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A New Plasticity Model for Concrete in Compression Based on Artificial Neural Networks

Lyamine Briki[1] and Kamel Djeghaba[2]

[1]*Civil Engineering Department, University of Batna, Batna, Algeria*
[2]*Civil Engineering Department, University of Annaba, Annaba, Algeria*
lyabri@yahoo.fr

Abstract

In this paper, a new approach is proposed to investigate the characteristics behavior of concrete under uniaxial and biaxial compression using the theory of plasticity. This approach is based on artificial neural networks (ANNs), especially radial basis function (RBF) in conjunction with the models of theory of plasticity. The main advantage of the proposed approach is to estimate the quality of the results with accuracy equivalent to the experiments. Another advantage of the proposed ANNs models are that it takes into account the uniaxial as well as the biaxial compression strain. The proposed models were evaluated against several experimental results available in the open literature for the behavior of the force and deformation of the two types of compression tests. Good agreement has been found between our models and those presented elsewhere.

Keywords: *Concrete; uniaxial/biaxial compression; plasticity; failure criteria; artificial neural networks.*

1. Introduction

For the nonlinear analysis of concrete, different types of materials, model-plasticity, damage models, models damage-plasticity, micro plate models, and so on, have been developed. On the basis of many theoretical and experimental results, these models were used to accurately describe the behavior characteristic of concrete compressive stresses in various states. The concrete shows different characteristics depending on its behavior in stress states.

The uniaxial compression test is a test that has been widely studied well to know the compressive strength of concrete. In terms of the behavior of the concrete under hydrostatic loads, the latter has a non-linear behavior [1]. In the biaxial compression, Kupfer *et al*. [2] reported that the maximum concrete strength increases to 125% of the uniaxial strength as the ratio of the two orthogonal constraints. This improvement was confirmed in the case of biaxial compression tests such as Liu *et al* [3]; Nelissen [4]; Tasuji *et al*. [5].

In recent years considerable research effort has been devoted to the development of analytical models that can accurately predict the response of concrete at a variable load. The first models were based on the theory of elasticity. Newer models typically use solid mechanics theories including the theory of plasticity, damage theory and fracture mechanics allowing the description of specific aspects of the response of concrete with a more or less sufficient accuracy and effective. To describe the characteristic behavior of concrete in compression, the plasticity model has been widely used because of its simple and direct representation of the state of multiaxial stress [6, 7].

However, existing plasticity models using a single failure criterion is limited to describe the complex behavior of the concrete. Single failure criterion and plastic deformation matching is not sufficient to accurately describe the complex and variable behavior of concrete based on combinations of constraints. Usually, their application is limited to the test data used for model calibration. For a good agreement with the results of other tests, the parameters used in existing plasticity models must be adjusted. The development of a constitutive model based on the plasticity requires the definition of a decomposition rule of the total deformation, the elastic constitutive relation of the material, plastic-breaking surfaces which limit the elastic range and the flow rule that defines the evolution of the internal variables. A model material in the context of multi-surface plasticity for gross concrete was formulated by Pivonka et *al*. [8]. If the introduction of multiple fracture surfaces may facilitate the definition of the entire lamination surface, it can complicate the determination by against the flow equations. A plasticity model using three independent fracture surfaces was developed by Park and Kim [9] to describe the nonlinear behavior of concrete in different compression stress states.

Recent work includes the neural network approach have been developed by Zhao and Ren [10] used the ANN to test the experimental data in order to acquire the failure criterion of concrete strength. Penumadu and Zhao [11] found by treating the triaxial behavior of sand and gravel in terms of non-linear stress-strain relations, the change in volume at low and high levels of stress is well captured by feedback network neurons.

An attempt was made to implement artificial neural networks for modeling the stress-strain sands with varying distribution of grain size and history constraints [12].

2. Artificial Neural Networks (ANNs) Modeling

Artificial neural networks are powerful tools for the prediction of nonlinearities using modeling philosophy similar to that used in the development of most conventional statistical models [13]. Artificial neural networks are promising computational techniques capable of mapping and capturing all features and sub-features embedded in a large set of data that yields a certain output. A network that has successfully captured governing relationships between input and output data can be used as a prediction tool for cases where the output solution is not available [14].In the implementation of ANNs, data are categorized as input samples and target samples [15]. During the learning process, the neural network output is compared with the target value and a network weight correction via a learning algorithm is performed in such a way to minimize an error function between the two values [16].

