Prediction of Ultimate Strength of Reinforced Concrete Beams Subjected to Torsion using Artificial Neural Networks

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Abstract

Artificial Neural Networks (ANN) have been applied to structural engineering in recent years. Most of the researches are based on backpropagation neural networks due to its well-studied theory. A backpropagation neural network has been used to predict the ultimate torsional strength of reinforced concrete rectangular beams. The effects of the parameters, such as the number of nodes in the input, output and hidden layers and the pre-process of the training patterns, on the behaviour of the neural network have been investigated. The algorithm called 'resilient propagation algorithm' has been used to the performance of the neural network. After training, the generalization of the neural network was tested by the patterns not included in the training patterns. Once the neural network has been trained, the ultimate torsional strength of reinforced concrete is obtained very easily and efficiently. Based on the ANN results, a parametric analysis was carried out to study the influence of parameters affecting the ultimate torsional strength of reinforced concrete beams and these results are compared with the equations of ACI-code.

تقييم المقاومة القصوى للعتبات الخرسانية المسلحة المعرضة للالتواء باستخدام الشبكات العصبية الصناعية

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طبقت الشبكات العصبية الصناعية في مجال الهندسة الانشائية في السنوات الاخيرة حيث ان معضم البحوث استخدمت الشبكات العصبية العكسية.في هذا البحث استخدمت الشبكات العصبية الصناعية لتقييم مقاومة الالتواء القصوى للعتبات الخرسانية المسلحة والمستطيلة، فتمت دراسة تأثير المتغيرات المختلفة للشبكة مثل عدد العقد في طبقة الإدخال والإخراج والطبقات المخفية ، والمعالجة المسبقة لنماذج تدريب الشبكة على سلوك وأداء نموذج الشبكة العصبية وكم ا استخدمت دالة الإرجاع العكسي لتدريب الشبكة العصبية. وبعد إنهاء تدريب الشبكة العصبية تم اختبار استقراء الشبكة بواسطة استخدام نماذج مختلفة غير موجودة في نماذج التدريب وعندها تم الحصول على مقاومة الالتواء القصوى للعتبات الخرسانية المسلحة بصورة بسيطة وكفوءة . واستنادا إلى النتائج المستحصلة من تلك الشبكات العصبية تم دراسة تأثير العوامل المختلفة المؤثرة على المقاومة القصوى للعتبات الخرسانية المسلحة ومقارنتها مع معادلات مدونة معهد الخرسانة الأمريكي (ACI-Code)

Introduction

Torsional moment develops in structural concrete members as a result of asymmetrical loading or member geometry, or as a result of structural framing. For example, spandrel beams built integrally with the floor slab are subject to torsional moment resulting from the restraining negative bending moment at the exterior end of the slab. The restraining moment is proportional to the torsional stiffness of the spandrel beam. In complex structures such as helical stairways, curved beams, and eccentrically loaded box beams, torsional effects dominate the structural behavior. Torsional moment tends to twist the structural member around its longitudinal axis, inducing shear stresses. However, structural members are rarely subjected to pure torsional moment. In most cases, torsional moments act concurrently with bending moment and shear forces.

During the first half of the twentieth century, structural codes were silent regarding torsion design. Torsion was looked at as a secondary effect that was covered in the factor of safety considered in the design. Demand for more complex structures, improved methods of analysis, new design approaches, and the need for more economical design required a better understanding of the behavior of reinforced concrete members subjected to torsion. In the second half of the twentieth century, research activities helped engineers understand many aspects of behaviour of concrete members under torsion [1].

A neural network is an interconnected network of processing elements that has the ability to be trained to map a given input into the desired output. If the training data use the results of experiments carried out on reinforced concrete beams, the neural network gives the torsion strength capacity without making any assumption about the behaviour of the beam. Neural network modeling techniques have been successfully applied to different areas of structural engineering. Some of these were on structural analysis and design (Vanluchene and Sun 1990[2]; Hajela and Berke 1991[3]; Chuang et al 1998 [4]; Jenkins 1998 [5]; Waszczyszyn 1998 [6]) and some others were on structural damage assessment (Wu et al. 1992 [7]; Buenfeld and Hassanein 1998 [8]). The application of neural network in structural mechanics is described by Topping and Bahreininejad 1997 [9]. In this paper, an artificial neural network is developed for the prediction of the torsional strength of reinforced concrete rectangular beams and the results obtained are compared with those determined according to the ACI code for reinforced concrete.

Neuron Model and Network Architectures

Neural networks are made up of simple elements called neurons operating in parallel. The neuron model and the architecture of a neural network describe how a network transforms the input values to output values. A neuron (Fig. 1) is the basic unit of the neural network.

