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THE NEURAL NETWORK-BASED ANALYSIS OF SIZE EFFECT IN CONCRETE FRACTURE

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Abstract
Modelling of material behavior generally involves the development of a mathematical model based on observations and experimental data. An alternative way discussed in this paper, is neural network based modelling which is a subfield of artificial intelligence. The main benefit in using a neural network approach is that the network is built directly from experimental data using the self organizing capabilities of the neural network. In this paper, size effect in fracture of cementitious materials is modelled with a back-propagation neural network. The results of the neural network based size effect law look viable and very promising. A large concrete member without initial crack can resist some stress. The neural network based size effect law behaves asymptotically in the case of larger sizes.

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1 Introduction

It is a common observation that while computers can perform symbolic manipulation faster and more reliable than humans, people outstrip machines easily in many areas of information processing. This observation has led many scientists to view the facts of our brains that carried out highly significant about the style of computation. Many attempts have been made to solve problems by using simplified principles of nervous systems. These attempts include expert systems, fuzzy logic and neural networks.

Development of neural networks was mainly driven by the desire to develop computational models of the human brain. A small neuron in the human brain is meaningless unless it works together within a parallel network system. In other words, a human brain is a massively parallel system. Von Neumann type computers have shortcomings in this respect because of their serial computings.

The most important property of neural networks in engineering problems is their capability of "learning" directly from examples. The other important properties of neural networks are their correct or nearly correct responses to incomplete tasks, their extraction of information from noisy or poor data, and their production of generalized results from the novel cases. This has been particularly observed in previous studies (Arslan and Ince,1994,1995) as well as in the study.

2 Neural Networks

Neural networks are basically immerse the imitations of behaviour of human brain. Even a quite simple neural network of small size when compared to the human brain, has some powerful characteristics in knowledge and information processing due to the similarity to the human brain in computation. This makes neural networks as a powerful tool for engineering applications.

Neural Networks solutions puts a fundamentally different approach in dealing with modeling problems than traditional methods. The main advantage of neural networks is that experimental and field data are utilized directly, without simplifying assumptions. All arrangement for organization and learning are formed internally within the network.

The idea of a neural network was originally conceived as an attempt to model the biophysiology of the human brain, to understand and explain how the brain operates and functions. The goal was to create a model capable of human thought process. Neural networks attempt to achieve these intelligent capabilities by using a densely interconnected system of simple computational elements that operate in parallel. The central motivation underlying the development of artificial neural system is to provide a new type of computer architecture in which knowledge is acquired and stored over time through the use of adaptive learning algorithm.

Neural network technology brings completely different concepts to computing. Neural computing is a non-algorithmic method of computing which is able to take full advantage of massively parallel computer architectures. Neural networks learn an application, they are trained through examples rather than programmed by software. Neural networks distribute abstract forms of information throughout a network in the form of interconnection weights, rather than storing specific information in specific locations like computer memory.

Rumeldardt et. al.(1986) derived a learning algorithm for a formalized model of a biological neuron so called “perceptron” networks with hidden units based on Widrow and Hoff learning. Their learning algorithm is called backpropagation and is now the most widely used learning algorithm.

A wide variety of neural networks have been reported in the literature. Each type of neural network has an advantage in different tasks. Some of them are suitable in optimization problems while others are useful in adaptation and learning . However, the backpropagation networks probably the most widely used neural networks (Rumeldardt et. al.,1986).

Due to noisy data in experimental results on size effect, a size effect theory can be established based on artificial neural networks. This will be very meaningful and a reasonably well approximation to the size effect.

3 Backpropagation neural networks

Backpropagation is a specific learning law. However, the term is often used to refer as a network architecture that uses the backpropagation algorithm. The backpropagation learning law is used for updating the weights of each layer based on the error present at the network output. The processing units in a backpropagation neural network always consist of at least three layers; an input layer, a hidden layer, and an output layer. For some applications more than one hidden layer is used. The presence of these hidden layers allows the network to present and compute more complicated associations between patterns. The number of neurons in the input layer is equal to the number of inputs and each of these neurons receives one of the inputs. The output of the neurons in the output layer is the output of the network. The number of neurons in the hidden layer is up to the discretion of the network designer. Too few neurons in the hidden layer will not allow the network to produce accurate maps from the input to the desired output, while too many neurons will result in difficulties in dealing with new types of input patterns.

