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# Fiber Cement Composition Simulator Using Artificial Neural Networks

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**Abstract:** The backpropagation algorithm was utilized to implement a fiber cement composition simulator. Six predictors were used: Synthetic fiber supplier, content of synthetic fiber, supplier of the softwood cellulose pulp, refinement degree of softwood cellulose pulp, content of softwood cellulose pulp and refinement degree of hardwood cellulose pulp. The combination of the 6 predictors generated compositions that were used as the Artificial Neural Network (ANN) target in relation to the variables: Modulus of rupture ($y_1$), toughness ($y_2$) and water absorption ($y_3$) of the fiber cement composites at the total age of 28 days that were used as the neural network input. The ANN performance was 97.3 % of correct classification with kappa coefficients varying between 0.89 and 0.93. The results suggest that the ANN approach can be used to simulate the composite formulation based on mechanical and physical characteristics using historical data set from experimental results.

**Key words:** Mixture proportioning, mechanical properties, physical properties, composite, fiber reinforcement, artificial neural network

## INTRODUCTION

Tropical and equatorial countries are known for their plant and wood fiber production and the consequent generation of products for commercial, agricultural and industrial activities (Wood, 1997). The resulting cellulose has considerable potential for fiber-cement production in favorable conditions for the buildings market.

The use of vegetable fibers as reinforcement in cement based composites has enormous potential in the field of recycled materials for civil construction. The optimized composites with hybrid reinforcement of synthetic and cellulose fibers display acceptable performance behavior when compared with fiber cement produced with asbestos fibers (Bezerra *et al*., 2006). The high level of availability of non-conventional fibrous material also supports their potential utilization throughout sustainable methods of production of building components (Soroushian *et al*., 1995).

In several developed countries, cellulose fibers derived from hardwoods or softwoods are used for the production of cement composites. This is done by adaptation of the former asbestos-cement production processes (Savastano *et al*., 2003). In Latin American countries (e.g., Brazil, Colombia and Chile), new products utilizing regionally available raw-materials and production systems are required to meet consumer requirements in each application area (Bentur, 1989; Heinricks *et al*., 2000). Formulation and dimensioning models aimed at the efficient production are needed, based on industrial processes.

Neural network methodology has been successfully applied to many engineering processes and more recently in cement and concrete-related research (Um *et al*., 2000). Compared with the rule-based system, the neural network system allows a much more precise representation of complex relationships between the inputs and the outputs (Lippmann, 1987). A neural network can make a generalization regarding the unknown situations based on known experience or examples. A neural network can also provide an output decision for unfamiliar inputs by the generalization of the output decisions from familiar inputs. By virtue of this property, a neural network-based system, unlike a conventional rule-based expert system, can handle the inexact and incomplete inputs. Even if the user could not provide answers to some of the queries, the system can nevertheless arrive at a recommendation based on the available knowledge about this problem.

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In this study, we investigate the feasibility of using a neural network as a simulator of experimental results provided by different fiber cement compositions. The most common and widely used model, that of multi-layer perceptron trained by back propagation algorithm with gradient decent, is employed.

The purpose of this research is to present a simulator of fiber cement composition based on artificial neural networks. Such a simulation can facilitate the engineering of projects and applications by predicting and evaluating the experimental results of the fiber-cement composition before conducting real scale tests.

**Neural network approach:** An artificial neural networks is a computational system made up of a number of basic processing element. These elements, or artificial neurons, are simple and highly interconnected. An artificial neuron receives information (signals) from other neurons, process it and then relays the filtered signal back to the other neurons. The receiving end of a neurons has incoming signals X1, X2,... and Xn. Each of them is assigned a weight, which is given based on experience and which may change during the training process.

