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# THE ANALYSIS OF TIME DEPENDENT DEFORMATION IN R. C. MEMBERS BY ARTIFICIAL NEURAL NETWORK

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## ABSTRACT

In the past ten years, Artificial neural networks have emerged as analysis and solving technique with capabilities suited to many structural analysis problems. Diverse problems in engineering may be solved accurately with computers. In structural engineering many solution techniques exist. Artificial neural networks have evolved as a new computing paradigm, and many engineering applications have been studied. In this paper the time dependent deformation such as; creep, shrinkage, in R. C. members have been calculated by means of Artificial Neural Network (ANN) and the results have been compared with the experimental study given by other authors.

**Key Words:** Artificial neural network, Time dependent deformation, Concrete

## BETONARME ELEMANLARDAKI ZAMANA BAĞLI DEFORMASYONLARIN YAPAY SINIR AĞLARI ILE ANALIZI

## ÖZET

Geçen on yıl içerisinde, yapay sinir ağları pek çok yapı analizinde başarı ile uygulanmış bir problem analiz ve çözüm tekniği olarak ortaya çıkmıştır. Mühendislikteki çeşitli problemler bilgisayar ile tam olarak çözülebilir. Yapı mühendisliğinde bir çok çözüm tekniği mevcuttur. Yapay sinir ağları yeni bir hesaplama tarzı ortaya çıkarmış ve bir çok mühendislik uygulaması bu metot ile çalışılmıştır. Bu çalışmada, betonarme elemanlardaki sünme ve rötre gibi zamana bağlı deformasyonlar yapay sinir ağı tekniği ile hesaplanmış ve sonuçlar ilgili referanslarda verilen deneysel çalışmalar ile karşılaştırılmıştır.

**Anahtar Kelimeler:** Yapay sinir ağları, Zamana bağlı deformasyon, Beton

## 1. INTRODUCTİON

The explosion of interest in artificial neural network is apparently due to their ability to learn, to make decisions, and to draw conclusions from partial information. Neural networks has already been applied successfully to analysis of structures to simple truss design, material behavior, size effect in concrete fracture (Arslan, A., Ince, R. 1994) dynamic analysis of bridges (Vanluchene, D., Roufei, S. 1994) estimating concrete strength, damage detection in structure and so on have been studied.

A number of machine learning paradigms have been used in the past to solve structural analysis and design problems. These paradigms were implemented using either a symbolic, connections, genetic algorithm approach or fuzzy logic. Of these, the connectionist approach has, of late, attracted considerable interest, and the results of a number of applications in structural analysis, design and material behavior area have been published recently (Berke, L., Hayela, P., 1991). Today great deal of phenomenon and problems in engineering and other disciplines may be solved accurately with this technique. In civil engineering, there are several reliable and robust solution techniques.

However, an established solution technique that has the properties of neural networks does not exist and because of this. Many engineers have started to develop interest in neural networks. This papers describes configuring and training of a neural network for time dependent deformation of Reinforcement Concrete (R. C.).

The specific problem considered is a member of R. C. design where, given a geometry and a loading. For this problem a two-layer neural network is trained using the Hopfield algorithm with patterns representing time for diverse loading conditions.

## 2. ARTİFİCİAL NEURAL NETWORK

Artificial neural networks are defined as type of information and recognition system whose architecture is in spired by the structure of human biologic neural systems. In neural networks or connectionist models of computation, attempts are made to simulate the powerful pattern recognition capabilities of the human brain and to use this capability to represent and manipulate knowledge in the form of patterns. The initial systematic study of ANN may be traced to the early 1940s to the papers by Pitts and Mc Culloch, who derived and explained theorems about models of neural system based on biologic structures. The first neural networks models were collectively called perceptrons and generally, they consisted of a single layer of neurons connected by weights to a set of inputs. Such a type of networks are shown in Figure 1 (Hopfield, J. J., 1988). A neural networks consist of layers of processing elements and weighted connections. Each layer in a neural networks consist of a connection processing elements (Pes). Each processing elements collects the values from all of its input connections, performs a predefined mathematical operation, and produces a single output value.

