PREDICTION OF ULTIMATE STRENGTH OF AXIALY LOADED REINFORCED CONCRETE SHORT COLUMNS USING ARTIFICIAL NEURAL NETWORKS

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Abstract: The present study deals with the analysis of short reinforced concrete columns subjected to axial load. One of efficient techniques is applied, known as artificial neural networks. The descent gradient backpropagation algorithm is employed for analysis. The optimum topology (which gives least mean square error for both training and testing with fewer number of epochs) is presented. The effects of the number of nodes in input and hidden layer(s), and selecting of learning rate and momentum coefficient, on the behaviour of neural network have been investigated. Due to slow convergence of results when using descent gradient backpropagation, the faster algorithm called "resilient backpropagation algorithm" has been used to improve the performance of the neural network and the results have been compared with those obtained using the descent gradient backpropagation algorithm.

تقييم التحمل الأقصى للأعمدة الخرسانية المسلحة القصيرة المحملة محوريا باستخدام الشبكات العصبية الصناعية

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الملخص: تتناول الدراسة الحالية تحليل الأعمدة الخرسانية المسلحة القصيرة المعرضة الى حمل محوري. تم التحليل باستخدام إحدى التقنيات الكفوءة المعروفة باسم الشبكات العصبية الصناعية. استخدمت خوارزمية الانحدار العكسي في تدريب نموذج الشبكة العصبية، حيث وجدت الشبكة المثلى (التي تعطي اقل معدل مربع الخطأ لنماذج التدريب والفحص بأقل عدد من الدورات). وكذلك فحص تأثير المتغيرات المختلفة للشبكة مثل عدد العقد في طبقة الإدخال والطبقات المخفية و اختيار معدل التعلم ومعامل الزخم على سلوك وأداء الشبكة العصبية. ونتيجة لبطئ الإنجاز عند استخدام خوارزمية الانحدار العكسي تم استخدام خوارزمية الإرجاع العكسي المرن لغرض تحسين أداء الشبكة. وقورنت النتائج من هذه الخوارزمية مع تلك الناتجة من استخدام خوارزمية الانحدار العكسي.

Introduction

Computer algorithms that mimic the biological neural network are called artificial neural network. In simple terms artificial neural network tries to imitate architectures and internal feature of brain and nervous system. Artificial neural networks are useful computation systems which can be trained to learn complex relationship between two or many variables or data set. They are composed of highly interconnection simple processing nodes or artificial neurons which process information by the dynamic state response to external output[1] as shown in Fig.(1).

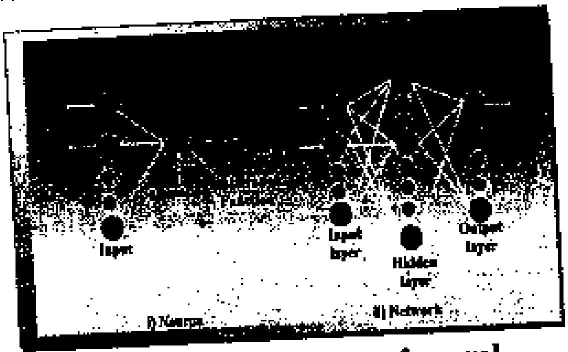

Figure (1) Architecture of neural Network

This technique has been successfully applied in various fields such as function approximation, control system, and classification[2]. Neural networks are much simpler than the human brain, it comprises from fewer components. It consists of a number of nodes, each node receives several inputs from neighboring element, but sends only one output. The neural network is trained to produce desired output or (set of outputs). The trained network can be used to generalize input that are not included in the training set.

This technique is used to investigate the ultimate resistance of short reinforced concrete columns subjected to axial load. The results of these investigations are presented and discussed to show the performance of the neural network model in dealing with this problem. It is proposed to find the relationship between input and output parameters using a feedforward backpropagation type neural network. The configuration and training of neural networks is a trial–and–error process due to such undetermined parameters as the number of nodes in the hidden layer, the learning parameter and the number of training patterns.