In a backpropagation network, no interconnections between neurons in the same layer are permitted. However, each neuron on a layer provides an input to each every neuron on the next layer. The backpropagation network uses supervised learning so the input and output patterns must be both known .

In feedforward phase, the input layer neurons pass the input pattern values onto the hidden layer. Each of the hidden layer neurons computes a weighted sum of its input, and passes the sum through its activation function and presents the activation value to the output layer. The weights between the layers are initially small random values. Following the computation of a weighted sum of each neuron in the output layer, the sum in passed through its activation function, resulting in one of the output values for the network.

The training process is successfully completed, when the iterative process has converged. The connection weights are captured from the trained network, in order to use in the recall phase.

A sigmoidal or so calded logistic function is used as the activation or transfer function f_j for modeling the nonlinear transformation.

$$f_j = \frac{1}{1+\exp[-\lambda x_j]} \tag{1}$$

where, λ is a constant, controls the shape of the activation function, and x_j is the total input to a neuron.

As stated previously, in the learning phase the network is presented with an input pattern and a corresponding output pattern. The network produces its own output pattern with the above described expressions by using its weights, which are initially incorrect. This calculated output is compared with the desired output value.

The training of a multi-layer backpropagation neural network, via the generalized delta rule, is an iterative process. By using the so-called delta rule, the convergence toward improved values for the weights may be stated as,

$$\Delta w_{ik} = \beta . \delta_{k} . o_{j} \tag{2}$$

where β is called the learning rate parameter, and δ_k is the error signal at an output neuron k, and o_j is the output of a neuron in layer j.

4 Size effect in concrete fracture

4.1 Early size effect tests

In general, the change of a structural property when the size of a structure changes is known as a size effect related to this property. It is well known that structures become more brittle as their size increases, but the classical procedure uses the same working stresses in design.

Because fracture in a concrete structural element is driven by the stored elastic energy released from the whole structure, this size effect can be well explained by fracture mechanics. The fact that the strength of brittle materials is affected by the presence of imperfections was first suggested by Griffith (1921). Due to his conclusion, it can be expected that the value of the ultimate strength will depend upon the size of specimens. As the specimen size increases, the strength is expected to decrease since the probability of presence of weak links increases. Traditionally, the size effect in fracture of concrete structural elements has been explained by means of Weibull's theory (Weibull, 1938, 1951). He showed that if tensile tests are performed on two geometrically similar specimens with different volumes, the corresponding ultimate strengths are different. It has also been concluded by Mihashi (1983).

The effect of specimen size on the fracture performance of concrete has been investigated by numerous researchers. Earlier studies have been conducted by Walsh(1972), Kani(1967), Leonhart and Walter(1961, 1962, 1963) and Rüsch et. al.(1962), but most of these studies are not performed on the relative dimension. The effect of specimen size on the fracture toughness of concrete has also been reported by Mindess(1984) and Nallathambi et. al.(1984). The main conclusion from the work reported by Mindess(1984) was that the fracture energy increased considerably in the case of large test specimens. Nallathambi et. al.(1984) determined the fracture toughness of concrete using both the energy (G_{Ic}) and the stress intensity factor methods (K_{Ic}). The result of the energy method (to give G_{Ic}) indicated that the fracture toughness increased substantially with increasing specimen size.

Besides, the statistically based size effect, the second size effect as referred to fracture-type size-effect in concrete fracture has been described repeatedly by Bazant et. al.(1984). This is referred to as Bazant's size effect law(1987) which has been shown to agree well with test data. Size effect in concrete behaviour has been extensively studied both experimentally and theoretically with a notable success (Bazant, 1984, 1987 and Bazant et. al.,1986). However, some published experiments indicate results contrary to Bazant's size effect law. A large concrete member without initial crack can resist some stress as contrary to the size effect law. Barr et. al.(1990) argued that the approximate size-effect law is shown to be only reasonably applicable according to their torsion test results. It has been concluded that the variation between actual experimental results and those determined from the application of the size effect law is significant. Some experimental studies have shown that the size-effect law is reasonably applicable, in particular for tests with more than three similar specimens. The variation between the experimental results and those calculated from the size effect law is higher in this type of experiments.