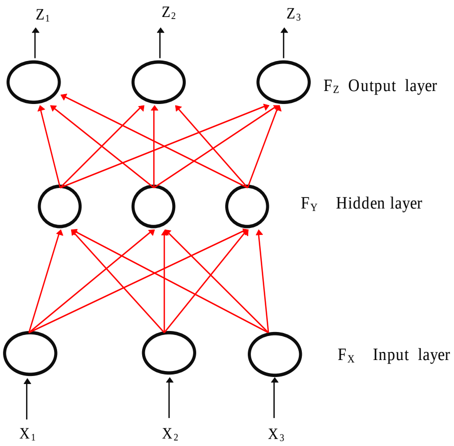



Figure 1. A typical neural network

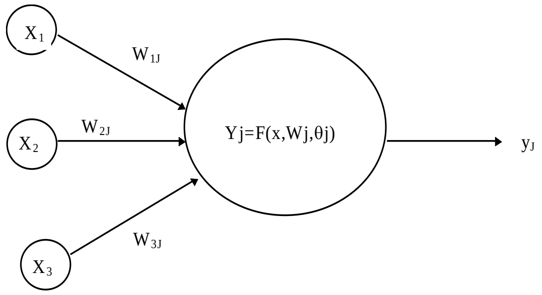
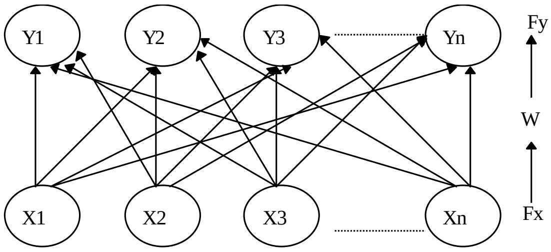



Figure 2. The processing element




$$\begin{array}{c|ccccc|} & Y_1 & Y_2 & Y_3 & \cdots & Yp \longrightarrow Fy \\ X_1 & W11 & W12 & W13 & \cdots & W1p \\ X_2 & W21 & W22 & W23 & \cdots & W2p \\ X_3 & W31 & W32 & W33 & \cdots & W3P \\ \vdots & \vdots & \vdots & \vdots & \cdots & \vdots \\ Xn & Wn1 & Wn2 & Wn3 & \cdots & Wnp \\ \downarrow Fx & & & & & \end{array}$$

Figure 3. Two layer net and weight matrix

Figure 2 illustrates a typical neural network with three layers denoted Fx, Fy, Fz. The bottom layer, Fx, accepts inputs into PEs X1, X2, X3. A collection of weighted connections (weights) connect the Fx PEs to the Fy PEs. The Fy PEs ,Y1,Y2,Y3 , are the hidden layer.Similarly, the Fy PEs are connected to the Fz PEs which from the output layer. Figure 3 illustrates the processing element and weigths. As an examples for two-layer neural network and weight matrix as below (Figure 3).

## 3. TİME DEPENDENT DEFORMATİON IN CONCRETE

When a concrete specimen is subject to load, its response is both immediate and time dependent deformation. Under sustained load the deformation of a specimen gradually increases with time and eventually may be many times greater than its instantaneous value. If temperature and stress remain constant, the gradual development of strain with time is caused by creep and shrinkage.

The creep and shrinkage of concrete structures are complex phenomena which are not yet understood completely. Creep and shrinkage have a considerable impact upon the performance of concrete structures, causing deflection increases as well as affecting stress distribution. In analyzing the effects of creep and shrinkage of concrete we not only come a cross the problem of safety against failure, but we also find our selves dealing with very important economic factors such as durability, serviceability and long-time reliability.

At any time t, the total concrete strain $\varepsilon$ (t) in a uniaxially loaded specimen consist of a number of components, which include the instantaneous strain $\varepsilon_e$ (t), the creep strain $\varepsilon_c$ (t), the creep shrinkage strain $\varepsilon_{sh}$ (t) and the temperature strain $\varepsilon_T$ (t). Thus, the total concrete strain $\varepsilon$ (t);

$$\varepsilon\,(t) = \varepsilon_e(t) + \varepsilon_c(t) + \varepsilon_{sh}(t) + \varepsilon_T(t) \qquad (1)$$

where

$\varepsilon_e(t) = \sigma o / Ec\,(t)$

$\varepsilon_c = 2.5 \cdot \varepsilon_e$

$\varepsilon_{sh} = 1.5 \cdot \varepsilon_e$

$\varepsilon_T = \int \alpha \cdot dt$

and

$\sigma_o$ : Sustained compressive stress
Ec (t) : Elastic modulus of concrete
$\alpha$ : The coefficient of thermal expansion

### 3. 1. Effect of Creep

The capacity of concrete to creep is usually defined in terms of creep coefficient, $\phi$ (t). Under a constant sustained stress, $\phi$ (t) is the ratio of the creep strain at time t to the instantaneous elastic strain

$$\phi\,(t) = \varepsilon c\,(t) / \varepsilon e \qquad (2)$$

and the creep strain produced by a constant sustained stress is therefore

$$\varepsilon c\,(t) = \phi\,(t).\ \varepsilon e \qquad (3)$$

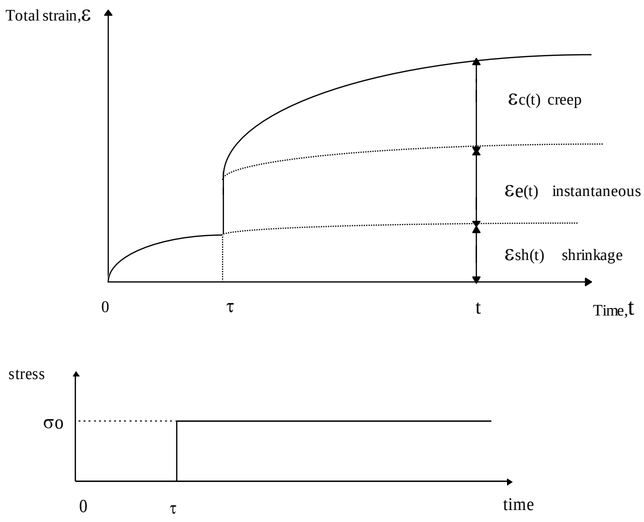



Figure 4. Concrete strain compenents under sustained

The strain components in a specimen loaded with a constant sustained compressive stress first applied at time $\tau$ are illustrated in Figure 4 (Ghali, A., Faure, R., 1986)

