Artificial neural networks in prediction of mechanical behavior of concrete at high temperature

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Abstract

The behavior of concrete structures that are exposed to extreme thermo-mechanical loading is an issue of great importance in nuclear engineering. The mechanical behavior of concrete at high temperature is non-linear. The properties that regulate its response are highly temperature dependent and extremely complex. In addition, the constituent materials, e.g. aggregates, influence the response significantly. Attempts have been made to trace the stress–strain curve through mathematical models and rheological models. However, it has been difficult to include all the contributing factors in the mathematical model. This paper examines a new programming paradigm, artificial neural networks, for the problem. Implementing a feedforward network and backpropagation algorithm the stress–strain relationship of the material is captured. The neural networks for the prediction of uniaxial behavior of concrete at high temperature has been presented here. The results of the present investigation are very encouraging.

1. Introduction

Modeling of the mechanical behavior of concrete at temperatures above ambient is necessary in the analysis of hypothetical accident situations in a nuclear reactor or other accidental fire situations. Design of fire resistant structural elements require realistic knowledge of the behavior of concrete at high temperatures. The response of concrete at high temperature and pressure is non-linear. The parameters that regulate its behavior, e.g. modulus of elasticity, comprehensive strength, ultimate strain, thermal conductivity, etc., are non-linear functions of temperature. Moreover, the properties of constituent materials, e.g. aggregates, influence the behavior of concrete significantly (Diederichs et al., 1987). Influence of temperature on the properties of concrete have been studied through many experiments. Most of the tests have been directed toward studies of the temperature dependence of various properties of concrete concerned with fracture, strength and deformation behavior at high temperatures under uniaxial conditions and in a steady state. These results are useful for the prediction of behavior of 1-D structural members such as beams and columns but constitutive equations and failure criterion for concrete which are derived from such tests cannot be applied to complex concrete structures like pressure vessels, slabs or other concrete
plate and shell elements directly, as they have mainly biaxial stress conditions and are subjected to considerable temperature variations. Recently, some sophisticated test instruments have been reported (Thienel, 1993) which allow the study of fracture and stress–strain behavior of concrete subjected to biaxial stresses at high temperatures. Experimental results under transient conditions, that are very realistic in the case of fire hazards, are now available. However, the analytical models developed so far are limited to uniaxial behavior only.

Simulating a reliable model is a mountainous task when the material in question experiences elastic and inelastic deformations, thermal dilatation, transient creep and cracking as well as degradation of its material properties with increasing temperature. Concrete is one such material and the difficulties encountered during modeling its response at an elevated temperature has been acknowledged by various researchers (Diederichs et al., 1989). Simulation with mathematical models is based on a semi-empirical relationship between the parameters that must be explicitly stated for computation. The exact relationships in some cases are yet to be ascertained.

Recently, a new programming paradigm, artificial neural networks (ANN) has been proposed to model complicated multiparameter material behavior (Ghaboussi et al., 1991; Mukherjee et al., 1995; Mukherjee and Rao, 1996). The basic advantage of artificial neural networks lies in the fact that it is able to automatically map a relationship from the supplied input and output parameters. Therefore, complicated relationships between various parameters can be found out by the network. Moreover, ANN is a model free estimator. Therefore, the parameters that are difficult to measure experimentally can be avoided. For example, the hardening parameter of concrete which is a function of temperature is difficult to measure. An ANN can be trained with the input of temperature only and the network should map the hardening parameter itself.

Artificial neural networks learn through examples. The examples are presented in the form of input and corresponding output parameters. The network then attempts to learn, or in other words map the relationship between the input and output from the examples presented to it. The input–output parameter can be generated from experimental results. As a result, the material behavior is captured directly from the experiments without describing the exact relationship between the parameters. The ‘trained’ network would contain adequate information about the material behavior to qualify as a material model. In a neural network the knowledge is stored in a distributed fashion. Therefore it is able to generalize the knowledge and predict reliably even for problems that are not a part of the training examples.

In a mathematical model the empirical rules and expressions are stated to constrain the fundamental laws of mechanics (like conservation law, symmetry requirements, invariance, etc.) relating various material properties like elastic behavior, yielding, strain hardening, etc. On the contrary, trained neural networks predict the material behavior ‘intuitively’. Consequently a neural network based model cannot guarantee to prove that the internal mechanism of the model is following the laws of mechanics. However, the fact that the backpropagation networks are trained with an exhaustive set of experimental data means that the model should approximate the laws of mechanics.

