DEVELOPMENT OF THE APPLICATION OF ARTIFICIAL NEURON NETWORKS ON THE STUDY OF THE RESISTANCE OF MATERIALS

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ABSTRACT

This paper which is a research in the field of Materials Science presents an approach to process modeling of beam deformation. Modeling is done using Artificial Neural Networks by basing on existing experimental studies with known results using the study of the resistance of materials. The comparative studies of these two methods are to find the approximate values and minimization of the deformation. We have many advantages of using Artificial Neural Network (ANN) in engineering. A case study is within in the field of civil engineering materials.

Keywords: *Materials sciences, Artificial Neural Networks, strength of materials, minimizing the values of the deformation.*

1. INTRODUCTION

The use of Artificial Neural Networks begins with an understanding of the operating principle of the elemental constituent of the neural networks which is the nerve cell. In fact, this research has been given a process modeling approach of the deformation of a beam and continues the research in the field of materials science. Subsequently, the comparative studies of these two methods have been finished to find the approximate values and the minimization of the deformation.

This modeling is done using the Artificial Neural Networks, based on an already existing resistance model, and thanks to experimental data coming from, on the one hand, and literature from a study companion and specific with the formulas of the resistance of materials, on the other. Artificial Neural Networks has the ability to classify knowledge, simulate and to make decisions that have given them a field of application in engineering, especially in the field of civil engineering materials.

2. METHODOLOGY

We will expose the methodology for determining the mechanical behavior of materials in two steps:

- Study of the resistance of materials
- Artificial Neural Networks

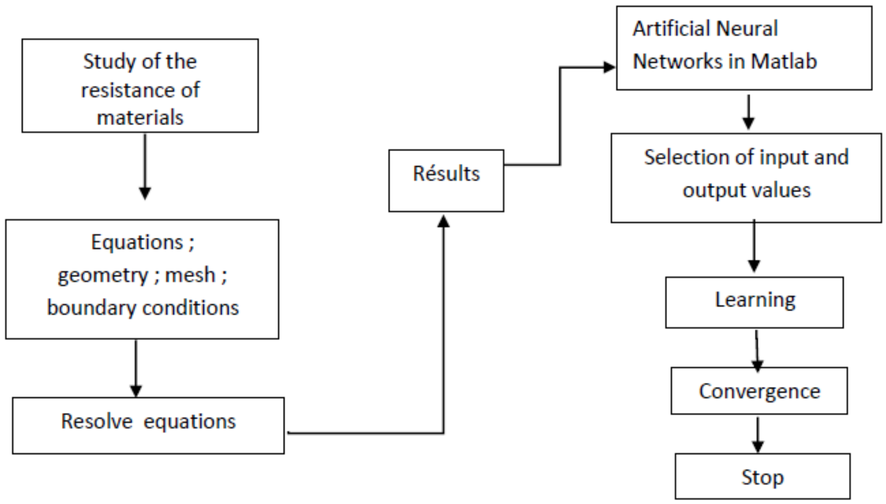

Fig -1 Methodology of the association of materials resistance and ANN

2.1 Study of the resistance of materials

We take the case of a single-flush beam and then determine the modeling of the linear and non-linear behavior of reinforced concrete structures. Following figure represents recessed beam of dimension of 3m of length, thickness 20cm and 50cm of height:

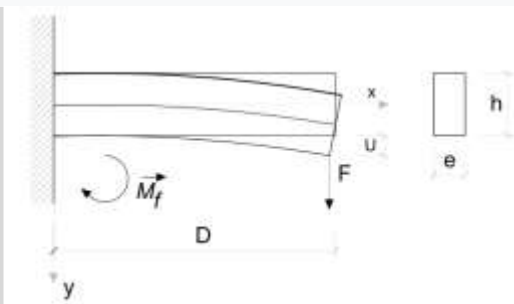

Fig -2 Recessed beam at one end and subjected to a force at the other end

2.2 Presentation of variables and equations

Among the parameters which define the values of the stresses, we distinguish the bending moments, the shearing forces. These values are given according to the results obtained and according to the length of the beam. In that case, the generalized constraints and the deformation are given by:

$$M(x) = -Fx$$

$$T(x) = -F$$

$$U(x) = \frac{-Fx^2}{6EI}(2D - x)$$
$$I = \frac{bh^3}{12}$$

Where x varies from 0 to D, such as D is the length of the beam.

