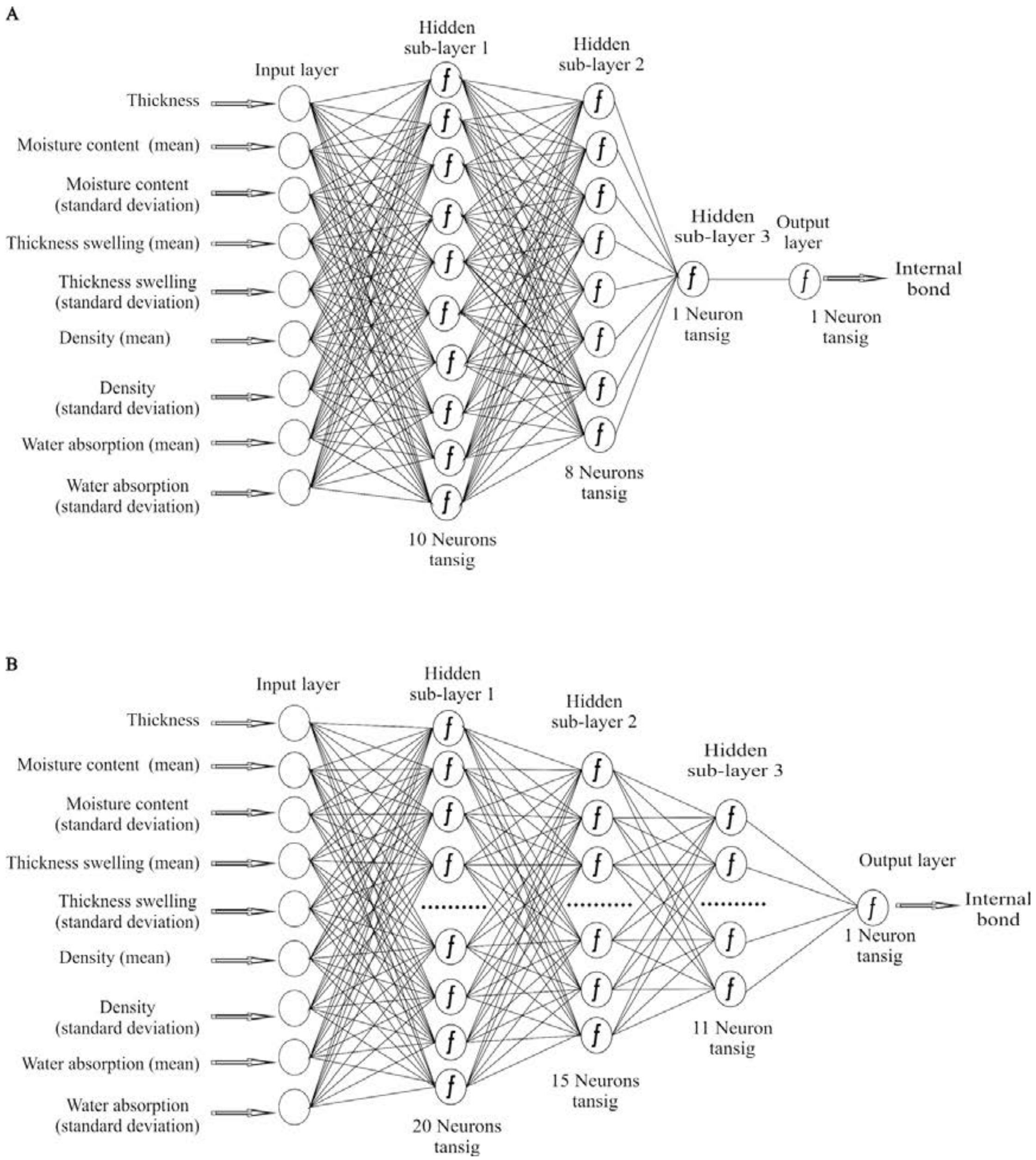

Figure 3. Structure of the ANNs obtained: (A) mean; (B) standard deviation.

works which guarantee a correct generalisation (Tompos et al., 2007) and also meet the criteria of the UNE-EN 326-2 standard (AENOR, 2001).

