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Predicting the Ultimate Load Capacity of R.C. Beams by ANN

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Abstract

The present study deals with the use of artificial neural networks ANN in predicting the ultimate load capacity of reinforced concrete beams. The data is collected from the numerical solution by finite element method of the simply supported beams with various properties, under the action of two point loads, symmetrically with the center. The data were arranged in a format such that input parameters cover the geometrical, reinforcements ratio and properties of beams and the corresponding output is the ultimate (failure) load. Results were compared with the available methods in the literature. It was found that the average ratio of numerical solution (finite element) to predicted failure loads of beams was 1.018 for neural network, and 1.21 for limit state theory. It is clear that neural network provides an efficient alternative method in predicting the ultimate load capacity for R.C. beams.

Keywords: Reinforced Concrete Beam, Ultimate Load, Neural Network, and, Backward–Propagation.

تقدير الحمل الأقصى للعتبات الخرسانية المسلحة باستخدام الشبكة العصبية الاصطناعية

الخلاصة

يتناول البحث الحالي استخدام الشبكة العصبية الاصطناعية في تقدير التحمل الأقصى للعتبات الخرسانية المسلحة، جمعت البيانات من الحلول العددية بطريقة العناصر المحددة للعتبات الخرسانية بسيطة الاستناد ذات خواص متعددة تحت تأثير حملين نقطيين متناظرين في وسط العتب . نظمت البيانات ورتبت كبيانات داخلة لتغطي التغاير في الأبعاد , نسبة التسليح وخواص العتبات الخرسانية لتعطي البيانات الخارجة متمثلة بقيمة التحمل الأقصى. تم مقارنة النتائج مع الطرق المتوفرة في الدراسات السابقة ، قد كان معدل نسبة التحمل الأقصى باستخدام طريقة العناصر المحددة الى التحمل الأقصى باستخدام الشبكة العصبية هو ١,٠١٨ وكان معدل التحمل الأقصى باستخدام نظرية التحمل الأقصى ١,٢١ . وتبين جليا بان طريقة الشبكة العصبية هي طريقة كفوءة في تقدير التحمل الأقصى للعتبات الخرسانية المسلحة.

الكلمات الدالة : عتب خرساني مسلح ، التحمل الأقصى ، الشبكة العصبية ، التوليد خلفيا

Notation

As Area of steel reinforcement

ρ_b Balanced ratio of reinforcement

$\rho_{\max}$ Maximum ratio of reinforcement

$f'c$ Concrete cylinder compressive strength

f_y Yield point of steel reinforcement

P_u Ultimate load

Mn Nominal moment

Introduction

Plain concrete beams are inefficient as flexural members because the tensile strength in bending is a small fraction of the compressive strength .The tension caused by bending moment is chiefly resisted by steel reinforcement, while the concrete alone is usually capable of resisting the corresponding compression. When the load is gradually increased from zero to the magnitude that will cause the beam to fail, several different stages of behavior could clearly be distinguish. Eventually the carrying capacity of the R.C. beams is reached. Failure can be caused in one of the two ways, when relatively moderate amounts of reinforcement are employed, at small value of load the steel will reach its yield point, at that stress, the reinforcement yields suddenly and stretches a large amount and the tension cracks in the concrete widen visibly. The secondary compression failure occurs, when the strain in the remaining compression zone of the concrete increases to such a degree that crushing of the concrete, ensues at a load only slightly larger than that which caused the steel to yield [1].

Shui and Nilseen,[2] have determined the load –carrying capacity of perfectly plastic structures using a method based on a series of linear elastic solutions. Although the method aims at collapse analyses, it may also be used for obtaining estimates of load – deflection curves, stresses and strain on the way to final collapse.

Bonetti,[3] has an improved equation for prediction of the ultimate strength of the local zone in load transfer tests. The derivation of this formulation was a result of the investigation of the ultimate strength of plain and reinforced concrete blocks, concentrically loaded.

Chen et.al.[4] have provided a calculation method for the determination of the ultimate strength of structures. The accuracy of this method and applicability of the stress strain relationships were validated by comparing different existing confined concrete uniaxial constitutive relationships and experimental results.

Sanad and Saka [5] have explored the use of artificial neural networks in predicting the ultimate shear strength of reinforced concrete deep beams. One hundred eleven experimental data collected from literature cover the simple case of a simply supported beam with two point loads acting symmetrically with respect to the center line of span. The data was arranged in format such that 10 input parameters cover the geometrical and material properties of the deep beams and the corresponding output value is the ultimate shear strength.