Table -1 Order of magnitude of the mechanical behavior of concrete

Material	Young's module E (Mpa)	Poisson coefficient	Break limit (Mpa)
Concrete	30 000	0.2	20 à 40 (compression) 2 à 5 (traction)

2.3 Values to solicitations

The results of sagging moments and shear forces are shown in Figure 3 and 4.

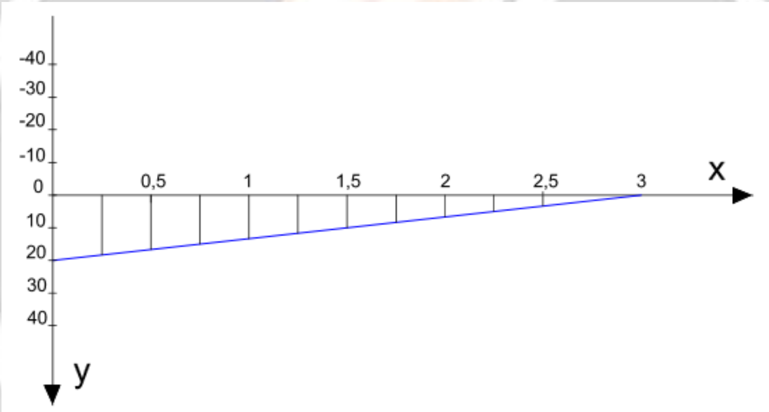

Fig -3 Flow chart of sagging moments

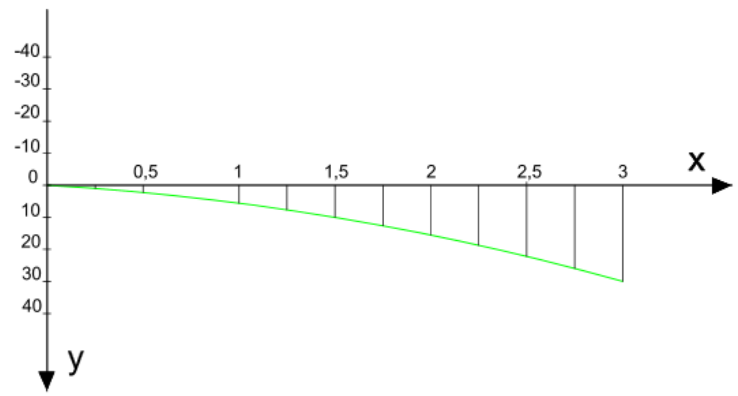

Fig -4 Diagram of shear forces

2.3 Artificial Neural Networks

a) Artificial Neural Network (ANN) Model

The multilayer backpropagation neural network was chosen in this study because of its popularity and its ability to achieve classification, prediction, and model optimization. The use of supervised learning requires knowledge of a desired output for any element of the set of input data. The multilayer backpropagation model consists of three types of layers, the input layer, one or more hidden layers, and an output layer.

In the prediction of the deformation of a beam, the set of input data is represented by the bending moments, the shearing forces. This represents the parameters of the input layer that are transmitted to the hidden layer. Finally, the output layer receives its input from the hidden layers. In our case the exit of the hidden layers represents the deformation.

b) Methodology and implementation

The first step is to identify the parameters to use for the forecast models. The data is divided into three parts. 70% of the data is used for learning, 15% for the test phase and 15% for validation. The implementation of an ANN model includes these three phases: learning, testing and validation.