Table 3 shows the results obtained for the mean and the standard deviation in the ANN testing process. The determination coefficient (R^2) indicates that the model obtained is capable of explaining 85% of the data calculated for the means and 96% for the standard deviations. In the case of R, the values obtained are very similar to the findings of other authors in studies on the application of ANNs to particleboard (Cook et al., 1991; Cook et al., 2000; García Fernández et al., 2008b) and higher than the values required by the UNE-EN 326-2 standard (AENOR, 2001). Moreover, the prediction errors calculated on the testing group are lower than 15% (see subsection 2.2), which means that the networks calculated can be regarded as valid (Cook and Chiu, 1997).

Table 2. ANN. Results of the training process

Parameter	Structure of the ANN	Linear regression model	R^2	R	E%
Mean	[9 10 8 1 1]	y=0.965x+0.019	0.96	0.98	2.57
Standard deviation	[9 20 15 11 1]	y=0.951x+0.002	0.97	0.99	5.27

R^2: determination coefficient, R: correlation coefficient, E%: prediction error.

3.2. Statistical process control

With the two networks obtained, it was checked that the 15 extra boards from the statistical control group met the two initial conditions imposed on the network and also that the production classification for the observed values was the same as the classification for the values calculated by the networks.

Table 3 shows the ANN results for the statistical control group. R^2 indicates that the networks obtained are capable of explaining 79% of the data calculated for the means and 88% for the standard deviations of the statistical control group. As in the prior testing process, the values of R are similar to those obtained by Cook et al. (1991), Cook et al. (2000) and García Fernández et al. (2008b), and higher than the 70% value specified in the UNE-EN 326-2 standard (AENOR, 2001) for accepting the correlation between the test results obtained by the standard method and by an alternative method. In addition, all the errors obtained are lower than 15% (Cook and Chiu, 1997).

Table 4 shows the results of the estimators for the mean and standard deviation of the internal bond strength, obtained from the 41 boards with a thickness of 16 mm within the overall group of 148 boards. The control lines (Table 5) and the Shewhart charts (Fig. 1) for the two variables were obtained from the estimators.

Both the real results of the mean and the standard deviation of the 15 boards from the statistical control group and the results obtained by the ANNs can be classified as in control (Fig. 1), which means 100% success has been obtained. As the three conditions imposed for the network to be accepted in statistical production control were met (R>0.70, E<15% and the same classification for the production values), it can be concluded that the ANNs obtained are valid and considerably improve process control by allowing earlier detection of problems in the final product (Morris et al., 1994).

Conclusions

The use of ANNs enabled the mean and standard deviation values of the particleboard internal bond strength to be obtained within acceptable margins using known data of thickness, density, moisture content, swelling and absorption.

The ANNs obtained met the criteria of the UNE-EN 326-1 standard (AENOR, 2001) for accepting test values from non-standard methods.

The ANNs met the criteria for them to be used in statistical process control, obtaining the same classification for all the points obtained, and therefore constitute a very useful complement in SPC.

Table 3. ANN. Results of the testing group and the statistical control group for the mean and the standar deviation

Group	Parameter	R^2	R	Linear regression model	E% (mean and range)
Testing	Mean	0.85	0.92	y=1.130x-0.050	7.86 (0.08 - 14.45)
	Standard deviation	0.96	0.98	$y=0.975x+5.82\cdot10^{-4}$	6.22 (2.84 - 7.75)
Statistical control	Mean	0.79	0.89	y=0.830x+0.096	5.37 (0.01 - 9.09)
	Standard deviation	0.88	0.94	$y=0.984x+7.91\cdot10^{-4}$	8.03 (0.34 - 16.34)

R^2: determination coefficient, R: correlation coefficient, E%: prediction error.

Table 4. Statistical data of the production control of 16 mm boards

Nº of data	Mean (N/mm²)	Mean of standard deviation (N/mm²)	c
41	0.56	0.04	0.97

Table 5. Shewhart chart control lines

Parameter	Upper control line	Centre line	Lower control line
Mean	0.69	0.56	0.43
Standar deviation	0.01	0.04	0.08

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