Tang [6] has explored the application of radial basis function neural networks (RBFN) to predict the ultimate tensional strength of reinforced concrete beams. A database on tensional failure of RC beams with rectangular section subject to pure torsion was retrieved from past experimental work in the literature, several RBFN models were sequentially built which were trained and tested.

Alcantara and Gasparini [7] have proposed a methodology for non destructive testing (NDT) of reinforced concrete structures using superficial magnetic field and artificial neural network, in order to identify size and position of steel bar embedded into concrete, magnetic induction curves were obtained by using finite element program.

Amayreh and Saka [8] have explored the use of artificial neural networks in predicting the failure load of castellated beams. 47 experimental data which were collected from the literature covered the simply supported beams with various modes of failure.

Rao and Babo [9] have demonstrated the applicability of (ANN) and Genetic algorithms (GA) for the design of beams subjected to moment and shear. The network has been trained with the design data obtained from the design expert in the field , after successful learning , the model predicts the depth of the beam , area of steel ,and spacing of stirrups for new cases

Finite Element Method

In the non linear finite element analyses of reinforced concrete beams under short term loading, material nonlinearity is considered using numerical model for deformation characteristics and ultimate load prediction. Both perfect-plastic and strain hardening plasticity approaches are employed to model the compressive behavior. A dual criterion for yielding and crushing in terms of stresses and strains is considered, which is complemented with a tension cut-off representation. Three conditions have to be considered in nonlinear stress-strain relation, based on the flow theory of plasticity, the yield criterion, the flow and hardening rule, and the crushing condition. Eight noded element (Ahmed shell element) with reduced integration rule was used for the idealization of concrete member. The reinforcing bar is represented by two node or three node axial element embedded anywhere within an element in the mid surface. Perfect bond is assumed between the reinforcement and the surrounding concrete. All simply supported beams have a cross section of (200*300) mm and the a/d ratio was variant from 4.5 to 9.5 .Figure (1) shows sample of beam finite element mesh for a/d ratio of 4.5.

Limit State Theory

Limit design and plastic design are often considered as synonymous terms. In steel design, the term plastic design includes not only the change in the pattern of moment beyond the yield point but also the increased resistance of cross section after its extreme fiber reaches the yield point. In reinforced concrete, limit design is used only to refer to the changing moment pattern. When yielding starts, deflection increased sharply and repeated loading would introduce an element of fatigue. Limit design is sufficient due to (1) a statically indeterminate member or frame cannot collapse as the result of a single yielding section, and (2) between first yielding and final frame failure there normally exists a large reserve of strength .[10]

Equations considered are as follows:

$$\left[\rho_b = \left[0.85\frac{fc^{'}}{f_y}\beta_1\frac{600}{600+f_y}\right]\right]$$

where ρ_b is the balanced steel ratio **… (1)**

for $f^{'}c \le 28MPa$ $\beta_1 = 0.85$ **….(2)**

for $f_c^{'} > 28MPa$

$$\beta_1 = \left[0.85 - \frac{0.05}{7} * (f'c - 28) \right] \geq 0.65 \quad \textbf{..(3)}$$

$$a = \beta_1 . c \quad \textbf{....(4)}$$

$$As * f_y = 0.85 . f'c . a . b \quad \textbf{....(5)}$$

$$z = d - (a/2) \quad \textbf{....(6)}$$

$$Mn = As . f_y . z = \frac{av . p_u}{2} \quad \textbf{....(7)}$$

$$P_u = \frac{2Mn}{av} = \frac{2Mn}{\frac{l}{3}} = \frac{6Mn}{l} \quad \textbf{....(8)}$$

where fc' is concrete cylinder compressive strength, f_y is steel yielding, d is effective depth of beam, *av* is distance from support to plastic hinge, Mn is nominal moment, and P_u is ultimate load capacity.

Neural Learning Using Back-Propagation[11]

One of the most powerful uses of a neural network is function approximation. Neural networks known as neural nets are computing systems which can be trained to learn a complex relationship between input variables and target data sets. The learning process is the most important part of the entire process. The objective of the learning process is to train the network so that the application of a set of inputs produces the desired or at least a consistent set of outputs. During training the network weights gradually converge to values such that each input vector produces the desired output vector.