Behaviour of Reinforced Concrete Columns

Under increasing load, it was found that columns with longitudinal and transverse reinforcement show a development of surface cracks[3]. These cracks eventually led to the spalling of concrete cover, at which time large pieces of concrete where observed to separate from the core. The spalling often resulted in some drop in load resistance, which was subsequently recovered. Post spalling behaviour varied depending on the characteristic of confined core concrete. The failure of high–strength concrete (HSC) columns is characterized by the formation of inclined shear sliding surfaces, separating the concrete core into two wedges[3]. The inclination of the shear sliding plane with the vertical axis varies from (25°) for low confined specimens to (45°) for highly confined specimens[4]. Columns with high strength concrete failed in a brittle and explosive manner unless they were confined with transverse reinforcement that can provide sufficiently high lateral confinement pressure. There is a consistent decrease in column deformability with increasing concrete strength[5]. When using low volumetric ratio of lateral steel, a sudden loss of strength was observed in columns immediately after the peak load. The failure was associated with hoop fracture, followed by buckling of longitudinal reinforcement and crushing of core concrete[5]. When increasing spacing between transverse bars, the column showed faster rate of strength decay. However, the behaviour of columns is highly affected by spacing and amount of transverse reinforcement. It has been found [6], for HSC columns confined with high–strength lateral steel, that the tie yield strength was developed at the peak strength of confined concrete only for well–confined concrete specimens. Steel stress lower than the tie yield strength, measured at the maximum strength of confined concrete, was observed for less confined concrete columns. Thus, an increase of the tie yield strength would result in an enhancement of the strength and toughness gains only for well–confined specimens with large ratios of lateral reinforcement. This indicated that the grade of transverse steel played a significant role in column confinement. Strength and ductility of unconfined concrete are known to be inversely proportional. When the volumetric ratio of transverse reinforcement is very low, the column shows brittle behaviour and the effect of concrete strength becomes insignificant. The passive confinement pressure is generated from tensile forces that develop in transverse reinforcement. Stress in transverse reinforcement is generated as a result of lateral expansion, which in turn is dependent on the mechanical properties of concrete. Therefore, the effectiveness of high–strength transverse reinforcement is dependent on the ability concrete to expand laterally without failure. Therefore, the reduction in the volumetric ratio can be compensated by an increase in the grade of transverse reinforcement[4].

Selection of Training Patterns

The experimental values used to train the neural network as training data are those obtained from available literature [4, 5, and 6]. The total data (patterns) are divided into two groups; training data, and testing data. The training data are used to train the network to find the relationship between the input and output parameters. Preparing of training data is a matter of considerable importance in training the neural network. The range of parameters used to produce training data are shown in Table (1). Although the neural networks interpolate data very well, the extrapolation of data has not in the same confidence. Therefore, the training data should be selected in such a way that it includes data from all regions of interest.

Selection of Testing Patterns

After training network, the weights and biases are fixed and the network can then be run with same or fresh sets of data. In testing the network at first it is necessary to run the network by using the training data to see whether the network produces good approximation to the known output for these data, and then to prepare further data which have not been used in training phase and run the network with these data to check the accuracy of this net. This property of network is called generalization. The generalization depends on the size of the training data set, the architecture of the network, and the complexity of the problem [1]. The number of testing data are taken randomly approximately as (16%) of total database. A more information of the progress of training is given by convergence history (learning curve), which is obtained by evaluating the MSE for the testing data at intervals during the course of training [7].

Input and Output Layers

The nodes in the input and output layers are usually determined by the nature of the problem. In this study the parameters which may be introduced as the components of the input vector consist of the width of column cross section (b), the depth of column cross section (d), the concrete compressive strength (fc'), the ratio of longitudinal reinforcement (ρ_l), yield stress of longitudinal steel (fy), the ratio of transverse steel (ρ_t), yield stress of transverse steel (fyt), and spacing of stirrups (st). The output vector is the ultimate axial load of columns (Pu). Table (1) summarizes the ranges of each variable.