In the present paper we show the strength of artificial neural networks in capturing the behavior of concrete at high temperature. The result from experimentation have been used directly to train the network. Therefore, all the complicating effects have been included directly in the model. Predictions of the neural network have been compared with those of the existing mathematical models. The results have been very encouraging.

2. Concrete under high temperature and high pressure

The behavior of concrete structures that are exposed to thermal loading is an issue of great practical importance. By the use of high strength concrete the economy of structures can be enhanced considerably in conventional house-building as well as in construction for energy
technology. This involves knowledge of the high temperature behavior of concrete because the structures may either in normal service or under catastrophic conditions (fire, reactor accident, etc.) be subjected to high temperature and they must be correspondingly designed.

During the heating of a concrete specimen several non-linear physical phenomena are observed. First the material expands. The thermal dilatation is governed by the coefficient of thermal expansion which is a non-linear function of temperature. Another effect is the decrease in stiffness in the form of Young’s modulus. The damage (Thelandersson, 1982) is mainly caused by (i) the thermal incompatibility between the aggregate and the cement paste and (ii) chemical decomposition of the cement paste. It is common to take temperature as an internal state variable (damage measure) and formulate a mathematical model on the basis of isothermal test data only. The drawback of this approach is that the material response depends strongly on the path in the stress–temperature space. This is known as the ‘temperature change effect’ observed in pure torsion and uniaxial compression tests. To explain this behavior some researchers have introduced an extra component of strain termed ‘transitional creep’ or ‘transitional strain’. It is not yet clear which mechanism causes transient creep, but it seems that between 100 and 200°C drying of the cement matrix is an important factor (drying creep), while at higher temperatures a change of the chemical structure of the cement matrix is primarily responsible for the observed strain (transitional thermal strain). Transitional thermal creep results in the relaxation and redistribution of the thermal stress, rendering the elastic stress analysis inappropriate for the structure that is heated for the first time (Khoury et al., 1985).

Diederichs et al. (1987) conducted an investigation at high temperature up to 600°C on HTR-concrete under uniaxial conditions. The investigation was carried out with different mix proportions and with different aggregates. They concluded that higher loss of strength was witnessed in the Rhine gravel concrete than with the basalt concrete when exposed to thermal conditions. The main difference in the deformation behavior of the two types of concrete was found in the thermal expansion, which depends mainly on the thermal expansion of the coarse aggregates.

Thelandersson (1982) proposed an analytical model in which the basic assumption is that moisture related effects are considered only indirectly and the model is less suitable in situations where the moisture is confined in the material. Thelandersson assumed the existence of a plastic and a viscoplastic yield surface. The viscoplastic yield surface is used to describe the time dependent effects, while the plastic surface is used to describe the instantaneous non-linear behavior. Both the surfaces change their sizes with the temperature, but they keep the same shape which contradicts the experimental data obtained by Ehm and Schneider (1985) and Kordina et al. (1986). Thelandersson (1987) presented an improved model in which the theory is greatly simplified (linearity in stress and creep neglected). The results deviate from the experimental results, for combinations of stress and temperature that approach failure. Thelandersson argues that to describe the various phenomena occurring when concrete is subjected to high temperature, it is necessary to adopt an approach in which the hygral and the thermochemical response are interdependent. A method to describe the interdependence at the linear level was presented, but the non-linear one is not introduced. An improvement was suggested by De Borst and Peeters (1989). The main proposal of this model was to outline the consistent approach to smeared crack analysis of concrete structures that are exposed to extreme thermal conditions. In that model the total strain rate is decomposed into a crack and concrete strain rate. Each strain rate is governed by a separate constitutive law which opens the possibility of constructing a consistent set of rate equations. The model showed the difficulties associated with incorporating a crack at higher temperatures. They argue that the classical smeared crack approach is ill suited, and instead they proposed a strain rate formulation in which the total strain was divided into individual components. Their algorithm is limited to the linear range only.
Khennane and Backer (1993) have suggested a model to capture the uniaxial behavior of concrete under high temperature. The basic formulation used in the model assumes that the total strain rate of concrete under first time heating can be decomposed into additive components of elastic strain rate, plastic strain rate, transient creep strain rate and the thermal strain rate. The elastic strain is governed by the Hooke’s law, where the modulus of elasticity \( E_T \) is a function of temperature \( T \). The plastic strain rate and the hardening parameter are path dependent. Therefore, they depend on the stress at any point in the stress–strain curve. The estimate of the hardening parameter is made by assuming the stress–strain curve in the plastic region to be a quarter of an ellipse in shape. The free thermal strain is obtained as a product of the temperature and the coefficient of free thermal expansion of the concrete \( \alpha \) which varies with temperature. However, the coefficient of free thermal expansion is expressed as a piece-wise linear function (constant for a certain range of temperature) due to its very complex behavior.