A learning cycle starts with applying an input vector to the network, which is propagated in a forward propagation mode which ends with an output vector. Next, the network evaluates the errors between the desired output vector and the actual output vector. It uses these errors to shift the connection weights and biases according to a learning rule that tends to minimize the error. This process is generally referred to as "error back-propagation" or back-propagation for short. The adjusted weights and biases are then used to start a new cycle. A back-propagation cycle, also known as an epoch, in a neural network is illustrated in Figure (2). For a finite number of epochs the weights and biases are shifted until the deviations from the outputs are minimized.

Network Data Preparation

Preprocessing the data by scaling was carried to improve the training of the neural network to avoid the slow rate of learning near the end point specifically of the output range due to the property of the sigmoid function, which is asymptotic to value 0 and1. The input and output data were scaled between interval 0.1and 0.9 [12].

Transfer Functions

The function that maps a neurons (or layer's) net output *n* to its actual output is called transfers function. The computation of the error of each neuron of the multilayer perceptron requires knowledge of the derivative of the activation function associated with that neuron Log-sigmoid transfer function .This form of sigmoid nonlinearity in its general form is defined by: [12]

$$a = \frac{1}{1 + e^{-n}} \quad \textbf{....(9)}$$

This function is useful for most neural network applications, and it maps values into the (0, 1) ranges (see Figure 3). Because the functions in the hidden and output layers are linear, the least-mean-square (LMS) networks were used. [12]

Data Range

The data that was collected from finite element programming (shell element) for R.C. beam analyses with various parameters are shown below in Table (1). The data was grouped into subset, Appendix (A) sample of data collected from finite element with (L/H) 4.5, training set of 990 beam results, and tested set 110 beam results. All beams were tested with concentrated two point loads acting symmetrically with respect to the center line of the span. All specimens were simply supported, laterally braced at load point and the reaction points. The basic is parameter that controls the load failure (ultimate load capacity) based on data works shown in table (1):

Net Performance on Testing Set

Figure (4) shows a graph that indicates the learning progress by hidden Neurons. This graph shows the progress of the network training performance against an Increasing number of hidden neurons as they are added to the network. This gives a statistical measure of the goodness of fit between the finite element and predicted outputs. This measure, called R-squared (the coefficient of multiple determinations) on the graph is performed each time a hidden neuron is added, as learning gets better and better the graph shows higher and higher values. The neural network developed by predictor which is used in predicting the failure load of beams is shown in Figure (4) below.

Artificial Neural Network Designed:

For obtaining the best data arrangement many trials were tried by swapping the rows shown in Table 1 once at a time and run the MATLAB software version 7each time a swap was made. The best arrangement, however, is the one that gives the highest network performance of the tested data and the least average error. Arrangement and rows swapping is necessary because the network performance is a function of how the rows are arranged. The performance of the best model is presented in Figures 5 - 7.

As shown in Figure (4) the best performed artificial neural network model has 4 input nodes, 980 hidden neurons, and one output node representing the failure load. The best network performance obtained is 0.99. They are very close in all trained data rows, which is an indication of how good the training is. The neural network had the best performance using 30 hidden neurons, which is the optimum number of neurons. As shown in Figures 5 and 6 the learning progress of hidden neurons reached the maximum value of 1 at 15 hidden neurons.

Figure 7 shows the comparison between finite element methods (numerical data) with NN ultimate load testing; the best network performance obtained is 0.982. They are much closed with numerical data. Figure (8) shows the relative importance of each input parameter. It is noticed that the importance of inputs is distributed such that each input contributes significantly in the prediction of the output, which shows the highest importance factor is reinforcement ratio 81.54%, the geometry L/H effect ratio 10.5998, the effect of the compressive strength f_c' on the ultimate load is 5.7939 and for yield point of steel reinforcement is 2.0581, which agrees with the analysis methods of beams.

Analysis of Results

There are number of analysis approaches that can be used in predicting the failure load of beams such as code approach and limit state theory approach, among these approaches limit state theory was selected to perform a comparative study. Other methods are not selected due to the fact that either they require additional information that is not available in the data or they are very sensitive to patch length or they are very conservative.

