USE OF ARTIFICIAL NEURAL NETWORKS AS A PREDICTIVE METHOD TO DETERMINE MOISTURE RESISTANCE OF PARTICLE AND FIBER BOARDS UNDER CYCLIC TESTING CONDITIONS (UNE-EN 321)

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(Received February 2010)

Abstract. Determining internal bond strength and thickness swelling after cyclic aging tests in humid conditions is essential to assess moisture resistance of particle and fiber boards. However, because operating procedures for these types of tests take at least 3 wk, their use in daily finished product control is impractical. To solve this problem, an artificial neural network was used as a predictive method to determine these values from the board properties of thickness, density, and moisture content in conjunction with thickness swelling and internal bond strength values obtained before the aging cycle. Using 113 boards, an artificial neural network was designed consisting of two separate feedforward multilayer perceptrons applying the hyperbolic tangent as the transfer function. Training was conducted through supervised learning after the input data had been normalized. In the testing group, the network attained a determination coefficient of 0.94 for internal bond strength and 0.92 for thickness swelling.

Keywords: ANN, internal bond strength, swelling, artificial neural network, particleboard, fiberboard.

INTRODUCTION

Moisture-resistant particle and fiber board, normally manufactured with urea–melamine–formaldehyde at a ratio of 15-20% melamine to urea, is used for demanding exposures requiring extensive quality control (Esteban et al 2002). Current European regulations stipulate that both types of board must pass testing for internal bond strength and thickness swelling after the aging cycle specified in the UNE-EN 321 standard (AENOR 2002). However, the 3-wk duration of this cycle makes the testing standard impractical in board production control. The

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delay in obtaining results from testing is problematic for the manufacturing industry in general (Morris et al 1994) and the wood-based panel industry in particular (Cook et al 2000). This makes it important to devise a method to relate results obtained after the aging cycle to board properties that are easier and quicker to measure.

One of the most commonly used predictive methods in several fields of science is the artificial neural network (ANN), a mathematical structure that attempts to imitate the functioning of the brain. ANNs consist of several interconnected neurons structured in a series of layers. The input layer receives the signals from the exterior and is responsible for sending them to the inner layer. The inner or hidden layer performs the calculations required to obtain the output. Lastly, the output layer shows the results obtained by the network. ANNs are capable of extracting knowledge from a series of sampling data and applying it to unknown data. The knowledge extracted is stored in connections between the different neurons that make up the network (Priore et al 2002).

There is no set rule as to how many neurons the hidden layer should have or whether it should include a single or more than one sublayer. The only guidelines are recommendations on the number of neurons the ANN should have in relation to the data available (Sha 2007) and that the network should be pyramidal (Vanstone and Finnie 2009). Therefore, the only way to obtain the hidden layer is by trial and error (Lin and Tseng 2000). A further consideration is that a structure with few neurons may not be capable of generalizing appropriately and, conversely, that having an excessive number of neurons does not greatly improve the network but rather makes learning more difficult (Cheng 1995).

The nature of ANNs as universal approximators (Hornik et al 1989; Hagan et al 1996) makes them a very useful tool for modeling processes in which obtaining a result from the initial data is more important than the relations between the variables involved (De Veaux and Ungar 1997). Major advances have been made with the use of ANNs in recent years in industrial process control, mainly because they are capable of modeling complex relations that conventional systems are unable to do and can adequately predict whether the characteristics of a product are in line with specifications (Sukthomya and Tannock 2005). ANNs have been widely used to characterize other materials such as cement (Baykasoğlu et al 2004), concrete (Bilim et al 2009; Özcan et al 2009; Sandemir 2009), and certain metals (Mukherjee et al 1995; Malinov et al 2001; Hassan et al 2009; Ozerdem and Kolukisa 2009; Reddy et al 2009). In the field of wood they have been used to identify species microscopically (Esteban et al 2009c), obtain physical properties (Avramidis and Iliadis 2005; Avramidis et al 2006), obtain mechanical properties of sawn timber using physical properties (Esteban et al 2009a), and to obtain mechanical properties of particleboard using manufacturing parameters (Cook and Whittaker 1992; Cook and Chiu 1997) and physical properties (Fernández et al 2008; Esteban et al 2009b) to predict possible production errors without having to wait for mechanical tests for bending strength, modulus of elasticity, and internal bond strength.