The mean-squared error (MSE) is a commonly used error function which tries to minimize the average error between the network's output and the target value.

$$MSE = \frac{1}{\mathrm{N}}\sum_{i=1}^{N} (y\text{-}y')^2 \qquad (1)$$

where N is the number of samples, y and y' are the measured and predicted values, respectively.

A. *Radial basis function (RBF)*

In a typical radial basis function (RBF) network (see Figure .1), the input layer is simply a receptor for the input data. The crucial feature of the RBF network is the function calculation which is performed in the hidden layer. This function performs a non-linear transformation from the input space to the hidden layer space. The hidden neurons’ functions form a basis for the input vectors and the output neurons merely calculate a linear (weighted) combination of the hidden neurons’ outputs [13].The c_i and λ_{i} are centers and standard deviations of radial basis activation functions. Commonly used radial basis activation functions are Gaussian and multiquadratic. A typical RBF network structure is given in Figure 1.

The parameters c_{ij} and λ_{ij} are centers and standard deviations of radial basis activation functions. Commonly used radial basis activation functions are Gaussian and multiquadratic. Given the inputs x, the total input to the i^{th} hidden neuron γ_i is given by (2).

$$\gamma_i = \sqrt{\sum_{j=1}^{l}\left(\frac{x_j - c_{ij}}{\lambda i_j}\right)^2}\ , i = 1,2,3,..L \tag{2}$$

where N is the number of hidden neurons. The output value of the i^{th} hidden neuron is $Z_{ij} = \sigma(\gamma_i)$ where $\sigma(\gamma_i)$a radial basis function is. Finally, the outputs of the RBF network are computed from hidden neurons as shown in (3)

$$y_k = \sum_{i=0}^{N} \omega_{ki} Z_{ki} \tag{3}$$

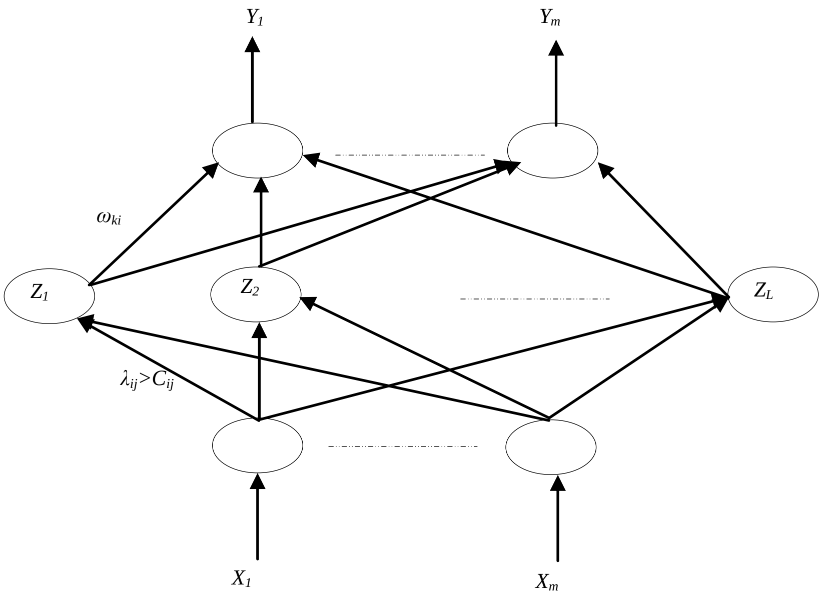

Figure 1. Radial Basis Function (RBF) Artificial Neural Networkstructure

where ω_{ki} is the weight of the link between the i^{th} neuron of the hidden layer and the k^{th} neuron of the output layer. Training parameters ω of the RBF network include ω_{k0}, ω_{ki}, c_{ij}, λ_{ij}, k = 1 ,2,…m, i= 1 ,2,...L, j = 1,2,…n.

The training and test data of the ANN models were obtained from experimental results given in previous works [11, 16]. The data are in matrix form consisting of inputs and target values and arranged according to the definitions of the problem. In this work, the numbers of input-output data pairs in the training, validation and test data sets are chosen respectively 41%, 26% and 33% of the full data set.