4.2 Size-Effect Tests Used In Training Phase of The Network

In the training phase of the developed neural network, only results of size effect tests which have been carried out at Northwestern University were considered. This is because of the experiments were performed under similar testing conditions in the same laboratory. These tests include three-point bending, uniaxial tension, eccentric compression, and cylindrical torque. First three experiments were reported by Bazant and Pfeiffer(1986, 1988).

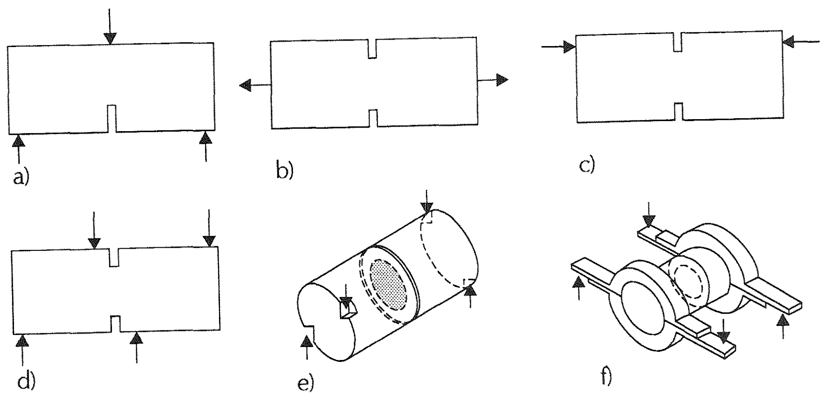

Fig 1. The specimen geometries used in training and testing of the network.

The same geometry, except the notches, was used in the three-point bending, uniaxial tension, four-point shear and eccentric compression specimen. (Fig.1a-d). All the specimens were of the same external shape. For each specimen size and each type, three specimens were tested. All the specimens were mixed in the same conditions and with the same mix proportions. The notches were introduced by means of a diamond saw into hardened specimens.

Recently Bazant and Prat(1988) applied the size effect law to mode-III fracture tests of cylindrical specimens with circumferential notches, subjected to torsion. Significantly different size of specimens were tested. The diameters of the cylinders were d=38.1, 76.2 and 152.4 mm. The length-to-diameter ratio was l/d=2. The torques were applied at each end as force couples in the way shown in Fig 1e.

Size effect tests on different specimens and loading conditions other than summarized above, certainly do exist. However, due to the complexity of the neural network solution, only the five summarized tests were considered initially. Some of the other size effect tests were taken as the control of the neural network analysis(Barr et al. 1990).A circumferentialy notched cylinder concrete specimen subjected to a torque has been tested. The test specimens were subjected to opposing couples via a pair of split collars.(Fig 1f.). The specimen diameters were d= 80, 100, 150 and 200mm, the length-diameter-ratio was constant at 2, and the notch-depth ratio was constant at 1/5.

5 NETICE Development

A backpropagation training neural network program, NETICE (Neural nETwork In Civil Engineering) has been developed. NETICE is written in C++, and also Quick BASIC 4.5 version was written due to widespread use of the language. NETICE presently being run on an IBM-compatible personal computer. The program allows a user-friendly input of datas. It gives an easy entrance of the number of input neurons, the number of hidden neurons, the number of output neurons. Also it is possible to change the other specific network parameters. The program structure is well designed to use applications in any field, but the primary goal to develop NETICE is to solve many problems in civil engineering.

NETICE has been tested on some civil engineering problems. These includes an eccentrically loaded r.c. column design and r.c. slab design problems (Arslan and Ince, 1994, 1995).The results were very promising. These and the other applications show that NETICE may be capable of learning to solve engineering problems in which analytical solutions exist. These tests were shown that one single program (NETICE) is capable of solving many problems in civil engineering, by simply changing the number of neurons and weights. This is one of the main advantage of NETICE to the conventional programs.

6 Neural network based approach to size effect in concrete fracture

6.1 Input and output to the neural network

The purpose of this investigation was to illustrate the neural network-based methodology and to show that this approach could be further developed to estimate the ultimate carrying capacity of any size of concrete specimens from the result of known size. However, generalizing the presented study to any shape and loading arrangement needs further research.

The experiment type was represented by the first 5 input terminals in the input layer. Each type of size-effect test was represented as a set of binary codes. The next input terminal was used to input of aggregate size, overall size and notch depth, overall size ratios of tests, respectively. The output of the neural network is only the normalized ultimate strength at failure (σ_N/f'_t) of each type of experiments.