The objective of this study was to design an ANN capable of predicting internal bond strength and thickness swelling values of moisture-resistant particle and fiber board after an aging cycle in humid conditions using thickness, density, and moisture content data in conjunction with thickness swelling and internal bond strength values obtained before the aging cycle.

MATERIAL AND METHODS

Testing

The study used 46 particleboards classified as P3 in accordance with the UNE-EN 312 standard (AENOR 2004) and 67 fiberboards classified as MDF.H in accordance with the UNE-EN 622-5 standard (AENOR 2007). The boards measured 2440 × 1220 mm and were of different thicknesses. The panels were sampled randomly from daily production of two production lines at a single manufacturing facility. The adhesive used was urea–melamine–formaldehyde.

The following tests were performed on all boards: thickness swelling as per UNE-EN 317 (AENOR 1994a), in which swelling is obtained after immersion in water at 20°C for 24 h; determination of internal bond strength as per UNE-EN 319 (AENOR 1994b), in which the resistance of the panel to a tensile force applied in the perpendicular direction of the panel faces is obtained; moisture content as per UNE-EN 322 (AENOR 1994c), in which the moisture content is determined by drying in an oven to an anhydrous state; and density as per UNE-EN 323 (AENOR 1994d) followed by determination of internal bond strength and thickness swelling after cyclic aging as per UNE-EN 321 (AENOR 2002). The test procedure in this case states that the test pieces must first undergo the following cycle three times: submersion in water at 20°C for 70 h, cooling at –12 to –25°C for 24 h, drying at 70°C for 70 h, and cooling at 20°C for 4 h. After this treatment, which lasts 3 wk, the test pieces are reconditioned to constant mass and the two properties are determined.

For preparation of the test pieces and expression of results, the standards followed were UNE-EN 325 (AENOR 1994e) and UNE-EN 326-1 (AENOR 1995). The cutting was done in accordance with the requirement that at least one test piece is taken from the edge of the panel after trimming and that all the test pieces for a single test are at least 100 mm apart. Table 1 shows the number and size of the test pieces required for each test. All test pieces were conditioned to constant weight in a conditioning chamber at 20 ± 2°C and 65 ± 5% RH. The testing equipment used was: 120S Sartorius Analytic balance with a range of 0-120 g and 0.1 mg scale division; Mitutoyo Digimatic digital caliper with a range of 0-300 mm and 0.01 mm scale division; Mitutoyo IDF 1050 thickness gauge with a range of 0-50 mm and 0.01 mm scale division; Memmert WNB-29 thermostatic baths with a range of 10-95°C and 0.1°C scale division; P-Selecta freezing cabinet with a range of –40-40°C and 1°C scale division; Heraeus D-6450 oven with a range of 0-300°C and 1°C scale division; and a Microtest universal testing machine with a load cell of 5000 N, class 1.

The laboratory is accredited for these tests by the Spanish Accreditation Entity (ENAC) in accordance with the standard UNE-EN ISO/IEC 17025 "General requirements for the competence of testing and calibration laboratories" (AENOR 2005). All the standards referenced are European, except UNE-EN ISO/IEC 17025, which is international.

Artificial Neural Network

For modeling the relations between initial properties and swelling and internal bond strength tests after cyclic aging, two separate ANNs (subnetworks) were designed to improve the performance of each individual network (Sha and Edwards 2007). The input, or independent, variables used were thickness, density, and moisture content of the panels as well as thickness swelling and internal bond strength before cyclic aging. The output, or dependent, variables were thickness swelling and internal bond strength after cyclic aging.

Table 1. Test pieces.

Test	Testing standard	Test pieces/panel	Total test pieces tested	Test piece sizes (mm)
Moisture content	UNE-EN 322	4	452	50 × 50
Density	UNE-EN 323	6	678	50 × 50
Internal bond strength	UNE-EN 319	8	904	50 × 50
Thickness swelling	UNE-EN 317	8	904	50 × 50
Internal bond strength	UNE-EN 321	8	904	50 × 50
Thickness swelling	UNE-EN 321	8	904	50 × 50