The parameters setting of the RBF network (the number of hidden layer and the spread value) are automatically optimized using the minimum value of the mean square error (MSE) in the validation data set. In the two case of the radial basis function neural network, the spread value was 1 for the uniaxial case and 0.05 for the biaxil case. The best values of the hidden layer are 6 and 19 for the both cases uniaxial and biaxial models, respectively.

B. Applying the neuro-computational technique

Figure 2 shows the performance of the RBF during a training session, and the best validation performance is at epoch 6. In this network, minimum MSE for best model in case of training is 7.70278 10^{-5}. Here, the errors obtained from the validation set are monitored during the training.

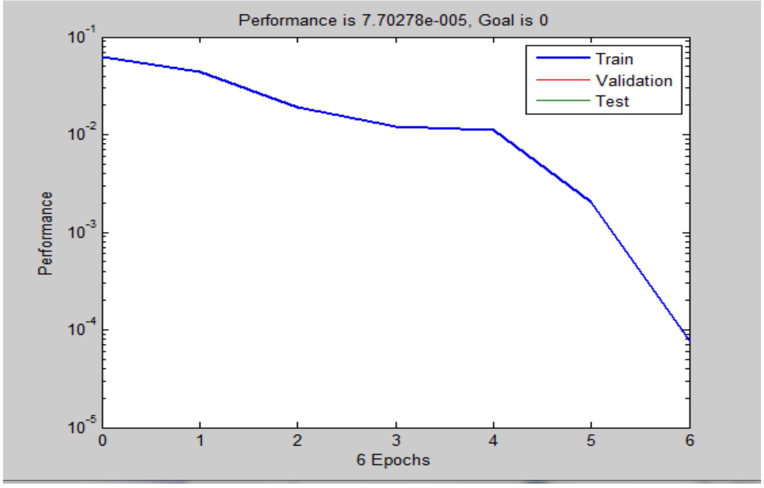

Figure 2. Snapshot of Neural Networks Performance Plot for Uniaxial Compression

Next, the training performance of the developed neural model for the case of biaxial compression. The model is trained in 19 epochs and the minimum MSE for best model in case of training is 9.20581 10^{-4} (see Figure 3).

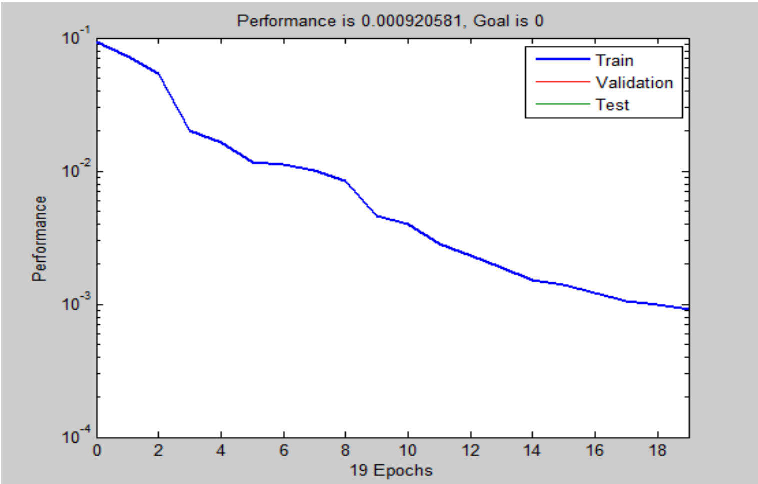

Figure 3. Snapshot of Neural Networks Performance Plot for Biaxial Compression

3. Numerical Results and Discussion

For verification, the numerical results obtained by the proposed model were compared with the results of existing tests for different stress states and properties of materials.

Numerical results on the behavior of concrete compressive uniaxial with different compressive strength and elastic modulus were compared with the results of the test by Hognestad et *al*. [17], and Desayi Krishnan [18] (see Figure .4).