In this type of multi-layer perceptrons network, the weighted connections feed activation only in the forward direction from the input layer to the output layer. A three-layered perceptron, trained by a back propagation algorithm network, is able to approximate the shape of an arbitrary nonlinear function by precisely adjusting connection weights between neurons. The three-layered neural network consists of an input layer, a hidden layer and an output layer. Each layer has a group of neurons and the output of a neuron in one layer equals input to all the neurons of the next layer. In the operating phase, the user sets the values of the input neurons and the neural network produces the output values. In the training phase, the user simultaneously sets the input and corresponding output values. Then all the weight values are modified using the back propagation algorithm; it performs a gradient descent method in which weights of the connections are updated using partial derivatives of error with respect to the weights.

In this study, the three-layered back-propagation neural network is adopted to simulate different compositions tables from desired experimental results (Fig. 1). There are three nodes in the input layer. These nodes represent the modules of rupture, toughness and water absorption. The number of nodes in the hidden layer is chosen based on the empirical approaches.

The output of a hidden layer node is given as Eq. 1. The output of an output layer node is given as Eq. 2. Equation 3 shows the sigmoid activity function.

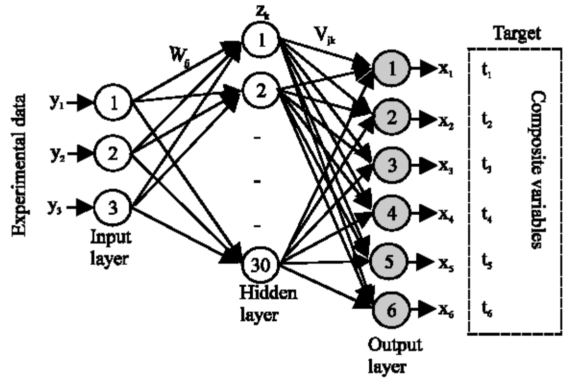


Fig. 1: Artificial neural network architecture used to cement composition simulation

$$z_j = f\left(\sum_{i=1}^{n} w_{ij} y_i\right) \tag{1}$$

$$x_k = f\left(\sum_{j=1}^{m} v_{jk} z_j\right) \tag{2}$$

$$f(\alpha) = \frac{A}{(1 + e^{-B*\alpha})} - C \tag{3}$$

Where,

A, B and C represent the sigmoid parameters that will control the threshold values of the artificial neurons. Figure 1 shows a particular case of Eq. 1 and 2 with n = 3, m = 30 and k in the interval (Wood, 1997; Heinricks *et al*., 2000) $k \in N$.

The training of the back-propagation neural network is composed of two steps. The first step is to calculate the results of the input samples in the forward direction from the input to the output layer. The second step is to correct the interconnection weights and the threshold values of the nodes in the hidden and output layers. The process moves from the output layer to the input layer. These two steps are repeated in turn until the desired network training error is made. Considering the gradient search technique, the network error is related to a minimization of a cost function.

## MATERIALS AND METHODS

The matrix of the composite was composed of ordinary Portland cement CPIIF type (ABNT, 1991), specific surface area of 600 $m^2\ kg^{-1}$), carbonate filler (specific surface area of 450 $m^2\ kg^{-1}$) and amorphous silica (specific surface area of 22500 $m^2\ kg^{-1}$ and pozzolanic activity equal to 814 mg $g^{-1}$). Polyvinyl Alcohol (PVA) fibers were used as reinforcement with 6 mm of cut length and average 15 μm diameters. Three types of cellulose pulp were used to assist with filtering in the fiber cement production and to assist with reinforcement in the hardened composite: Brazilian *Pinus taeda* unbleached kraft pulp (approximate Kappa number 45), Chilean *Pinus radiata* kraft pulp (approximate Kappa number 25) and bleached eucalyptus (mix of *Eucalyptus saligna* and *Eucalyptus grandis*) kraft pulp. The Kappa number (Appita, 1985) is an indirect measurement of lignin content. It is of particular interest in the characterization of unbleached kraft pulps. The major properties of cellulose fibers are described in Table 1. The Schopper-Riegler (SR) number is a measurement of the drainability of a suspension of pulp in water. It is determined and expressed as specified in SCAN-C19:65 (Scandinavian, 1964). In an attempt to simulate the Hatcheck method for sheeting fabrication, the pads of cement composite were produced in laboratory scale by slurring the raw material in water solution (20% of solids) followed by vacuum drainage of the excess water and by pressing. Hardened pads were wet-diamond-sawn with dimensions of 40×160 mm. Test specimen depth equalled the thickness of the pad, which was in the region of 5 mm. Twenty specimens for each formulation were subjected to wet curing for seven days. They were then allowed to air cure until the execution of mechanical tests which were conducted in the same environment (Eusebio *et al*., 1998).