A feedforward multilayer perceptron was chosen for the structure of both networks. The nature of perceptrons as universal function approximators (Hornik et al 1989; Hagan et al 1996) makes them highly appropriate for modeling relations between results of cyclic testing in humid conditions and initial results. A hyperbolic tangent sigmoid function (Eq 1) was used as the transfer function or neuron processing function. This is equivalent to the hyperbolic tangent function and improves network performance by producing an output more quickly (Demuth et al 2002). It is one of the most frequently used functions in the references consulted (Cook and Chiu 1997; Baykasoğlu et al 2004; Avramidis and Iliadis 2005; Avramidis et al 2006; Fernández et al 2008; Bilim et al 2009; Esteban et al 2009b).

$$f(\theta) = \frac{2}{1 + e^{(-2\theta)}} - 1 \qquad (1)$$

$f(\theta)$ = Output value of the neuron.
θ = Input value of the neuron.

To improve the generalizing ability of the ANNs, the input data were normalized (Sarle 1997; Rafiq et al 2001) in accordance with Eq 2.

$$\theta' = \frac{\theta - \theta_{min}}{\theta_{max} - \theta_{min}} \qquad (2)$$

θ' = Value after normalization of vector X.
θ_{max} y θ_{min} = Maximum and minimum values of vector X.

The subnetworks were trained through supervised learning (Hagan et al 1996; Haykin 1999). This was done by dividing the entire data set into two subgroups chosen randomly without repetition: the training group (82 data, 73% of the total) and the testing group (31 data, 27% of the total). These intervals were within the range of those used by other researchers in the field of wood-based boards (Cook and Whittaker 1992; Cook and Chiu 1997; Fernández et al 2008).

The learning algorithm chosen was the resilient backpropagation algorithm, because it improves learning performance in the case of sigmoid transfer functions (Demuth et al 2002). To avoid the problem of network overfitting, the early-stopping method was chosen. Overfitting is observed as a decrease in the training group error coupled with an increase in the testing group error, indicating that the network is adapting perfectly to the training group data but has lost the ability to generalize (Hagan et al 1996; Haykin 1999). To design the structure of the inner layer of the network and avoid overfitting, a specific MATLAB® language program was developed using the Neural Network Toolbox® Version 4.0.2 from the MATLAB® Program Version 6.5.0, Release 13. This program generates successive perceptrons with differing numbers of neurons in the inner sublayers and assesses the ability of each perceptron to generalize by comparing the evolution of the training and testing group errors every 100 epochs. The training process in each network was regarded as finished when an increase in the testing group error occurred in conjunction with a decrease in the training group error. Lastly, the program assessed the different networks obtained and selected the one best adapted to the desired result (Fig 1).

```
Initilize_data
Preprocessing_data
// Sublayer loops
for h=1 to 15
  for i=1 to h
    Create_neural_network (net)
      // Training loop
      for k=1 to 100
        Train(net)
          Run_Regression_test(net, Training_set)
        Simulate(net)
        Run_Regression_test(net, Validation_set)
          Avoid_estabilización_del_resultado
        Avoid_overfitting
      end for //k
  end for //i
end for //h
Get_best_net
Display_results
...
```

Figure 1. Pseudocode of the optimization program for the hidden layers of the multilayer perceptron.

The correlation coefficient (R) and prediction error (E%) (Eq 3) were used to assess the structure chosen. The subnetworks obtained were regarded as correct if they met the condition $R > 0.70$ specified in the UNE-EN 326-2 standard (AENOR 2001) used to accept test results obtained by nonstandard test methods and if E% <15% (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 the network.
V_{obs} = Test value observed.

RESULTS AND DISCUSSION

Tables 2 and 3 show the test results for all boards. Not all of the panels met the specifications of the testing standards. The best structures obtained for both subnetworks had two sublayers in the hidden layer. For the property of internal bond strength, the sublayers had 6 neurons each and had 8 and 4 for swelling (Fig 2).

The number of data available for training was slightly lower than Sha's recommendation (Sha 2007) for mathematically defining the network, although the aim was to obtain a network capable of generalizing appropriately from the input data rather than create a unique network in which all the parameters were fully defined (Tompos et al 2007).

The training process results for the two subnetworks and the correlations obtained between the observed and predicted values are shown in Table 4 and Fig 3.

The numerical results and the classifications (correct/incorrect) of the tests for the ANN testing process are shown in Tables 5 and 6. Table 7 and Fig 4 show the correlations in the

Table 2. P3 particleboard test results.