To validate the model three combinations of load and temperature that can occur in a real situation have been used. The first combination consists of a variable load and a constant temperature (isothermal condition). The second combination consists of variable temperature and a constant loading and the third consists of a combined variation of both load and temperature. The model provided better results than the previous models. In the isothermal condition case, the simulation is satisfactory in the elastic zone, but it gradually deviated from the experimental results in the plastic zone with the increase in temperature. In the constant load case the simulated response calculated by considering the load effects on the properties give more accurate results than by not considering the effects. However, both results deviate widely from the experimental result with increasing temperature. In the restrained case, the results of this model maintained the nature of actual experimental result but they deviated widely in value.

In this paper, we demonstrate the power of artificial neural networks (ANN) in the prediction of stress–strain relationships in concrete at high temperature. ANN has produced far superior results than the previous semi-analytical expressions. A comparison between the existing semi-analytical predictions and those by ANN is presented. Moreover, using the methodology described here an ANN for biaxial behavior can be developed, for which no analytical model exists. The present work is a step towards that goal.

3. Artificial neural networks

Artificial neural networks were developed to model the human brain. The concept of neural networks is discussed in detail elsewhere (Mukherjee et al., 1996). A brief description is included in the following section.

3.1. Artificial neurons

An artificial neuron is a very approximate model of the biological neuron. It can carry out a simple mathematical operation and/or compare two values. An artificial neuron gets input from other neurons or directly from the environment. The path connecting two neurons is associated with a certain variable weight which represents the synaptic strength of the connection. The input to a neuron from another neuron is obtained by multiplying the output of the connected neuron by the synaptic strength of the connection between them. The artificial neuron then sums up all the weighted inputs coming to it.

\[
x_j = \sum_{i=1}^{m} w_{ij} o_i
\]

where \( x_j \) is the summation of all the inputs for neuron \( j \), \( w_{ij} \) is the synaptic strength between neurons \( i \) and \( j \), \( o_i \) is the output of neuron \( i \), and \( m \) is the total number of neurons sending input to neuron \( j \).

Each neuron is associated with a threshold value and a squashing function. The squashing function is used to compare the weighted sum of inputs and the threshold value of that neuron. If the threshold value is exceeded by the weighted sum the neuron goes to a higher state, i.e. the
output of the neuron becomes ‘high’. Many different squashing functions are used in different applications. In the present work a backpropagation learning algorithm has been used. This algorithm necessitates the use of a continuous, differentiable weighting function. Therefore, a sigmoidal squashing function has been used here as follows:

\[ o_j = \frac{1}{1 + e^{-ax_j}} \]  \hspace{1cm} (2)

where \( o_j \) is the output of neuron \( j \), \( x_j \) is the summation of all the weighted sums of the inputs for neuron \( j \), \( \theta_j \) is the threshold value of neuron \( j \), and \( a \) is a parameter which controls the slope of the squashing function.

The output of the neuron for a given input can be controlled to a desired value by adjusting the synaptic strengths and the threshold values of the neuron. In an ANN several neurons can be connected in a variety of ways. Many different types of neural networks have already been developed. The network architecture has to be selected keeping the problem at hand in mind. The present work requires training with a set of examples in a supervised manner. Therefore, a feedforward network is most suitable. A brief description of the feedforward network follows.

3.2. Feedforward networks

In a feedforward network the neural units are classified into different layers. The network consists of one input layer, one or two hidden layers and one output layer of neurons. Fig. 1 presents a typical feedforward network. It may be noted that all the neurons between two successive layers are fully connected, i.e. each neuron of a layer is connected to each neuron of the neighboring layer. However, there is no connection between neurons of the same layer or the neurons which are not in successive layers. The input layer receives input information and passes it onto the neurons of the hidden layer(s), which in turn pass the information to the output layer. The output from the output layer is the prediction of the net for the corresponding input supplied at the input nodes. Each neuron in the network behaves in the same way as discussed in Eqs. (1) and (2). There is no reliable method for deciding the number of neural units required for a particular problem. This is decided based on experience and a few trials are required to determine the best configuration of the network.