The mechanical and physical properties evaluated at 28 days of total age were modules of rupture, toughness and water absorption. Mechanical behavior based on the Rilem recommendations (49 TFR) (RILEM, 1984) was employed using a four point bending configuration. A span of 135 mm and deflection rate of 1.5 mm $min^{-1}$ were used for all tests with an EMIC DL30000 universal testing machine. This machine was equipped with a load cell of 1 kN. Physical characterization followed the specification of Brazilian Standard NBR-9778 (ABNT, 1987).

The combination of the 6 predictors generated compositions that were used as the Artificial Neural Network (ANN) target in relation to these variables: ($y_1$) modulus of rupture, ($y_2$) toughness and ($y_3$) water absorption of the fiber cement composites at the total age of 28 days, used as the neural network input. The predictors under analysis were ($t_1$) synthetic fiber supplier (Japanese: 0, Chinese: 1); ($t_2$) content of synthetic fiber (1.2% by mass of dry raw-materials: -1, 2.4% by mass of dry raw-materials: 1); ($t_3$) supplier of the softwood cellulose pulp (Brazilian: -1, Chilean: 1); ($t_4$) refinement degree of softwood cellulose pulp (unrefined: -1, refined: 1); ($t_5$) content of softwood cellulose pulp (1.2% by mass of dry raw-materials plus 2.8% of hardwood pulp: -1.4% of

Table 1: Properties of cellulose fibers and pulps

| Sample | Refinement degree | Length (mm) | Coarseness ($mg100m^{-1}$) | Drainability (°SR) | Fines (%)[a] |
|---|---|---|---|---|---|
| Chilean softwood pulp | Unrefined | 1.85 | 32.73 | 13.0 | 9.11 |
| | Refined | 1.22 | 11.30 | 66.0 | 48.94 |
| Brazilian softwood pulp | Unrefined | 1.72 | 42.80 | 13.0 | 8.06 |
| | Refined | 1.24 | 11.56 | 70.0 | 25.28 |
| Hardwood pulp | Unrefined | 0.70 | 6.92 | 19.0 | 10.97 |
| | Refined | 0.68 | 5.77 | 69.0 | 10.95 |

[a]Percentage by mass of fibers with length under 0.07 mm

softwood pulp and no hardwood pulp in the formulation: 1) and ($t_6$) refinement degree of hardwood cellulose pulp (unrefined: -1, refined: 1 and no hardwood pulp in the formulation: 0).

The ANN was implemented in C++ language. The algorithm used was the error backpropagation with momentum. This strategy is used to improve the weight corrections during the ANN training by making weight changes in a direction that is a combination of current gradient and the previous gradient. This is a modification of the gradient decent method, used in the error backpropagation algorithm when some training data are very different from the majority of the full data.

Mathematically the weight change is represented by:

$$\begin{aligned} w_{jk}(t+1) &= w_{jk}(t) + \Delta w_{jk} \\ &+ \mu[w_{jk}(t) - w_{jk}(t-1)] \end{aligned} \tag{4}$$

Where $\Delta W_{jk}$ is the weight correction in real time step t and is the gradient correction and μ is the momentum constant term.