Table (1) Input and output parameters

Item	Parameters	Units	Range of parameters	
			From	To
Input parameters	b	mm	175	250
	d	mm	225	300
	l	mm	900	1500
	$fc()$	MPa	52.6	124
	ρ_l	–	0.0111	0.0419
	fy	MPa	400	475
	ρ_t	–	0.0091	0.049
	fyt	MPa	392	1000
	st	mm	50	225
Output parameters	Pu	kN	3573	8415

Number of Hidden Layers and Nodes in Each Hidden Layer

The number of hidden layers and the number of nodes in each hidden layer are not straightforward to ascertain[8]. No rules are available to determine the exact number. However, the choice of the number of hidden layer and number of nodes in the hidden layer depends on the network application. Although using a single hidden layer is sufficient in solving many functional approximation problems, some problems may be easier to solve using two hidden layer configurations[9]. The number of nodes in the hidden layer is selected according to the following rules:

1) The maximum error of the output network parameters should be as small as possible for both training patterns and testing patterns.
2) The training epochs (number of iterations) should be as few as possible.

In the present work the network is tested with one and two hidden layer configurations with an increasing number of nodes in each hidden layer(s). Fig. (2) illustrates the network response as the number of nodes in one–and two–hidden layer networks increases. The results show that the two–hidden layer network performs significantly better than the one–hidden layer network. The optimal configuration for the two–hidden layer network, with minimum mean square error (MSE), is (7:14) (7 nodes in the first hidden layer and 14 nodes in the second hidden layer). This configuration will be used in this case study. The figure also shows the effect of node number in the hidden layers on the required number of epochs for which the neural network converges. In this figure, a node number of 21(7:14) with (520) number of epochs (number of iterations) corresponds to the smallest MSE. The optimal configuration of the neural network is depicted in Fig.(3). The hyperbolic tangent (tansig) transfer function is used in first hidden layer and linear (purelin) transfer function in both second hidden and output layers.

Learning Rate and Momentum Coefficient

The learning rate and momentum coefficient are two important parameters that control the effectiveness of the training algorithm. When using the steepest descent algorithm with momentum (*GDM*), the network performance can be improved by finding optimal values for learning rate (α) and the momentum coefficient (mc). The effect of learning rate (α) and momentum coefficient (mc) on the behaviour of neural network is studied by using the combination of (α) [from 0.05 to 0.5] and (mc) [from 0.1 to 0.9]. Each combination is trained with the selected network (two hidden layers 7–14) and with the same set of data and initial weight to 2000 epochs. The results are illustrated in Fig. (4). From this figure the learning rate of 0.1 in combination with momentum coefficient of 0.8 gives the best performance than the others. These values give the least MSE=0.00204, and are chosen for the proposed network. The convergence history of this network is shown in Fig.(5). Table (2) shows the properties of this network.

Table (2) Properties of the proposed network

Network	*Epochs*	*MSE training*	*MSE testing*
(7–14–1)	2000	0.00204	0.0029

on the behaviour of reinforced concrete columns is studied. The results are shown in Figs. (9) to (12).

Figure (9) shows the effect of concrete compressive strength (fc□) on the ultimate resistance of reinforced concrete columns. When increasing the compressive strength, the ultimate resistance is found to increase. The increase in the concrete compressive strength from 60 to 120 MPa caused an increase in the ultimate axial load capacity of 36.47%. The comparison of the experimental results with the obtained relationship shows good agreement.

Figure (10) shows that the increase of the ratio of longitudinal reinforcement leads to increase in the ultimate resistance of columns. The increase in longitudinal reinforcement ratio from 0.01 to 0.05 leads to an increase in the ultimate axial load capacity of 33.07%. The experimental results also show the same trend of relationship.

Figure (11) shows the variation of ultimate resistance of columns with the ratio of transverse reinforcement. The figure indicates that an increase in the ratio of transverse reinforcement leads to increase in the ultimate resistance. For an increase in transverse reinforcement ratio from 0.015 to 0.05, the increase in the ultimate axial load capacity is 16.96%. Same trend of behaviour is also obtained by the experimental results as depicted in Fig. (11).

The effect of the spacing of ties is depicted in Fig. (12). In this figure, it can be seen that the increase of spacing of ties leads to decrease in the ultimate resistance of columns. For an increase in spacing of ties from 60 to 225 mm, the decrease in the ultimate axial load capacity is 5.77%.