In a feedforward network the knowledge is stored in a distributed manner in the form of synaptic strengths and thresholds. Thus it can be generalized, i.e. it may be used for situations for which the network has not been trained. Initially, the synaptic strengths and the threshold values are allocated randomly. To train the network for specific knowledge a set of training examples is prepared. A training example consists of a set of values for the input neurons and the corresponding values for the output neurons. Several of such input–output pairs are prepared carefully to reflect all the aspects that the network needs to learn. All the training examples together form the training set. In the beginning of the training process, as the synaptic strengths and thresholds are selected randomly the output predicted by the network for a particular input and the output supplied in the corresponding training examples may not match. However, the synaptic strengths and the thresholds can be adjusted so that the network predicts the output correctly. As several examples are to be learnt by the network there must be a sufficient number of neural units in the network. The adjustments in the synaptic strengths and thresholds are carried out following a ‘learning algorithm’. The backpropagation algorithm has been used in the present work for this purpose.
3.3. The backpropagation algorithm

The backpropagation algorithm is a generalized form of the least mean square training algorithm for perceptron learning (Lippmann, 1987; Hecht-Nielsen, 1989). It uses the gradient search method to minimize the error function which is the mean square difference between the desired and the predicted output. The error for \( p \)th example is given by

\[
E_p = \sum_j (d_j - o_j)^2
\]  
(3)

where \( d_j \) is the output desired at neuron \( j \) and \( o_j \) is the actual output of neuron \( j \).

As presented in Eqs. (1) and (2) the output \( o_j \) is a function of synaptic strengths and outputs of the previous layer.

\[
o_j = f(\beta_j) = f\left(\sum_k w_{jk} o_k\right)
\]  
(4)

The error can be minimized by moving along the steepest descent direction on the error surface

\[
\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial \beta_j} \frac{\partial \beta_j}{\partial \beta_j} = \frac{\partial E}{\partial \beta_j} o_i = \delta_j o_i
\]  
(5)

where, \( \delta_j \) for a neuron is

\[
\delta_j = f'(\beta_j) \sum_k \delta_k w_{kj}
\]  
(6)

and \( f' \) indicates the first order derivative of the function and \( k \) indicates a neuron in the layer which is successive to the layer which contains neuron \( j \).

Therefore, the weight matrix can be adjusted recursively for each example

\[
w_{ij}(t + 1) = w_{ij}(t) + \eta \delta_j x_i
\]  
(7)

where \( \eta \) is an adjustable gain term which controls the rate of convergence.

The above operation is repeated for each example and for all the neurons until a satisfactory convergence is achieved for all the examples present in the training set.

For the present investigations an artificial neural network simulator (Mukherjee et al., 1996) is used. The networks have been trained using an IBM compatible PC 486 machine. A feedforward network is adopted for training purposes. The error is reduced using a backpropagation algorithm. A sigmoid function is used as the threshold function. The function produces an output between 0 and 1. Therefore, the range input and output is scaled between these two values.

4. ANN for uniaxial mechanical behavior of concrete under high temperature and pressure

The behavior of concrete at high temperature and pressure has been modeled using the feedforward artificial neural network. Extensive experimental work has been reported earlier (Anderberg and Thelandersson, 1976). These have been used here for neural training. The behavior of concrete under three different conditions namely

- varying load under isothermal conditions
- varying temperature under constant load
- varying temperature under total restraint

have been considered.