### 3. 2. Shrinkage

### 3. 2. 1. The Hilsdorf Model

Hilsdorf found that as the Water / Cement ratio increases and the relative humidty drops, shrinkage increases. His relationship can be expressed as

$$\varepsilon_{sh}\infty = \beta_1 \cdot p \cdot \sqrt{\frac{100 - H}{100}} \qquad (4)$$

where

$\varepsilon_{sh}$ : final shrinkage of concrete
$\beta_1$ : proportionality coefficient
p : total porosity
H : relative humidity

## 4. NEURAL NETWORK ANALYSİS OF TİME EFFECTS

The problem considered in this paper takes an axially loaded column shown in Figure 5.

For the artificial neural network analysis, let be consider a short column as shown above, and the numerical values

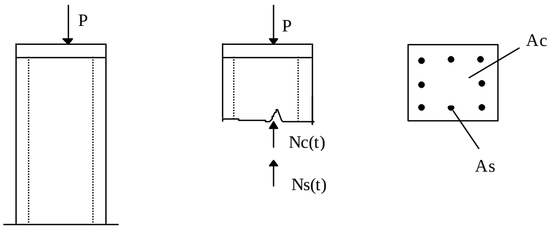



Figure 5. Axially-loaded short column

P = 1000 kN, Ac = 90000 $mm^2$, As = 1800 $mm^2$

$\tau o$ = 10 days, $\rho$ = 0.02, Ec($\tau$o) = 25 Gpa, Es = 200 Gpa

The Hopfield network had been used for analysis of this problem.The basic hopfield paradigm consist of a set of processing elements which compute the weighted sum of the inputs, and quantize the output to zero or one. The modified transfer function used a sigmoid, and a reactive delay.The output of each processing element is coupled back to the inputs of ever other processing element except itself. In order to the analysis of this problem the data had been used in above. These data also had been used as input vector for neural network. As an output vector had been used the results that its given by (Gilbert R. I., 1988). The training patterns of the neural network were taken from (Ghali, 1986). A total of 12 training data sets were presented to the network. The training phase took about 12000 iterations,using the above data. Maximum error was 9.66 % for these training data sets. The training error is commonly defined as

$$\text{Error} = \sum_{i=1}^{n} \left( t_i - O_i \right)^2 \qquad (5)$$

Where $t_i$ is the i th. element of the target vector and $O_i$ is the i th. output vector. A summary of the numerical results calculated step by step method (SSM) and neural networks analysis results for the axially loaded column example contained in this paper is presented in Table 1.

Table 1. Results of Numerical and Artificial Neural Networks Solutions

| Results of step by method | | | | | | Neural network result | | | |
|---|---|---|---|---|---|---|---|---|---|
| Pattern | Ec ($\tau$i) (MPa) | Esh ($\tau$i,+) | Length of Time Step (days) | Creep Train $\varepsilon$c(t) | Shrinkage Strain $\varepsilon$sh(t) | $\varepsilon$c(t) | $\varepsilon$sh (t) | $\varepsilon$c (t) | $\varepsilon$sh(t) |
| 1 | 25 000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 26 300 | 100 | 10 | 180 | 100 | 150 | 85 | 0.83 | 0.85 |
| 3 | 28 000 | 200 | 15 | 340 | 200 | 350 | 150 | 1.03 | 0.75 |
| 4 | 29 000 | 300 | 25 | 486 | 300 | 475 | 270 | 0.97 | 0.9 |
| 5 | 29 600 | 400 | 50 | 608 | 400 | 580 | 380 | 0.95 | 0.95 |
| 6 | 29 900 | 500 | 150 | 712 | 500 | 750 | 450 | 1.05 | 0.9 |
| 7 | 30 200 | 600 | 9750 | 804 | 600 | 800 | 580 | 0.995 | 0.966 |

## 5. CONCLUSİONS

Artificial Neural Networks have many attractive features that may be helpful in developing important modules in integrated structural analysis system problem. The real usefulness of neural networks in structural engineering is not in replacing existing algorithms approaches for predicting structural response, as a computationally efficient alternative, but in providing concise relationship that capture previous design and analysis experiences that are useful for making design decisions. In this paper, the artificial neural network results hadn't been explained step by step. Because a MS thesis study continue about this topic. The study show that artificial neural network technique can be used in structural analysis problems, specially design by reinforcement concrete successfully.

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