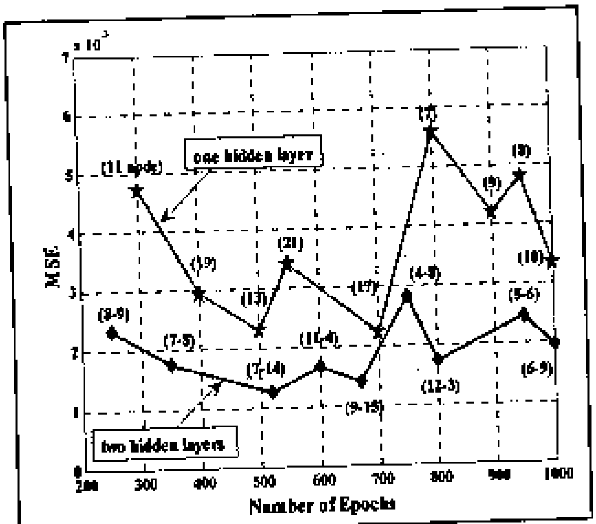

Figure (2) Performance of network with one and two hidden layer(s)

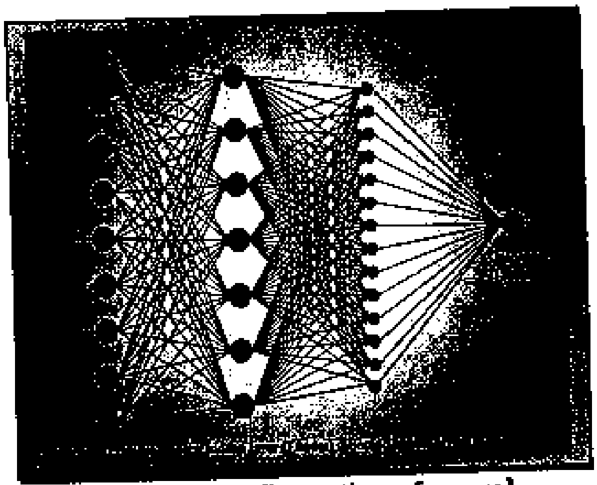
Figure (3) Configuration of neural network (7-14)

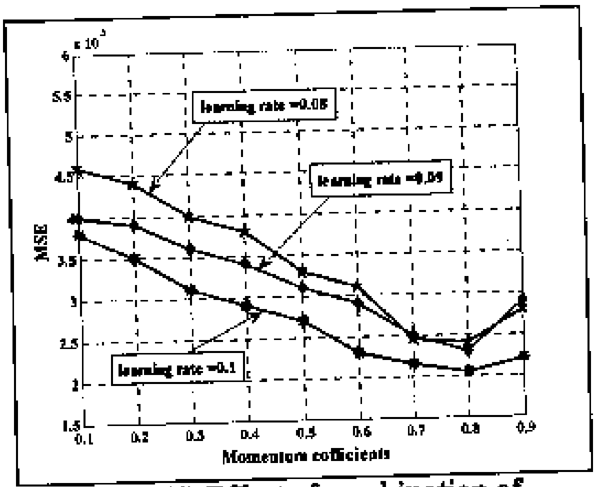

Figure (4) Effect of combination of learning rate and momentum

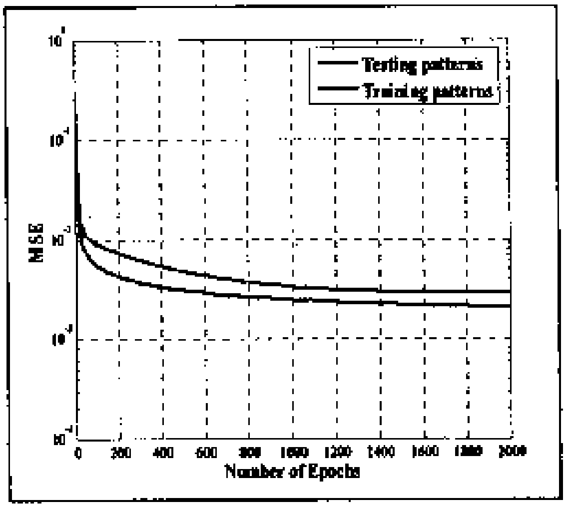

Figure (5) Convergence history for both training and testing data for (7-14) net based on GDM