6.2 Architecture of the neural network

A backpropagation neural network architecture was used in this investigation. The input and output layers were described in the previous section. In addition to the input and output layers one hidden layer was used. The initial investigations showed that when more hidden layers or nodes are used, the network would not converge. If the network is smaller, it would not converge either. The network well converged with one hidden layer of 10 nodes. The general view of the neural network architecture shown in Fig 2.

6.3 Training of the neural network

A total of 21 training data sets were presented to the neural network. The number of training data sets were varied with the test method due to the availability in the literature. The training phase took about 850000 iterations, using the given data. At the end of the training stage, the mean error was 4.76 % and the maximum error within the test methods was 8.75 %. It has been observed that the network was capable of learning the relationship between the structural element size and ultimate strength. It is certainly possible to train the network further to give less error. However, the network can overfit the data. In this case it learns irrelevant details of the individual data, rather than learning the generalized structure of the data.

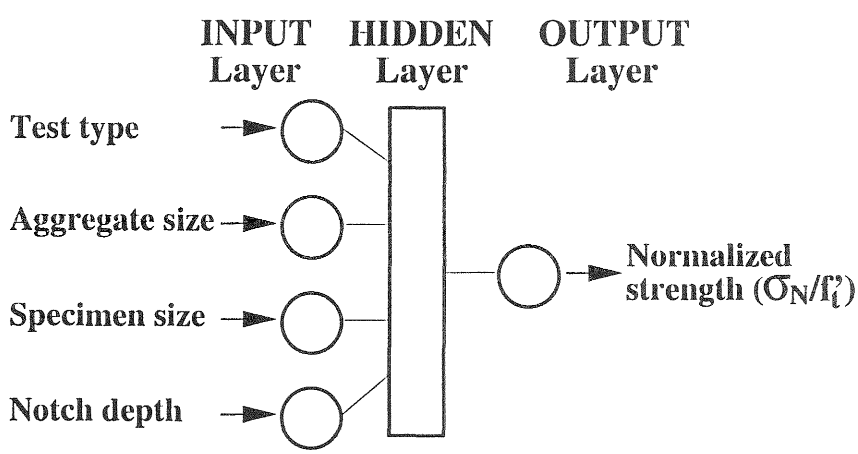

Fig 2. General architecture of the neural network.

6.4. Testing of the Neural Network

After the neural network was trained on the 21 training cases in 5 different test methods, it was tested to see how well it would recognize other test conditions, such as these corresponding to failure state of specimens. The results of these are shown in Table 1. As can be seen the network was able to adequately recognize the complete failure of specimens. The ultimate strength values are nearly zero, which means that complete failure (a/d=1) occurred. Only the result of three-point bending test seems a little higher. While this error may be due to a variety of different causes, it was felt that this was most likely due to the network not being provided with enough information, or being more unstable of this type of tests with respect to the others. Nevertheless, the network was able to detect the global failure. An important observation is that although the failure case was not used for training, the results were very close to the exact solution. This shows the typical advantage of using neural network in uncompleted tasks.

The network were also tested with some other size effect test results reported in the literature. Barr's (1990) torsion tests for size-effect were used as the control data couples in the recall phase of the trained neural network. These were give in Table 2. The results of the comparison of the actual value and network values were also impressive, since this testing procedure is based on the network trained with different mode-III specimen and testing conditions. The maximum error occurred at 19.17%. Particularly, when the coefficient of variation of the tests is considered (8.2%), this error is not so high.

Table 1. Neural network results at a/d=1 and a/d=0

a/d	d/d_a	σ_N / f_t'				
		Three-point Bending	Uniaxial Tension	Eccentric Compression	Four-Point Shear	Cylindrical Torque
1	12	0.1303	9.43E-5	9.37E-6	0.019	8.29E-5
1	3	0.2115	1.27E-5	2.23E-5	0.016	8.02E-5
0	12	0.3162	0.9627	0.9600	0.7791	0.1320
0	3	0.5033	0.9683	0.9947	0.8615	0.4988

Table 2. Barr's torsion test results.

d/d_a	Experimental Output	Network Output	Percent Error [%]
8	0.408	0.356	12.74
10	0.346	0.338	2.31
15	0.386	0.312	19.17
20	0.291	0.300	1.35