4.1. Varying load under isothermal conditions

The behavior of concrete under isothermal conditions is relatively simple. Under this condition, concrete experiences instantaneous mechanical strain only. For the isothermal stress–strain relationship without sustained loading, creep does not take place. Therefore, only the properties that constitute the elastic and the plastic response in the material are considered in the model. In this case a strain driven model is used. The strain driven model has strain controlled input and stress is obtained as the output. It may be noted that the neural networks can be trained from experimental results. Therefore, only those input parameters should be chosen that can be measured easily experimentally. In this case, the input nodes are provided with current strain (\( \varepsilon \)), temperature (\( T \)), elastic modulus (\( E_T \)) at that temperature, compressive strength (\( f_{cT} \)) and ultimate strain (\( \varepsilon_{uT} \)). At the output node current stress (\( \sigma \)) was obtained (Fig. 2). A configuration of two hidden layers with five nodes at each layer was taken. The training set consisted of the experimentally observed stress–strain relationships at
temperatures 20, 265, 500 and 650°C (Anderberg and Thelandersson, 1976). The network was initialized with random weights and thresholds. The difference between the output required and the actual output at the output node is backpropagated to train the network. This process is repeated for all the examples that the net is to learn. The examples are presented repeatedly. The present network was trained for a number cycles and at the end of training the RMS difference between the desired and the obtained output over all the examples obtained was 0.000484. The curves produced by the ANN after training gave a good agreement with the experimental data. The trained network was further asked to predict the relationship at 165°C and 400°C. Although the network predicted a behavior very close to the experimental curves the predictions of the network showed an undulation that is not seen in published experimental results (Anderberg and Thelandersson, 1976).

The experimental curves, for various properties of concrete under varying temperatures (Fig. 3) are extremely irregular and seems to be anomalous in some local regions (Fig. 3b). Therefore, when the experimentally observed input parameters were used these irregularities were moulded into the network. Therefore, the consistency in behavior at different temperatures was lost. Khennane and Backer (1993) in the mathematical model have used idealized curves avoiding local aberrations. The idealized curve is obtained by assuming piece-wise linear functions within two

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**Fig. 2.** Network configuration for training isothermal curve (strain-driven uniaxial).

**Fig. 3.** (a) Compressive strength of concrete. (b) Ultimate strain of concrete. (c) Modulus of elasticity of concrete. (d) Coefficient of thermal expansion of concrete.
The predictions of the net along with the experimental results are presented in Fig. 4. The performance of the network is a very good for the whole range of input and it was marginally better than that of the semi-analytical expression. To examine the generalization achieved by the network a new temperature, which was not a part of the training examples was input. The predictions of the network showed very good agreement with the experimental observations. However, the predictions diverged slightly from the experimental values in the extreme parts of the curve. This divergence can be attributed to target values close to 0 or 1. It may be noted that all input and output values are scaled between 0 and 1. Towards the extremities of this range the slope of the sigmoidal function is very low. Therefore, the rate of learning for these values is very slow. It is desirable to keep the range of target values between 0.2 and 0.8. This can be achieved by adding a scalar term with the desired values and selecting a suitable factor so that the maximum and minimum values fit within 0.2 and 0.8. The performance of the network showed a marked improvement after this. The predictions of the network at temperatures 165, 300 and 450°C have been presented in Fig. 5. The experimental results for 165°C are presented too. The agreement between the ANN prediction and the experimental work is very good. Experimental results are not available for any other temperature. However, the predictions of the ANN seem to be realistic, and they agree very well with the experimental results in the vicinity.
4.2. Varying temperature under constant load

The behavior of concrete under constant load and varying temperature has been studied. When the temperature of concrete varies, it is subjected to thermal expansion. The effect of sustained loading causes transient creep. Therefore, the effect of thermal expansion and transient creep must be taken into account for modeling the response of concrete under a sustained load. Therefore, an additional parameter, the coefficient of thermal expansion, is included in the input. The coefficient of thermal expansion can be measured easily. Therefore, this term has been included in the network. The network on its own is expected to model the creep deformation and no additional term is included for creep. The input nodes for training this network consist of current temperature \( T \) (temperature at a point in the temperature–strain curve), load level \( \eta \) (constant load expressed in terms of percentage of original compressive strength), modulus of elasticity at that temperature \( E_T \), compressive strength \( f_T \), ultimate strain \( \varepsilon_{\text{ult}} \) and the coefficient of the thermal expansion \( \Omega_T \). The output is strain \( \varepsilon \) corresponding to the given load level and temperature. The idealized values of the properties of concrete as mentioned earlier have been used.

The next step is to select a configuration for the hidden layers of the network. The method of this selection is not formalized yet. Therefore, some trials have been taken to evolve a good configuration. A systematic study was conducted to find a suitable network configuration. Finally, a network consisting six nodes at the input, two hidden layers, each containing 18 nodes and an output containing one node was chosen. The network was trained until the RMS difference between the predicted and the desired output over all the examples was within an acceptable limit. The results of the network after training is discussed below.