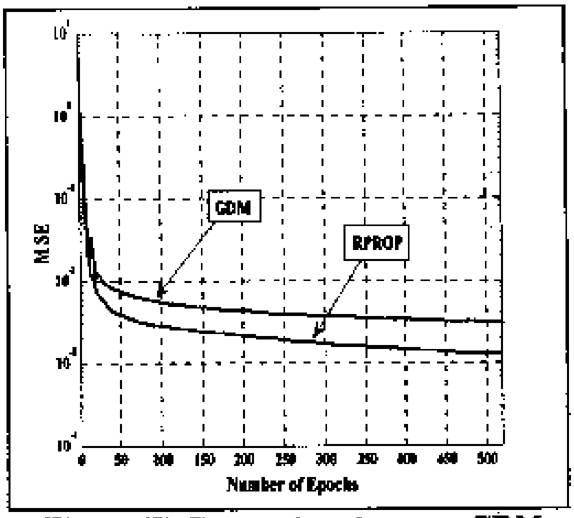

Figure (8) Comparison between GDM and RPROP algorithms

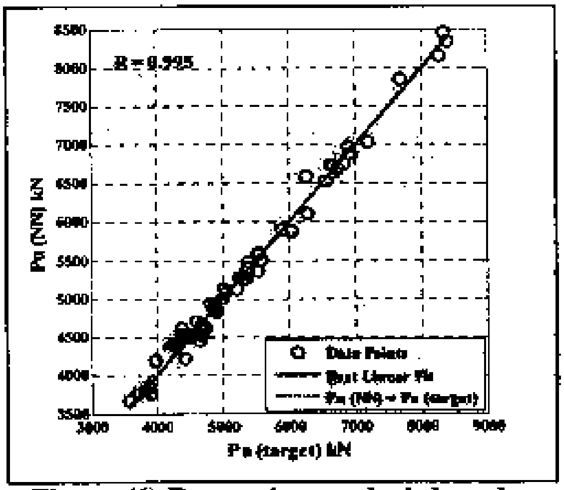

Figure (6) Regression analysis based on GDM for training data

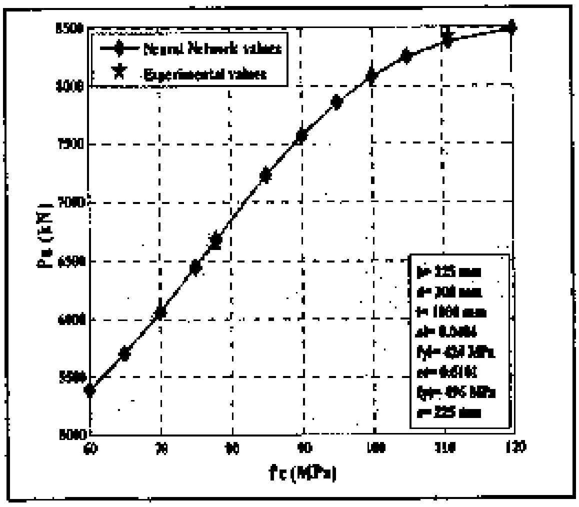

Figure (9) Variation of ultimate axial load capacity with variation of cylinder compressive strength