		Density (kg/m^3) UNE-EN 323				Moisture content (%) UNE-EN 322			
Thickness (mm)	Number of panels	$\bar{x}$	σ	Minimum	Maximum	$\bar{x}$	σ	Minimum	Maximum
10	1	776	—	776	776	10.8	—	10.7	10.8
16	15	688	24	662	731	10.3	0.6	9.6	11.7
18	2	695	12	687	703	10.3	0.2	10.2	10.5
19	9	694	47	641	808	10.1	0.4	9.2	10.4
22	10	676	25	624	716	10.2	0.6	8.8	11.4
25	4	663	14	648	681	10.7	0.6	10.3	11.6
30	5	655	13	639	675	10.0	0.5	9.39	10.5
		Thickness swelling (%) UNE-EN 317				Internal bond strength (N/mm^2) UNE-EN 319			
Thickness (mm)	Number of panels	$\bar{x}$	σ	Minimum	Maximum	$\bar{x}$	σ	Minimum	Maximum
10	1	4.7	—	4.7	4.7	1.39	—	1.39	1.39
16	15	4.5	1.8	2.2	9.3	0.89	0.12	0.62	1.14
18	2	10.2	4.4	7.1	13.3	0.74	0.03	0.72	0.76
19	9	6.2	3.7	1.7	10.7	0.91	0.23	0.72	1.46
22	10	6.5	2.9	2.1	10.5	0.80	0.09	0.65	0.92
25	4	7.0	3.6	3.6	10.7	0.83	0.06	0.78	0.90
30	5	7.5	2.5	3.8	10.7	0.64	0.10	0.54	0.76
		Thickness swelling (%) UNE-EN 321				Internal bond strength (N/mm^2) UNE-EN 321			
Thickness (mm)	Number of panels	$\bar{x}$	σ	Minimum	Maximum	$\bar{x}$	σ	Minimum	Maximum
10	1	7.2	—	7.2	7.2	0.85	—	0.85	0.85
16	15	8.3	2.2	2.7	12.3	0.48	0.12	0.27	0.70
18	2	14.9	0.1	14.8	15.0	0.35	0.01	0.34	0.35
19	9	8.5	3.5	3.1	13.2	0.48	0.15	0.37	0.83
22	10	10.1	3.1	6.1	14.8	0.38	0.10	0.19	0.57
25	4	10.0	3.0	6.8	13.1	0.30	0.11	0.15	0.41
30	5	10.2	3.8	4.0	13.3	0.27	0.07	0.18	0.36

Table 3. MDF.H. fiberboard test results.

		Density (kg/m^3) UNE-EN 323				Moisture content (%) UNE-EN 322			
Thickness (mm)	Number of panels	$\bar{x}$	σ	Minimum	Maximum	$\bar{x}$	σ	Minimum	Maximum
10	1	771	—	771	771	8.5	—	8.5	8.5
12	1	785	—	785	785	7.7	—	7.8	7.7
16	9	737	14	713	759	8.0	0.6	7.2	8.8
18	7	744	41	685	796	7.8	0.2	7.4	8.1
19	17	746	42	689	850	8.0	0.5	7.5	9.1
22	11	713	36	656	766	8.1	0.6	7.0	9.1
25	5	675	63	581	712	8.2	0.8	7.2	9.0
28	1	750	—	750	750	7.6	—	7.6	7.6
30	11	689	15	666	711	8.4	1.0	7.3	10.4
35	4	688	17	665	705	8.8	0.7	7.8	9.4
		Thickness swelling (%) UNE-EN 317				Internal bond strength (N/mm^2) UNE-EN 319			
Thickness (mm)	Number of panels	$\bar{x}$	σ	Minimum	Maximum	$\bar{x}$	σ	Minimum	Maximum
10	1	9.5	—	9.5	9.5	1.12	—	1.12	1.12
12	1	6.5	—	6.5	6.5	0.84	—	0.84	0.84
16	9	4.8	1.6	0.9	6.2	0.94	0.14	0.78	1.19
18	7	4.4	1.4	2.5	6.6	1.26	0.35	0.84	1.77
19	17	4.4	1.1	2.4	6.1	1.10	0.28	0.79	1.65
22	11	3.0	0.6	1.9	4.1	1.15	0.28	0.78	1.65
25	5	8.2	10.4	2.2	23.7	1.13	0.15	0.92	1.26
28	1	4.1	—	4.1	4.1	0.83	—	0.83	0.83
30	11	3.3	1.0	1.6	4.9	1.16	0.25	0.76	1.47
35	4	3.6	0.9	2.7	4.7	1.10	0.20	0.85	1.35
		Thickness swelling (%) UNE-EN 321				Internal bond strength (N/mm^2) UNE-EN 321			
Thickness (mm)	Number of panels	$\bar{x}$	σ	Minimum	Maximum	$\bar{x}$	σ	Minimum	Maximum
10	1	6.8	—	6.8	6.8	0.51	—	0.51	0.51
12	1	8.5	—	8.5	8.5	0.28	—	0.28	0.28
16	9	8.2	2.3	4.4	11.6	0.56	0.17	0.30	0.74
18	7	8.7	3.4	3.8	12.7	0.47	0.31	0.12	0.98
19	17	6.8	2.8	2.4	10.9	0.58	0.24	0.13	1.06
22	11	5.8	3.0	2.4	11.6	0.50	0.28	0.12	1.01
25	5	6.4	3.5	2.2	10.0	0.42	0.26	0.15	0.77
28	1	14.0	—	14.0	14.0	0.28	—	0.28	0.28
30	11	6.8	2.3	4.0	11.6	0.37	0.17	0.15	0.61
35	4	7.0	2.7	3.6	10.2	0.39	0.20	0.24	0.69