The predictions of the network along with experimental and theoretical investigations (Khennane and Backer, 1993) are presented in Fig. 6. It can be observed that the network’s prediction follows the experimental results very closely. Only at the 67.5% load level does the extreme value have a slight deviation. This may be due to the very small value of the output in that region.

The existing analytical model (Khennane and Backer, 1993), agrees well with the experimental observations at lower temperatures but it deviates sharply from the experimental results as the temperature increases. The ANN, on the other hand, was in close agreement with the experimental results throughout the range. This demonstrates the power of the ANNs to capture a very complex relationship which is usually intractable even by very sophisticated analytical models. Predictions of the ANN for new examples were obtained for load levels of 27.5, 30, 38, 42, 50 and 60% (Fig. 7) which fall in between the available experimental results.
results. The predictions obtained from the ANN agreed very well with the trend of the experimental results.

It may be pointed out, that the neural network training was not provided with any additional information about the difference in the values of various parametric properties under varying temperature due to different sustained load levels. These values are difficult to measure at different load levels. Therefore, the network is designed in such a fashion that the user is not required to input those values. The load levels ($\eta$) had been provided in the input node and the properties under the load free ($\eta = 0$) condition were provided. It is assumed that the neural networks, being model free estimators will be capable of mapping the relationship of the parameters under the loaded condition from the values at the load free state.

4.3. Varying temperature under totally restrained conditions

The neural network modeling was explored to simulate the response of concrete under variation of temperature when subjected to heating under restrained conditions. The stress developed under such a condition is due to restraining the elastic, plastic and thermal strains of the specimen. It consists of six nodes in the input, two hidden layers each containing 12 nodes and an output. The input contains temperature ($T$), the modulus of elasticity at that temperature and loading condition ($E_T$), compressive strength ($f_{ct}$), ultimate strength ($f_{ult}$), the coefficient of thermal expansion ($\alpha_T$) and the rate of heating (l) and the output was the restrained stress ($\sigma$). The experimental results available for a rate of heating of 5°C min$^{-1}$ was utilised for training the network. The ANNs prediction obtained after training is shown in Fig. 8 along with the experimental and analytical results. The ANN showed close agreement with the experimental observations. The analytical results, however, were far from the experimental results. This reinforces the claim of effectiveness of the ANNs in capturing complex material behavior intuitively which is impossible hitherto even by sophisticated analytical models.

The response for a heating rate of 4°C min$^{-1}$ has been predicted with the help of the network. The experimental results for this heating rate is not available. The ANNs prediction maintains the general trend of the response under such conditions.

5. Concluding remarks

The response of concrete under high temperature and pressure is highly non-linear. The parameters that influence its behavior are also non-linear. Hence, a large number of parameters are required for modeling of the behavior of such material with a mathematical equation. In addition, reliable values of these parameters are difficult to measure. Therefore, the mathematical models are often erratic in their prediction. The ANNs, with their capability to learn directly from experimental observations are an attractive alternative. The ANNs are model free estimators. Therefore, the input of difficult-to-measure parameters can be avoided in an ANN. However, the ability of the ANN to learn and generalize complex relationships must be tested against reliable experimental observations. The main hindrance faced while modeling with a artificial neural network is the non-availability of sufficient experimental results. However, with the limited data available for the present problem the prediction of the network is extremely satisfactory.

Guidelines on the configuration of ANNs are not well established. Therefore a trial and error approach is adopted in the selection of network size, training examples and test problems. Past experience plays an important role for selection of the various attributes of the net.

The sigmoidal threshold function has a very small slope towards its extremities. Therefore, the network faces difficulty in learning the points with output values close to 0 or 1. The input data should be scaled so that the output values should lie between 0.2 and 0.8 to facilitate fast learning.

In this paper, three different situations of loading on concrete have been investigated: varying load under isothermal conditions; varying temperature under constant load; and varying tempera-
ture under total restraint. In all these situations
the ANN has been very effective in predicting the
stress–strain behavior of concrete. The perfor-
mance of the ANN was remarkably superior to
the existing mathematical models in the second
and third conditions. This has encouraged us to
attempt the prediction of the stress–strain behav-
ior of concrete at high temperature subjected to
biaxial stresses. Due to the complexity of the
problem mathematical models of this case are
scant. Investigation by neural networks of the
problem is already in progress and will be re-
ported in the future.

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