The neural network developed is used together with method to obtain the failure loads of 110 beams reserved for testing that are not employed in training. The average ratio of numerical failure load predicted by finite element load to predict failure load in this set of data is 1.018 and for the limit state theory 1.21 for beams having reinforcement less than $0.5\rho_b$ and increased the variation with increased reinforcement ratio to reach for all data to 1.24. These values clearly show that the Neural Network performs much better than the methods selected in this study.

Conclusions

It has been shown that artificial neural networks can effectively be used to predict the failure loads of R.C. beams. It has also been shown that the network predicted the outputs with acceptable accuracy, covering the range from length to depth ratio are from 4.5 to 9.5. It should be noted that once the network was trained, the time required outputting results for a given set of inputs was instantaneous. This indicates the potential of neural networks for solving time-consuming problems.

For selecting the best configuration of the networks, there are no special guidelines, and trial and error approach should be employed that takes into consideration the best network performance, average error and the best network performance for the testing data. Among the number of configurations tried, it is found that a network with a performance of 0.982 and an average error of 0.018 is the best.

In the comparative study it is found that the failure load values obtained from the artificial neural network are much more accurate than those determined from limit state theory.

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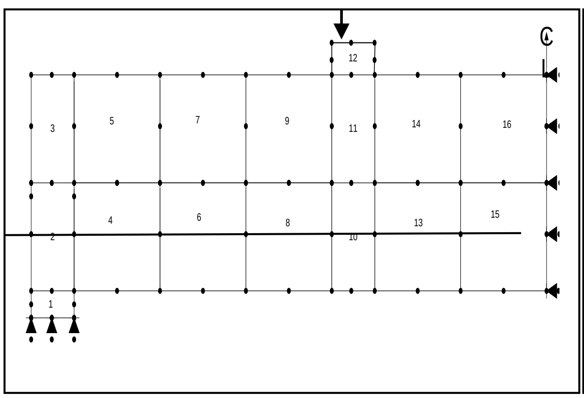

Figure (1) Finite Element Mesh for Beams (L/H) 4.5

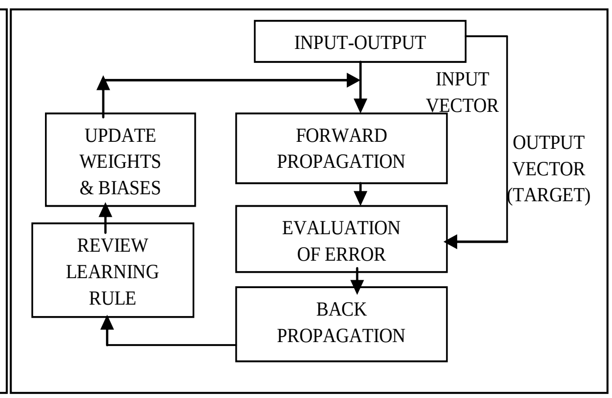

Figure (2) Back-Propagation Cycles [11]