testing groups between the observed and predicted results. All test results were correctly classified by the ANN in relation to their test value except one, which was Panel 4 in the thickness swelling test (Table 5). These data would, however, fit the specifications laid down in the standard UNE-EN 326-2 (AENOR, 2001) for nonstandard methods, which establishes a minimum correlation coefficient (R) of 0.70.

The values of the determination coefficient (R^2) for the testing groups were 0.94 (internal bond strength) and 0.92 (thickness swelling), which means that the networks obtained were capable of explaining 94 and 92% of the test values observed (Table 7). The correlation coefficients obtained from the testing groups were higher than those obtained by other authors (0.85-0.90) when applying ANNs to wood-based boards (Cook and Whittaker 1992; Cook and Chiu 1997; Fernández et al 2008). They were also higher than the correlation coefficient found on applying an ANN to predict the results of a long-term test for another product, ie the standard 28-da compressive strength test used for the characterization of cement properties ($R = 0.83$) (Baykasoğlu et al 2004).

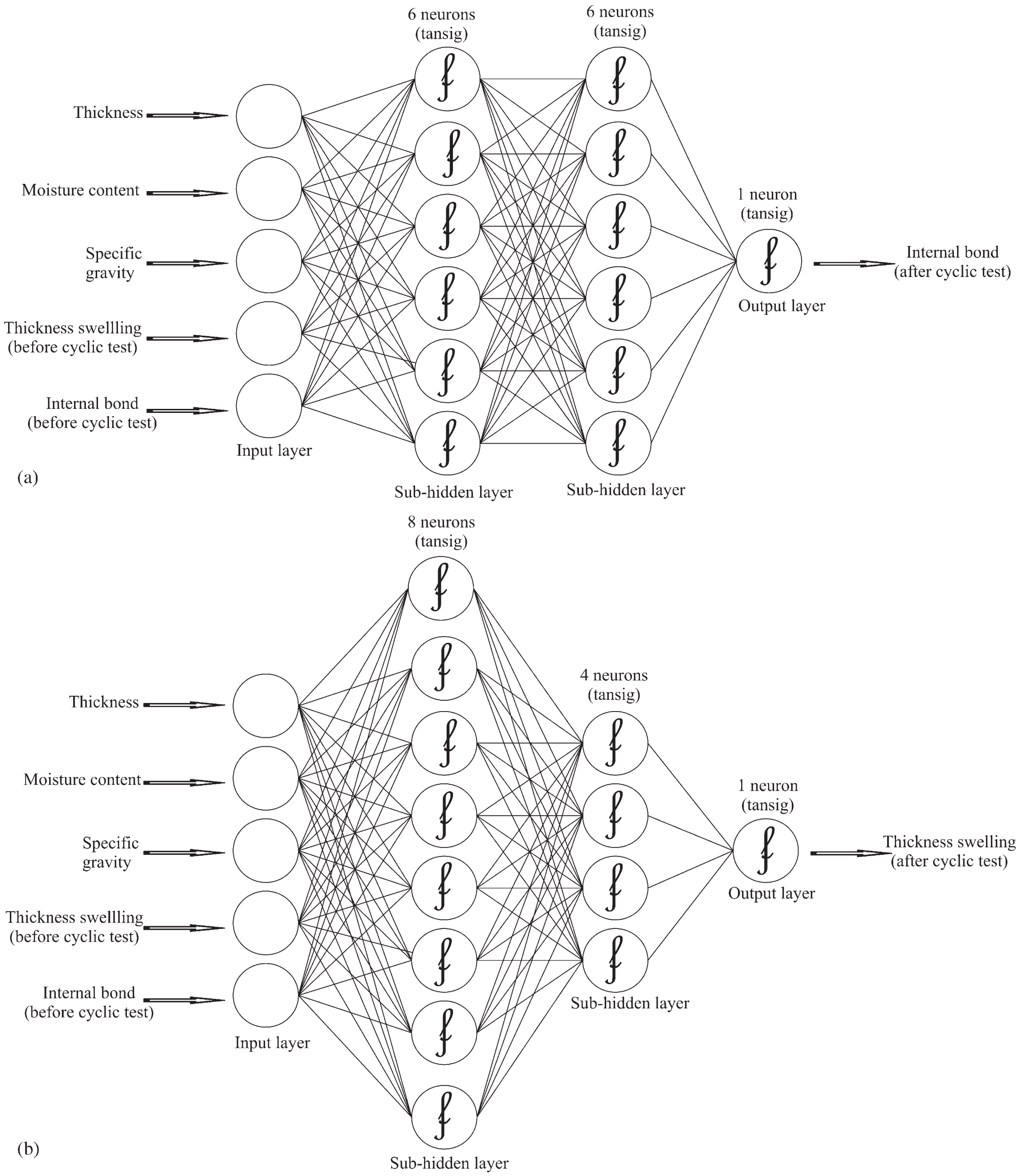

Figure 2. Neural network structure for (a) internal bond strength test and (b) thickness swelling test after cyclic aging.

The R values of both networks were also higher than the requirements of the UNE-EN 326-2 standard (AENOR 2001) for accepting results obtained by nonstandard test methods ($R > 0.70$). Moreover, the prediction error results of the two networks were lower than the specifications of Cook and Chiu (1997) and Malinov et al (2001), who established 15% as acceptable and 20-30% as rejects. Therefore, because the two initial conditions were fulfilled, the network

Table 4. Training process results.

Subnetwork	Property	Network structure	R	Linear regression model	$\bar{x}$ E (%)
1	Internal bond strength	[5 6 6 1]	0.97	y = 0.934·x + 0.032	10.26
2	Thickness swelling	[5 8 4 1]	0.95	y = 0.914·x + 0.672	11.07