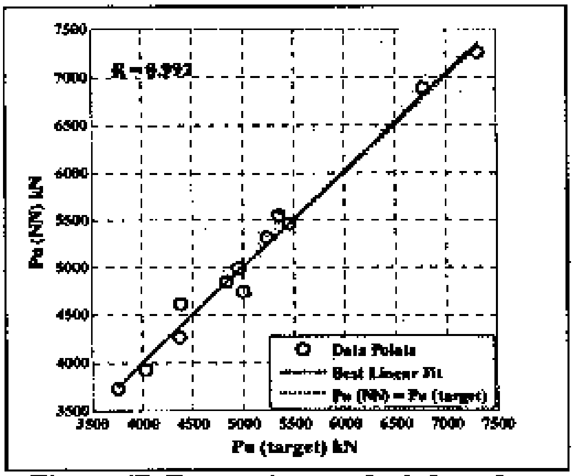

Figure (7) Regression analysis based on GDM for testing data

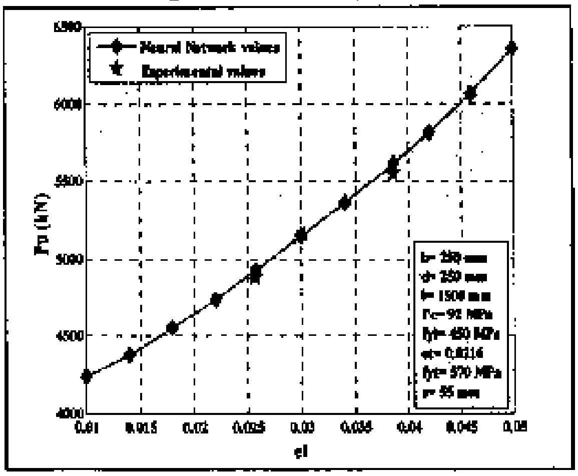

Figure (10) Variation of ultimate axial load capacity with variation of longitudinal reinforcement ratio

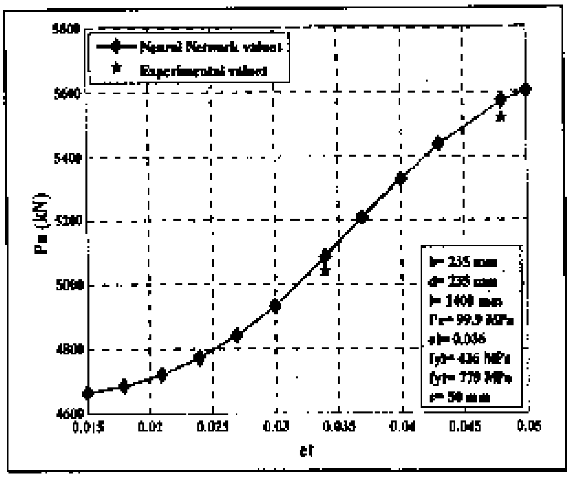

Figure (11) Variation of ultimate axial load capacity with variation of transverse reinforcement ratio

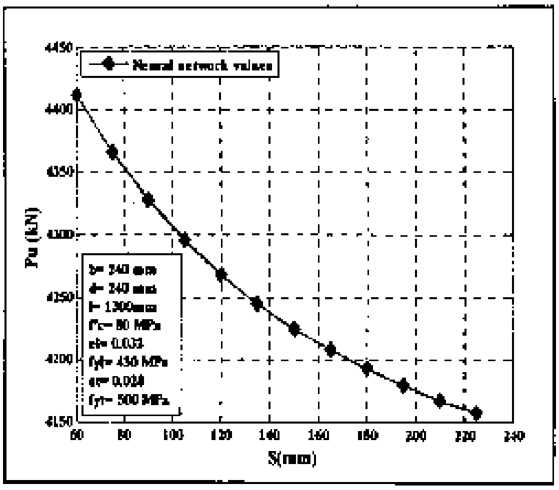

Figure (12) Influence of spacing of ties on ultimate axial load capacity

Conclusions

In the present study, an artificial neural network model is used for the analysis of short reinforced concrete columns subjected to axial load. A multi-layered feedforward backpropagation neural network, has been used. The results of the analysis are presented to demonstrate the simplicity and accuracy of this model in predicting the behaviour of reinforced concrete columns.

References:

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Notation:

b: width of column cross section (mm).

d: depth of column cross section (mm).

fc□: cylinder compressive strength of concrete (MPa).
fy: yield strength of longitudinal steel (MPa).
fyt: yield strength of transverse steel (MPa).
GDM: steepest descent with momentum.
l: height of column (mm).
mc: momentum coefficient.
R: correlation coefficient.
RPROP: resilient backpropagation.
st: spacing of ties (mm).
wi: weight value.
α: learning rate.
ρ_l : volumetric ratio of longitudinal reinforcement in column cross section.
ρ_t : volumetric ratio of transverse reinforcement, defined as volume of transverse steel divided by volume of core concrete, measured center to center of hoop perimeter.