The purpose of the learning or training phase is to determine the connection parameters of the network using the optimization technique. The test phase consists of checking the network determined during the learning phase on unused data during the learning phase, and examining the capacity of the network to generalize the learning examples (by comparing the actual output of the network with the desired exit). The validation phase is performed on the last part of the data. This learning is supervised.

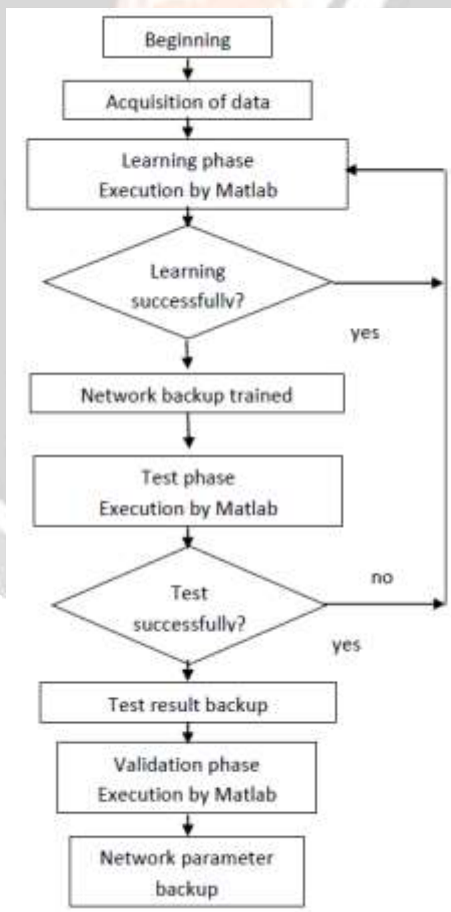

Fig -5 ANN development methodology

First of all, we determine the type of learning algorithm to use in our research. After several attempts, the Levenberg-Marquardt algorithm proves to be the most efficient and the most reliable. In that case, we have found that 110 iterations as being the limit of the convergence process. The learning was based on the Levenberg-Marquardt algorithm with error-gradient backpropagation with standard Tansigmoid transfer functions corresponding respectively to the hidden and output layers.

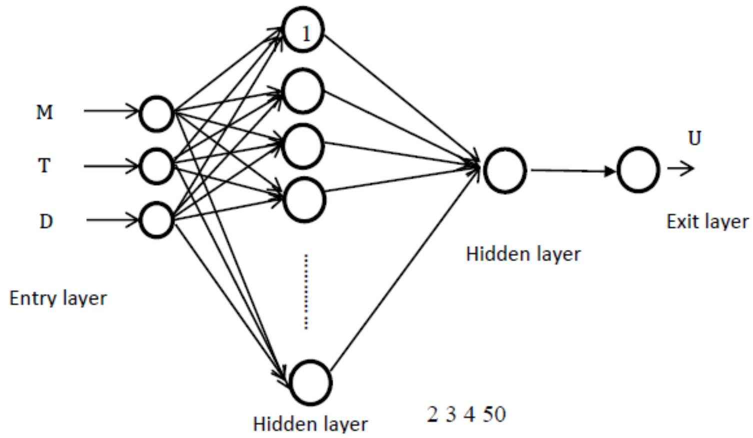

Fig -6 Adopted architecture

3. RESULTS

3.1 Weighted sum of the neuron inputs of the output layer

The output calculated by the ANN is defined by:

$$y(h) = f\left(\sum_{i=1}^{n} W_i x_j\right)$$

The weighted sum of the inputs of the neuron of the output layer is given by the following formula:

$$h = \sum_{i=1}^{n} W_i x_j$$

W_i is the matrix of the weight and one gives the following result.