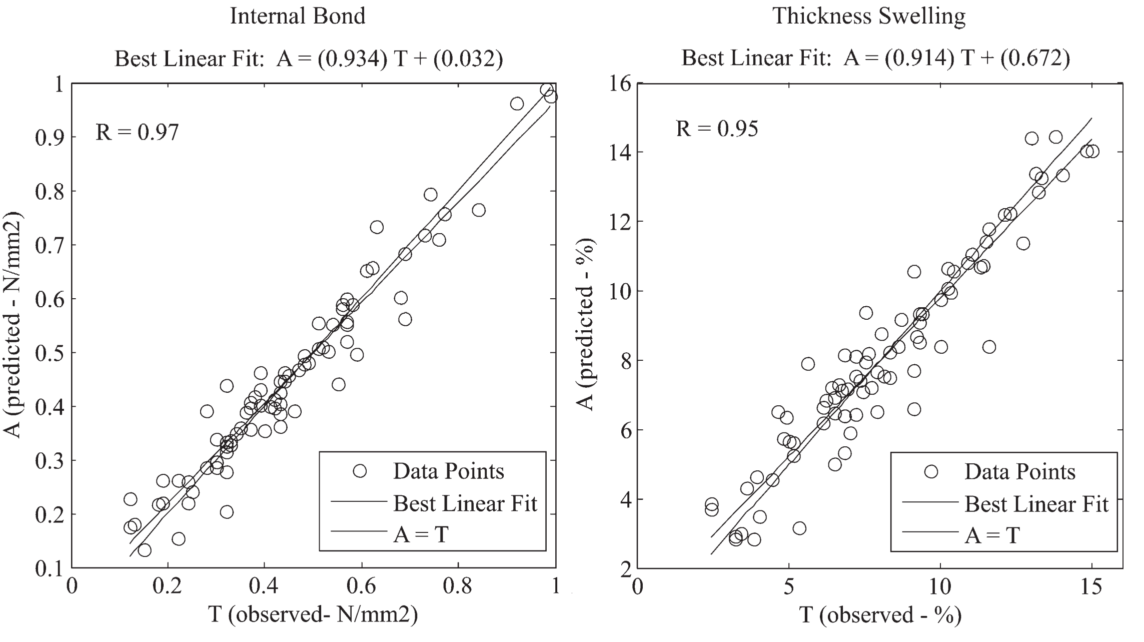

Figure 3. Correlation between observed and predicted values in the training group for internal bond strength and thickness swelling after cyclic aging.

Table 5. Numerical results and test classifications in the ANN testing process for the thickness swelling test.

	P3 particleboard					MDF. H fiberboard			
	ANN		Test			ANN		Test	
Panel no.	Mean (%)	Result	Mean (%)	Result	Panel no.	Mean (%)	Result	Mean (%)	Result
1	9.4	Correct	8.9	Correct	16	7.6	Correct	6.9	Correct
2	17.7	Incorrect	14.8	Incorrect	17	2.4	Correct	2.4	Correct
3	13.4	Incorrect	12.3	Incorrect	18	2.0	Correct	2.2	Correct
4	**10.3**[a]	**Correct**	**12.3**	**Incorrect**	19	12.5	Correct	11.6	Correct
5	10.5	Correct	9.9	Correct	20	10.4	Correct	9.2	Correct
6	3.2	Correct	3.1	Correct	21	8.1	Correct	7.9	Correct
7	3.2	Correct	2.7	Correct	22	7.4	Correct	8.8	Correct
8	4.3	Correct	4	Correct	23	2.3	Correct	2.4	Correct
9	5.8	Correct	7.2	Correct	24	3.2	Correct	3.1	Correct
10	8.5	Correct	10.5	Correct	25	9.9	Correct	8.5	Correct
11	7.8	Correct	7.2	Correct	26	7.3	Correct	8.4	Correct
12	11.4	Correct	11.3	Correct	27	5.8	Correct	6.5	Correct
13	12.0	Correct	12	Correct	28	4.9	Correct	5.7	Correct
14	10.6	Correct	9.1	Correct	29	4.1	Correct	3.9	Correct
15	7.5	Correct	7.6	Correct	30	6.1	Correct	7.2	Correct
					31	12.2	Correct	10.2	Correct