The overall nominal strength- specimen size variation for each of the proposed specimens are given in Fig 3. It can be clearly seen from the neural network based size effect that all curves behave asymptotically in the case of larger sizes. In fact, this is an agreement to the results of the multi-fractal scaling law proposed by Carpinteri and Ferro(1994). The maximum effect of the size were observed in cylindrical torque (a/d=1/4) and three-point bending specimens. However, eccentric compression specimen represents a higher decrement within a narrow size variation. The strength of concrete is equal to that of the aggregate itself at $d/d_a < 1$. However, the size-effect curves for torsion and three-point bending specimens represents the strength at $d/d_a = 1$ smaller than 1. This might because the assumed strength calculation procedure is no more valid around $d/d_a = 1$. The global shape of the size-effect curves of the two torsion specimens are quite similar. The only difference seems to be different asymptote value at larger sizes. This may because of ignoring the notch depth effect on the formula for calculation of maximum stress. It also has been observed from 3D finite element analysis for prismatic torsion specimens that the change of notch depth substantially affects the maximum stress in the proposed failure plane. (Arslan, 1991).

7 Conclusions

The network predicted output with an accuracy that is acceptable in most design considerations. It should be noted that once the network was trained, the time required to output results for a given set of input was nearly instantaneous on a personal computer. This indicates that a neural network may have considerable potential for solving time-consuming problems.

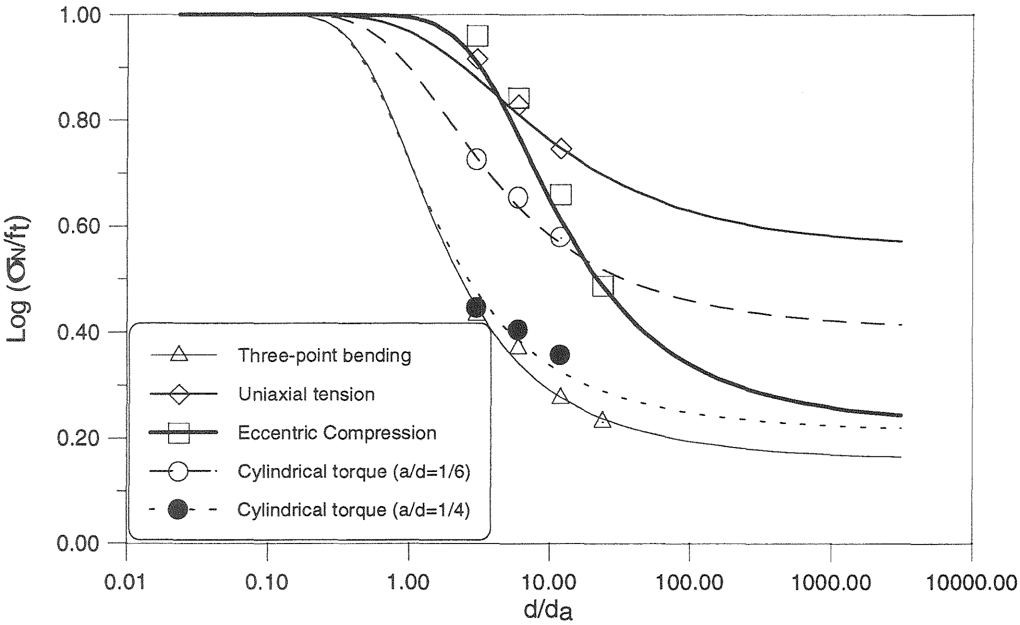

Fig 3. The neural network based size-effect curves.

The purpose of this article was to summarize the characteristics and to demonstrate the use of neural networks and their application to structural engineering problems. Because neural networks directly use the experimental results in training, there is no need to do any assumptions on material parameters. This is the main advantage of using neural networks, particularly for problems for which more than one calculation methods exists, or that are based on empirical approximations only. However, it should be noted that neural network theory is a phenomenological procedure. It does not follow a procedure based on the existing basic theories related to the problem, i.e. some physical properties and relations. It searches the target only based on the given experience, which is a unique property for humans. Consequently, the results given in this paper must be considered in a qualitative way only.

Although the unpredictable generalization remains to be solved, existing neural network algorithms have shown promising results on small problems. Neural networks are well suited to tasks which require faster computation. Their ability to generate complex mappings based on simple data may mean that their first applications are in complex and poorly defined problems.

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