The ANN was trained in two steps: (1) 60% of the data set was used for training and (2) the remained 40% of data set were used for ANN test. The targets used in ANN training were vectors representing the cement compositions. For example, the vector (1 -1 -1 1 1 0) represents a cement composition of Chinese synthetic fiber supplier; 1.2% by mass of synthetic fiber, Brazilian softwood cellulose pulp with maximum refinement, 4% by mass of softwood pulp and no hardwood pulp in the formulation. The data set was constituted with 32 formulations vectors. Each of them had 20 repetitions, totalizing a set of 640 experimental results.

For each of the 100 classifications performed an error matrix was generated. From this matrix, the kappa coefficients of agreement (Vierira and Mather, 2000) were derived to indicate the classification accuracy of the Artificial Neural Network (ANN). In general the classification accuracies obtained were high, with kappa coefficients varying between approximately 0.89 and 0.93.

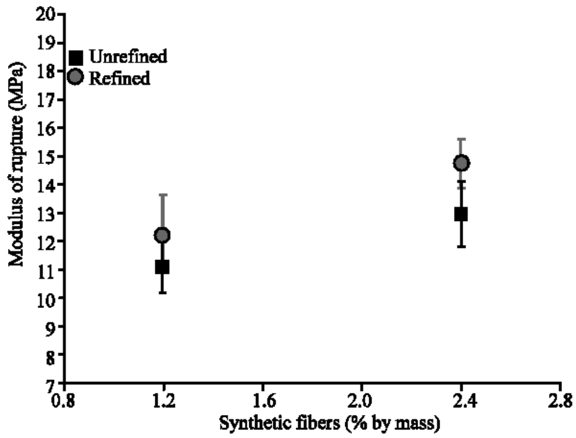


Fig. 2: Modulus of rupture x content of synthetic fiber associated with refinement degree of 1.2% by mass of softwood cellulose pulp. Vertical bars correspond to standard deviation of average results

## RESULTS AND DISCUSSION

The ANN simulation was tested using the experimental results and by comparing the ANN performance with the experimental data. A brief discussion about the experimental results will be made in the next paragraphs.

The presence of a higher concentration of PVA fibers associated with the effect of the refinement of the cellulose fibers contributed to the increase of the modulus of rupture of the composites. The strong adhesion of the fibers to the matrix reduced the pullout of fibers and increased the Modulus Of Rupture (MOR) of the composites at 28 days. Figure 2 depicts the variation of the modulus of rupture with the content of synthetic fiber associated with the refinement of the softwood cellulose pulp (Table 1). The highest percentage by mass of softwood cellulose pulp ($t_5$) correlatedto a negative effect in relation to the modulus of rupture ($y_1$) of the composites as indicated in Fig. 3. The Japanese synthetic fiber ($t_1$), the higher concentration of PVA fiber ($t_2$) and the high-level refinement of the softwood cellulose pulp ($t_4$) caused the more significant ($p<0.05$) increase of the $y_1$ variable as further explained by Bezerra and Savastano (2004).

The Japanese synthetic fiber ($t_1$), the increase of the content of synthetic fiber ($t_2$), the refinement of softwood cellulose pulp ($t_4$) and the addition of hardwood cellulose pulp ($t_5$) without refinement ($t_6$) contributed to the increase of the composite toughness ($p<0.05$) as highlighted in Fig. 4 and 5. The combination of long and short cellulose fibers probably related to more homogeneous distribution of fibers inside the composites with the favorable formation of multiple secondary cracks

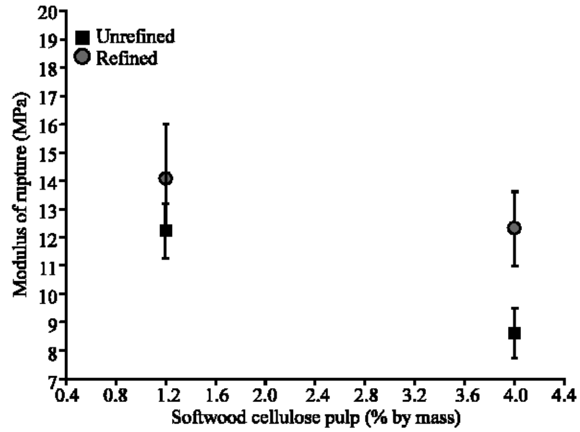


Fig. 3: Modulus of rupture x content of softwood cellulose pulp associated with refinement degree of the softwood cellulose pulp. Amount of synthetic fiber equal to 2.4% by mass. Vertical bars correspond to standard deviation of average results