[a] Letters in bold indicate erroneous classifications by the ANN.
ANN, artificial neural network.

Table 6. Numerical results and test classifications in the ANN testing process for the internal bond strength test.

P3 particleboard					MDF. H. fiberboard				
	ANN		Test			ANN		Test	
Panel	Mean (N/mm^2)	Result	Mean (N/mm^2)	Result	Panel	Mean (N/mm^2)	Result	Mean (N/mm^2)	Result
1	0.65	Correct	0.56	Correct	16	0.57	Correct	0.60	Correct
2	0.21	Correct	0.19	Correct	17	0.54	Correct	0.63	Correct
3	0.29	Correct	0.35	Correct	18	0.28	Correct	0.33	Correct
4	0.18	Correct	0.18	Correct	19	0.44	Correct	0.38	Correct
5	0.40	Correct	0.40	Correct	20	0.44	Correct	0.48	Correct
6	0.91	Correct	0.83	Correct	21	0.33	Correct	0.33	Correct
7	0.77	Correct	0.70	Correct	22	0.50	Correct	0.58	Correct
8	0.42	Correct	0.36	Correct	23	0.49	Correct	0.55	Correct
9	0.42	Correct	0.49	Correct	24	0.99	Correct	1.06	Correct
10	0.38	Correct	0.42	Correct	25	0.31	Correct	0.28	Correct
11	0.93	Correct	0.85	Correct	26	0.14	Correct	0.15	Correct
12	0.35	Correct	0.30	Correct	27	0.78	Correct	0.66	Correct
13	0.13	Correct	0.15	Correct	28	0.79	Correct	0.68	Correct
14	0.22	Correct	0.27	Correct	29	0.95	Correct	1.01	Correct
15	0.49	Correct	0.45	Correct	30	0.65	Correct	0.6	Correct
					31	0.35	Correct	0.42	Correct

ANN, artificial neural network.