$$\begin{pmatrix} 0.04 \\ 0.04 \\ 0.04 \\ 0.04 \\ 0.04 \\ 0.04 \\ 0.04 \\ 0.04 \\ \ldots \\ -2{,}19 \end{pmatrix} = \begin{pmatrix} 1.8555 & -1.8348 & 1.4466 \\ -1.3528 & -0.30181 & 2.7212 \\ 2.3116 & 1.3146 & 1.5314 \\ 2.5643 & 0.092914 & -1.658 \\ 0.78149 & -1.7302 & 1.5021 \\ 1.6514 & 1.74 & -1.8474 \\ 2.574 & 1.74 & -0.39068 \\ 0.37876 & 2.7016 & 1.2925 \\ 1.3723 & -0.77091 & 2.5704 \\ 0.56448 & 0.97221 & 2.9413 \end{pmatrix} \times \begin{pmatrix} 0{,}20 & 0{,}00 & 18{,}16 \\ 0{,}22 & 0{,}00 & 18{,}05 \\ 0{,}24 & 0{,}00 & 17{,}94 \\ 0{,}26 & 0{,}00 & 17{,}83 \\ 0{,}28 & 0{,}00 & 17{,}72 \\ 0{,}30 & 0{,}00 & 17{,}61 \\ 0{,}34 & 0{,}00 & 17{,}39 \\ 0{,}36 & 0{,}00 & 17{,}28 \\ \ldots & \ldots & \ldots \\ 3{,}20 & 25{,}05 & -1{,}20 \end{pmatrix}$$

3.1 Mean Squared Error (MSE)

In fact, the variation of the error is shown in Figure 7. This variation converges to a minimum value of the mean squared error or MSE, which verifies the quality of the simulation. We find this the MSE equal to 9,4953x10^{-7}.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(c_i - o_i)^2$$

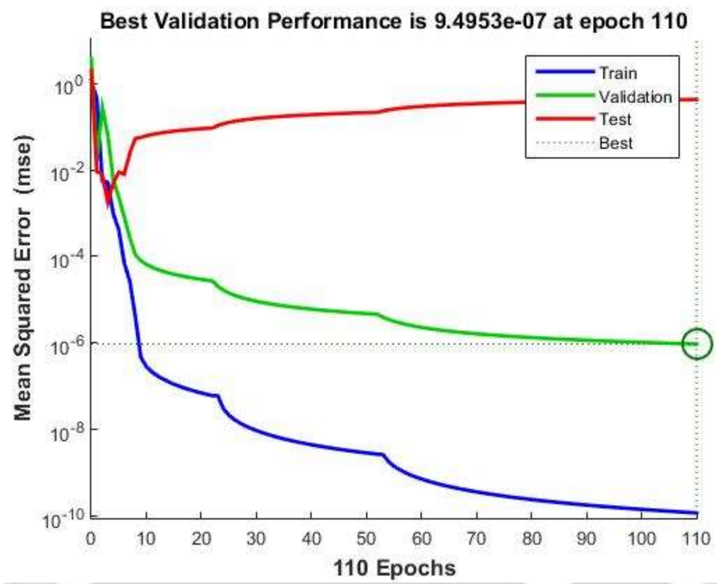

Fig -7 Performance curve

3.2 Gradient to the error

The gradient of the error is noted by:

$$\nabla E = \frac{\partial E}{\partial W_i}$$

We can write E in the form:

$$E = \frac{1}{2}\delta^2$$

From where:

$$E = \frac{1}{2}(d - y(h))^2$$

It is assumed that the output layer has only one neuron. The mean squared error E is:

$$\frac{\partial E}{\partial W_i} = \delta . f'(\textstyle\sum_{i=1}^{n} W_i x_i) . x_i$$