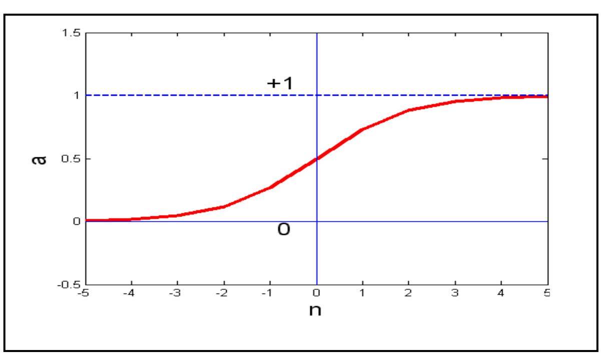

Figure (3) Log-Sigmoid Transfer Function

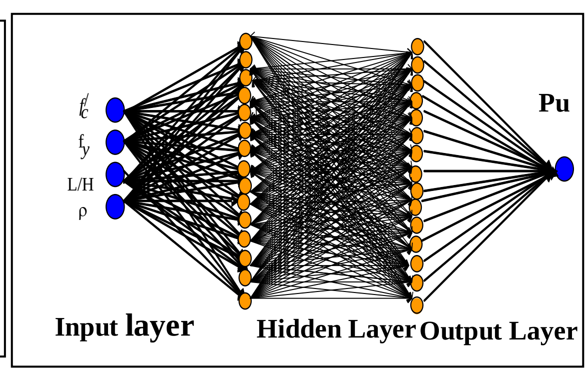

Figure (4) Architectural Graph of Multilayer Perception with two Hidden Layer

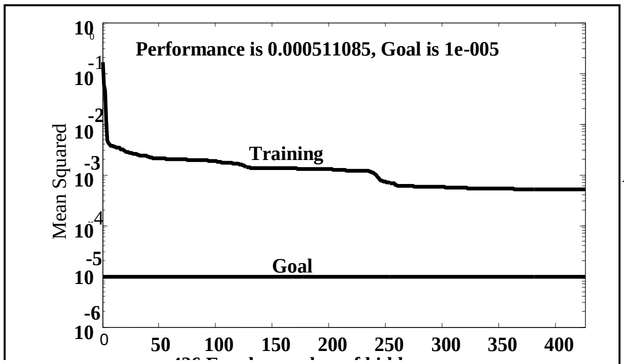

Figure. (5) Mean Squared Error of the Model MLS with Number of Epochs

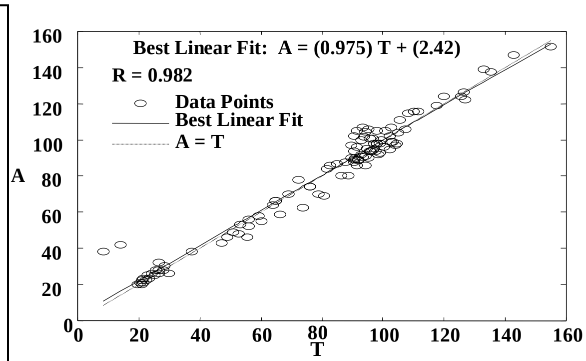

Figure (6) Progress of the Network Training Performance

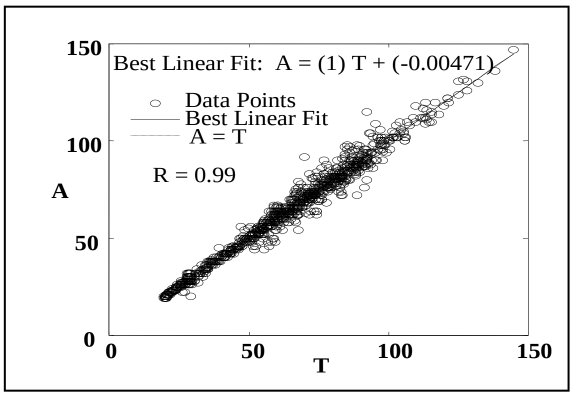

Figure (7) Comparison of Finite Element Method with Neural Ultimate Load Testing Performance

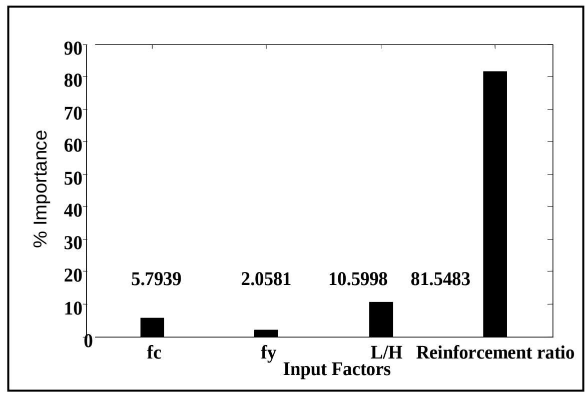

Figure (8) The Significance of Each Input in Prediction Output Value of the Best Model

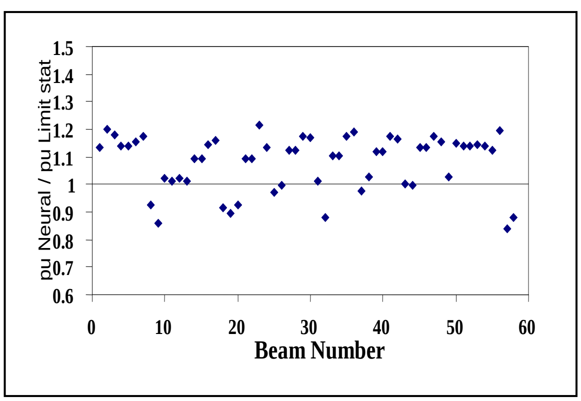

Figure (9) Ultimate Load in Neural and Limit State Theory for Reinforcement Less than 0.5 ρ_b