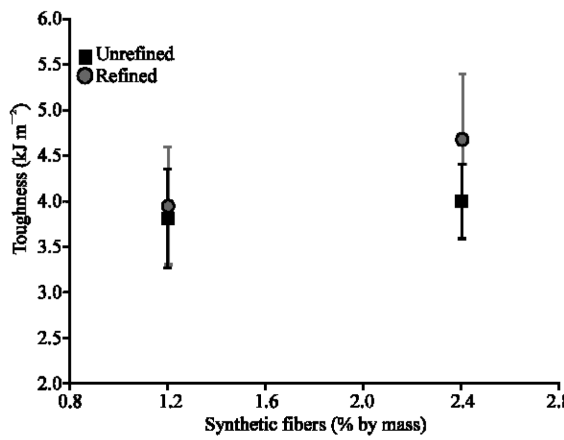


Fig. 4: Toughness x content of synthetic fiber pulp associated with refinement degree of 1.2% by mass of softwood cellulose pulp. Vertical bars correspond to standard deviation of average results

during the flexural tests. The synthetic fiber content ($t_2$) presented a positive interaction with the refinement of the softwood pulp ($t_4$) ($p<0.05$) as detailed by Bezerra and Savastano (2004).

Figure 6 shows that the values of water absorption, reduced for composites reinforced with refined softwood, are a consequence of the improved packing of the material. The increase of synthetic fiber content ($t_2$) led to the higher water absorption (Fig. 7).

All experimental data can be explored in the ANN simulator. The experimental results discussed in the

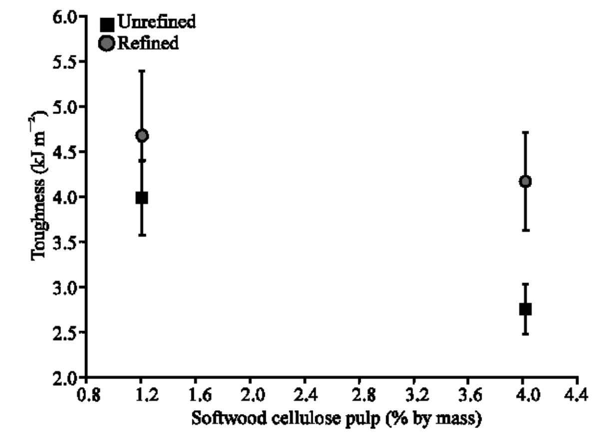


Fig. 5: Toughness x content of softwood cellulose pulp associated with refinement degree of the softwood cellulose pulp. Amount of synthetic fiber equal to 2.4% by mass. Vertical bars correspond to standard deviation of average results

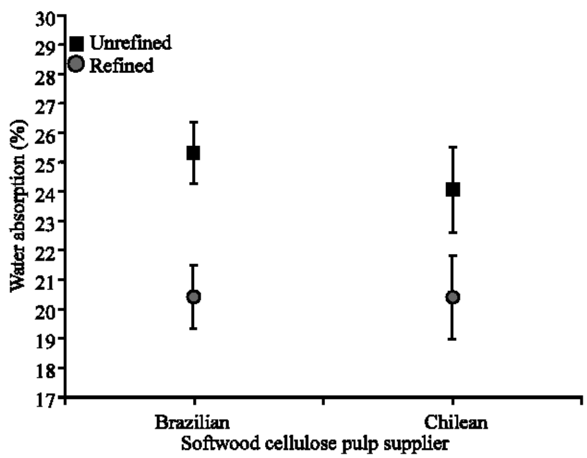


Fig. 6: Water absorption x softwood cellulose pulp supplier associated with refinement degree of 4.0% by mass of the softwood cellulose pulp. Amount of synthetic fiber equal to 2.4% by mass. Vertical bars correspond to standard deviation of average results