Table 7. Testing process results.

Subnetwork	Property	R	R^2	Linear regression model	$\bar{x}$ E (%)
1	Internal bond strength	0.97	0.94	$y = 1.02 \cdot x - 0.006$	11.17
2	Thickness swelling	0.96	0.92	$y = 1.07 \cdot x - 0.381$	10.10

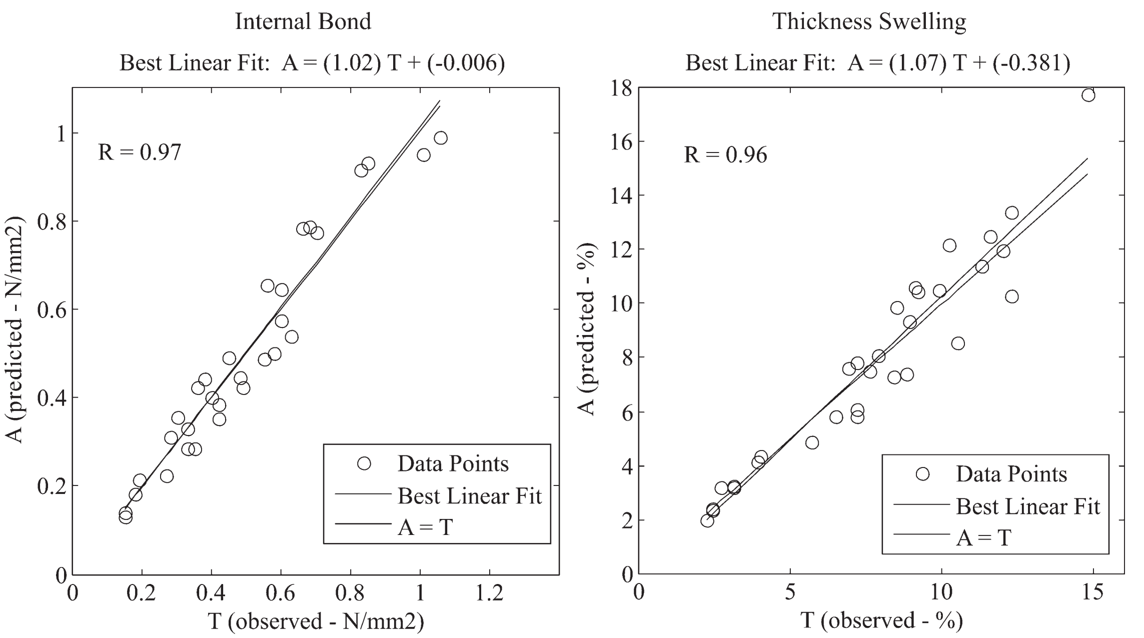

Figure 4. Correlation between observed and predicted values in the testing group for internal bond strength and thickness swelling after cyclic aging.

designed to obtain thickness swelling and internal bond strength after cyclic testing as per UNE-EN 321 (AENOR 2002) using initial data of thickness, density, and moisture content in conjunction with internal bond strength and thickness swelling values obtained before cyclic aging can be regarded as valid for the intended purpose.

CONCLUSIONS

1. The results of the neural network designed for this study were very close to data obtained by testing with determination coefficients higher than 90% in the two subnetworks.
2. These findings show the ability of ANNs to obtain moisture resistance results of particle and fiber boards under cyclic testing using initial data without the need for cyclic aging.
3. This study extends the fields where ANNs can be used in the wood-based board industry, making ANNs an important addition to in-factory testing.
4. Use of these networks will enable results of long-term testing to be predicted with a high degree of reliability, thereby anticipating problems directly affecting the moisture resistance quality of boards.

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