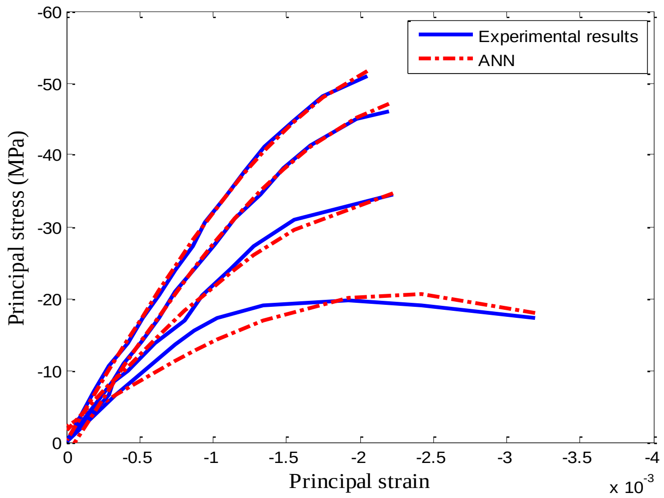

Figure 4. Comparison between ANN and Experimental Results on Uniaxial Compression (Hognestad et *al.* [17])

In the test by Hognestad et *al*. [17], $f_c = 20, 34.5, 46$ and 51Mpa and $E_c = 18700, 21550, 26900$ and 31600Mpa . In test Desayi and Krishnan [18], $f_c = 21.1, 31.2$ and 50Mpa and $f_c = 25000, 32000$ and 35700Mpa .

As shown in the Figure 4, the proposed model accurately describes the behavior in uniaxial compression of concrete with different compressive strengths and module of elasticity. Figure 4 shows the stress-strain relationship obtained from uniaxial compression tests and biaxial by Kupfer *et al*., [2] and Tasuji *et al*., [5]. In tests, $\sigma_2 / \sigma_2 = 0, 0.5, 1$. In Kupfer et *al*. [2], $f_c = 32$Mpa and $E_c = 29000$Mpa. In Tasuji *et. al*., [5], $f_c = 33.9$Mpa and $E_c = 19600$Mpa.

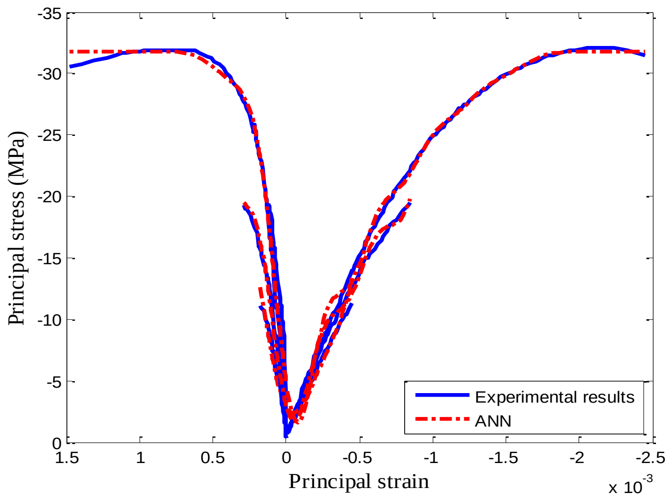

Figure 5. Comparison between ANN and Experimental Results on Biaxial Compression (Kupfer et *al*. [2])

As shown in Figure 5, the proposed model accurately describes the relationship principal stress and principal strain. Figure 5 shows the variations of the resistance to the biaxial compression by the ratio of constraints σ_2/σ_2 (Kupfer *et al.,* [2]; Mills and Zimmermanv [19]; Liu *et. al.,* [3]; Nelissen [4]; Tasuji *et al.,* [5]). The proposed model is in good agreement with the compressive strength of biaxial compression tests.

4. Conclusion

A plasticity model using a new neural network approach has been developed to describe the nonlinear behavior of concrete in the uniaxial and biaxial compressive stresses. In the proposed model, using the RBF neural network has been used to describe more accurately the behavioral characteristics of concrete in two stress states.

The proposed model was verified by comparing the results with those of the existing uniaxial and biaxial tests. The comparisons show that the proposed model is applicable for general use because it can predict most of the test results, using the basic properties of materials such as uniaxial compressive strength and modulus of elasticity. Based on this research, the following are concluded: 1) Models of concrete based on artificial neuronal network have been developed to model the plain concrete uniaxial and biaxial compressive behavior for different stress states and properties of materials. Simulations and predictions of this model are in good agreement with the experimental data. 2) These models can accurately represent the effects of softening plasticity. 3) For a wide range of confining pressures, the observed behavior of the concrete in terms of non-linear stress-strain relationship, the compression and expansion of the volume at high levels of stress (shear dilation effects), and the gradual reduction of the stress beyond the rupture (softening) are well captured by this model.

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