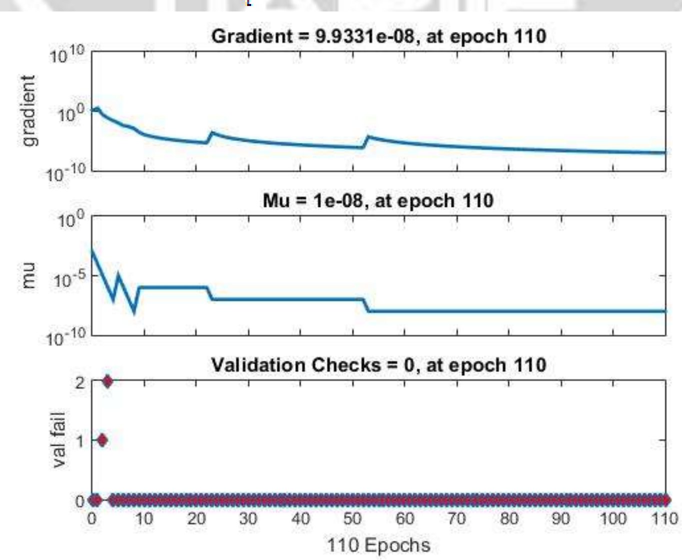

Fig -8 Gradient curve to error

3.3 Regression

The following regression illustrates that the relationship between the simulated output and the actual output is about 1 to 1. We find R = 0.99986.

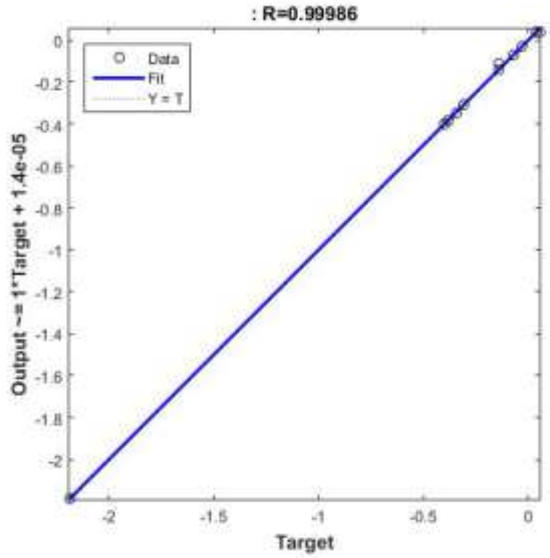

Fig -9 Regression curve

3.4 Desired and simulated output at the same frequency

Let the error at the output of the neuron k:

$$e_k = d_k - z_k$$

With:

d_k: the desired exit

z_k: the simulated exit by the ANN

The two responses will be at the same frequencies the desired and simulated output represented by the following figure:

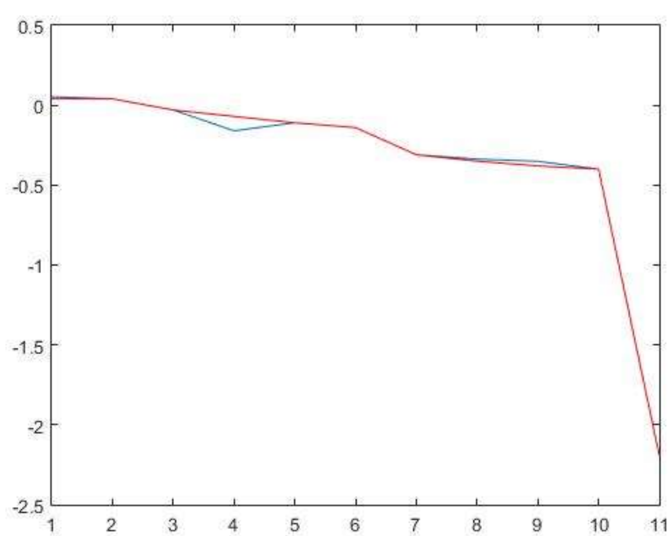

Fig -10 Chronogram of the desired and simulated exit

3.5 Comparison of results

The calculations were done well in order to obtain the deformation values from the geometry and the force applied to the beam. The maximum value of the desired output of the beam is greater than the simulated output. The ANN method is more efficient compared to the method of resistance of materials.

4. CONCLUSIONS AND OUTLOOK

We found that the ANN gives a better result compared to the resistance of the materials. For our next research, we would like to use Newton Raphson's method to find the best result.

5. DISCUSSIONS

For our next research, we could improve the results found by applying other methods. We noticed during this research the lack of data. The data collected is not satisfactory to apply.

6. REFERENCES

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