previous paragraphs were also obtained by using the simulator. Table 2 shows some experimental data and the corresponding compositions. Table 3 shows ANN output and the expected output used for test ANN. Table 4 shows a simulated composition obtained from ANN for different desired mechanical characteristics.

The results in Table 2 and 3 show that the ANN approaches can map the composite characteristics into its composition. The ANN output $x_i$ was considered: 1 when $x_i \geq 0.5$, 0 when $-0.5 < x_i < 0.5$ and -1 when $x_i \leq -0.5$. The ANN performance was 97.3 % of the correct classification with kappa coefficients varying between 0.89 and 0.93.

The ANN output adhered very well to the real composition variables. The only two exceptions shown in Table 3 are related to variable 1 (Chinese versus Japonese synthetic fiber). This discrepancy is due to the heterogeneous behavior of the composite as the incongruent results are contrary to the normal tendency of superior mechanical performance of composites reinforced with Japanese sybthetic fiber.

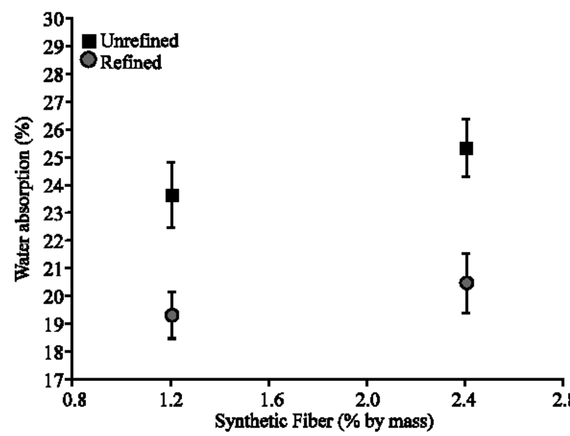


Fig. 7: Water absorption x content of synthetic fiber associated with refinement degree of 4.0% by mass of softwood cellulose pulp. Vertical bars correspond to standard deviation of average results

Table 2: Data obtained from experimental measurements and respective formulations

| | Formulation vectors[b] | | | | | | Experimental results[c] | | |
|---|---|---|---|---|---|---|---|---|---|
| Formulation number | $t_1$ | $t_2$ | $t_3$ | $t_4$ | $t_5$ | $t_6$ | $y_1$ | $y_2$ | $y_3$ |
| 7[a] | 0 | 1 | -1 | -1 | -1 | -1 | 12.99 | 4.06 | 22.63 |
| 19[a] | 1 | -1 | -1 | -1 | -1 | -1 | 14.05 | 4.20 | 23.54 |
| 22[a] | 1 | 1 | 1 | -1 | -1 | -1 | 11.51 | 4.32 | 23.60 |
| 28[a] | 0 | -1 | -1 | 1 | -1 | -1 | 15.41 | 4.65 | 20.63 |

[a]These results represent one of the 10 repetitions of the specified formulation. [b]($t_1$) synthetic fiber supplier (Japanese: 0, Chinese: 1); ($t_2$) content of synthetic fiber (1.2%: -1, 2.4%: 1); ($t_3$) supplier of the softwood pulp (Brazilian: -1, Chilean: 1); ($t_4$) refinement of softwood pulp (unrefined: -1, refined: 1); ($t_5$) content of softwood pulp (1.2% plus 2.8% of hardwood pulp: -1, 4% of softwood: 1) and ($t_6$) refinement of hardwood cellulose pulp (unrefined: -1, refined: 1 and no hardwood pulp: 0), [c]($y_1$) modulus of rupture (MPa), ($y_2$) toughness (kJ m$^{-2}$) and ($y_3$) water absorption (% by mass) of the fiber cement composites