Table (1) Variation Input Parameter

	f'_c	f_y	$\frac{L}{H}$	ρ
Min.	**20**	**250**	**4.5**	**0.0035**
Max.	**40**	**400**	**9.5**	**0.0505**

Appendix (A) Sample of data collected from finite element with (L/H) 4.5.

f'_c	f_y	$\frac{L}{H}$	ρ	P_u
20	250	4.5	0.0056	42
25	250	4.5	0.0056	42
30	250	4.5	0.0056	42
35	250	4.5	0.0056	42
40	250	4.5	0.0056	46
20	300	4.5	0.00466	42
25	300	4.5	0.00466	42
30	300	4.5	0.00466	42
35	300	4.5	0.00466	42
40	300	4.5	0.00466	42
20	350	4.5	0.004	42
25	350	4.5	0.004	42
30	350	4.5	0.004	42
35	350	4.5	0.004	42
40	350	4.5	0.004	42
20	400	4.5	0.0035	42
25	400	4.5	0.0035	42
30	400	4.5	0.0035	42
35	400	4.5	0.0035	42
40	400	4.5	0.0035	42
20	250	4.5	0.00765	60
25	250	4.5	0.009563	74
30	250	4.5	0.011379	88
35	250	4.5	0.012615	94
40	250	4.5	0.013787	106
20	300	4.5	0.00602	54
25	300	4.5	0.007525	68
30	300	4.5	0.00903	82
35	300	4.5	0.009925	92
40	300	4.5	0.010852	100
20	350	4.5	0.004889	52
25	350	4.5	0.0061	66
30	350	4.5	0.007213	76
35	350	4.5	0.008063	86
40	350	4.5	0.008812	94
20	400	4.5	0.004064	50
25	400	4.5	0.005075	62
30	400	4.5	0.005995	74
35	400	4.5	0.006702	82
40	400	4.5	0.007325	90
20	250	4.5	0.0153	82
25	250	4.5	0.019125	86
30	250	4.5	0.022757	102
35	250	4.5	0.02523	110

$f_c^{/}$	f_y	$\frac{L}{H}$	ρ	P_u
40	250	4.5	0.027575	122.5
20	300	4.5	0.01204	70
25	300	4.5	0.01505	86
30	300	4.5	0.01806	100
35	300	4.5	0.01985	118
40	300	4.5	0.021703	122
20	350	4.5	0.009778	70
25	350	4.5	0.0122	82
30	350	4.5	0.014425	94
35	350	4.5	0.016125	105
40	350	4.5	0.017624	119
20	400	4.5	0.008128	68
25	400	4.5	0.01015	84
30	400	4.5	0.01199	92
35	400	4.5	0.013404	115
40	400	4.5	0.014649	112
20	250	4.5	0.02295	86
25	250	4.5	0.028687	96
30	250	4.5	0.034135	117
35	250	4.5	0.037845	131
40	250	4.5	0.041362	147
20	300	4.5	0.01806	84
25	300	4.5	0.022575	90
30	300	4.5	0.02709	102
35	300	4.5	0.029775	114
40	300	4.5	0.032555	130
20	350	4.5	0.014667	80
25	350	4.5	0.0183	88
30	350	4.5	0.021638	100
35	350	4.5	0.024188	112
40	350	4.5	0.026435	124
20	400	4.5	0.012192	72
25	400	4.5	0.015225	84
30	400	4.5	0.017985	98
35	400	4.5	0.020106	110
40	400	4.5	0.021974	122
20	250	4.5	0.0306	84
25	250	4.5	0.03825	104
30	250	4.5	0.045514	120
35	250	4.5	0.05046	136
40	250	4.5	0.05515	152
20	300	4.5	0.02408	84
25	300	4.5	0.0301	100
30	300	4.5	0.03612	116
35	300	4.5	0.0397	132
40	300	4.5	0.043406	147
20	350	4.5	0.019556	86

$f_c^{/}$	f_y	$\frac{L}{H}$	ρ	P_u
25	350	4.5	0.0244	90
30	350	4.5	0.02885	108
35	350	4.5	0.03225	118
40	350	4.5	0.035247	138
20	400	4.5	0.016256	82
25	400	4.5	0.0203	96
30	400	4.5	0.02398	102
35	400	4.5	0.026808	114
40	400	4.5	0.029299	126