Table 3: Composition obtained from ANN output and real composition used

| ANN input[a] | | | ANN output | | | | | | Real composition[b] | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $y_1$ | $y_2$ | $y_3$ | $x_1$ | $x_2$ | $x_3$ | $x_4$ | $x_5$ | $x_6$ | $t_1$ | $t_2$ | $t_3$ | $t_4$ | $t_5$ | $t_6$ |
| 12.36 | 4.14 | 21.93 | 0.01 | -0.87 | -0.78 | -0.97 | -0.91 | -0.86 | 1 | -1 | -1 | -1 | -1 | -1 |
| 11.79 | 3.95 | 23.57 | 0.67 | 0.76 | -0.97 | -0.79 | -0.99 | -1.01 | 0 | 1 | -1 | -1 | -1 | -1 |
| 9.07 | 3.14 | 22.76 | 0.97 | 0.97 | 0.97 | -0.79 | -0.98 | -0.76 | 1 | 1 | 1 | -1 | -1 | -1 |
| 15.40 | 5.52 | 21.33 | 0.1 | 0.69 | 0.78 | 1.02 | 0.98 | -0.05 | 0 | 1 | 1 | 1 | 1 | 0 |

[a]($y_1$) modulus of rupture (MPa), ($y_2$) toughness (kJ/m$^2$) and ($y_3$) water absorption (% by mass) of the fiber cement composites, [b]($t_1$) synthetic fiber supplier (Japanese: 0, Chinese: 1); ($t_2$) content of synthetic fiber (1.2%: -1, 2.4%: 1); ($t_3$) supplier of the softwood pulp (Brazilian: -1, Chilean: 1); ($t_4$) refinement of softwood pulp (unrefined: -1, refined: 1); ($t_5$) content of softwood pulp (1.2% plus 2.8% of hardwood pulp: -1, 4% of softwood: 1) and ($t_6$) refinement of hardwood cellulose pulp (unrefined: -1, refined: 1 and no hardwood pulp: 0)

Table 4: Simulated composition obtained from ANN output

| ANN input[a] | | | ANN output | | | | | |
|---|---|---|---|---|---|---|---|---|
| $y_1$ | $y_2$ | $y_3$ | $x_1$ | $x_2$ | $x_3$ | $x_4$ | $x_5$ | $x_6$ |
| 12 | 4 | 20 | 0.98 | 0.98 | 0.97 | 0.98 | 0.97 | -1.02 |
| 10 | 3 | 24 | -0.93 | -1.02 | -0.99 | -1.02 | -1.01 | -1.02 |
| 9 | 5 | 20 | 0.98 | 0.98 | -0.95 | -1.01 | 0.997 | -1.02 |
| 14 | 6 | 21 | 8.82 | 0.98 | 0.98 | 0.95 | 0.87 | -1.01 |

[a]($y_1$) modulus of rupture (MPa), ($y_2$) toughness (kJ/m$^2$) and ($y_3$) water absorption (% by mass) of the fiber cement composites

## CONCLUSION

This study applied ANN methodology to develop a cement composition simulator based on an experimental data set. The developed ANN, trained with backpropagation algorithm with momentum, was used to predict the formulations from three composite characteristics: modulus of rupture ($y_1$), toughness ($y_2$) and water absorption ($y_3$). The results suggest that ANN approach can be used to simulate composite formulation from mechanical and physics characteristics while using historical data sets from experimental results. Because the input data used for the ANN training was collected from a specific experimental data set, the results presented in this study are strictly related to this database. However, the developed ANN methodology presented in this study could also be used in other experimental data sets.

The main advantage of using a simulator is the possibility to obtain *a priori* results about how a determined predictor in cement composition will influence its mechanical and physical properties.

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