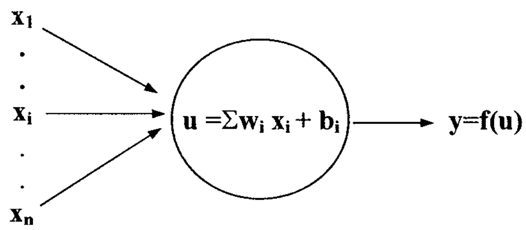

Fig. (1) illustrative simple neuron

Each neuron can receive an input vector (x_i) and perform a series of mathematical operations, including the calculation of a weighted sum $u=\sum Wixi+b$ (where Wi are called the weights and b is the bias) and can produce a unique output value through a transfer function, $f(u)$. Many transfer functions are available, but the step function, linear function, sigmoid function, and hyperbolic tangent transfer function are the more commonly used [10].

Typical neural network architecture is shown in Fig. 2. The architecture of a network provides a description of the number of layers in the network, the number of neurons in each layer, the transfer function for each layer, how the layers are connected to each other, and how they are connected to the input/output. The layers of a multilayer network play different roles. The function of the input layer is to receive input information from the outside. The function of the output layer is to communicate the result of the neural network predictions to the outside. All other layers are called hidden layers. The hidden layers link the input layer to the output layer. The function of the hidden layer is to extract useful features from the data set to produce an optimal mapping between the input and output values [10]. To train the neural network, various combinations of known input/output values (obtained, for example, from experiments) are required. The training process is indeed an optimization of the weight and bias at each node, to provide the best match between the network output and the actual values [10].

The type of problem to be studied determines the number of inputs and outputs for the network. Once the input and output layers are fixed, the number of hidden layers as well as the number of neurons in each hidden layer is often obtained through trial and error.

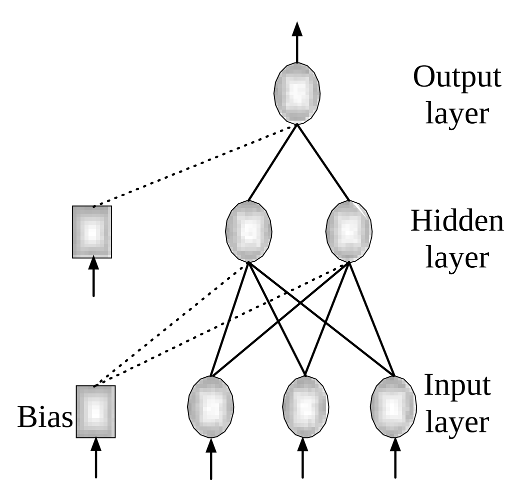

Fig. (2) Structure of a typical multilayer neural network

Experimental Data

To provide sufficient information to train and verify the neural network, a comprehensive set of data has to be collected. An extensive review of the literature was therefore conducted to compile a database of test results on RC beams that fail in torsion. All together, 102 test results were collected [11, 12, 13, 14 and 15]. The data used to build the neural network model should be divided into two subsets: training set and validating or testing set [16]. The validating set contains approximately 15% from total database [16]. The training phase is needed to produce a neural network that is both stable and convergent. Therefore, selection what data to use for training a network is one of most important steps in building a neural network model.

Model Development and Optimization

In developing a neural network model for application in this study, the performance of the model developed is tried to maximize speed of convergence and accuracy of prediction by investigating the network characteristics before experimenting with any future tests. The following processes are conducted.

(1) Input and Output Layer

The nodes in the input layer and output layer 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 total depth of beam cross section (h), the width of beam cross section (b), the concrete cylinder compressive strength (f'c),the ratio of longitudinal reinforcement (pl), yield stress of longitudinal steel (fy), the ratio of transverse steel (pw), yield stress of transverse steel (fsy), longer and shorter leg of stirrups (y1,x1) respectively, and spacing of stirrups (s). The output vector is the ultimate torsional strength of beams (Tu).

(2) Weight Initialization

The first step in the neural network computations, prior to training a neural network, is to initialize the weight factors between the nodes of the different layers [17]. The Gaussian distribution at specific range is used to overcome this phenomenon. In this study Gaussian weight-factor distribution at range between (-1 to +1) is used.

(3) Normalizing Input and Output Data Sets

Normalization (scaling down) of input and output data sets within a uniform range before they are applied to the neural network are essential to prevent larger numbers from overriding smaller ones, and to prevent premature saturation of hidden nodes, which impedes the learning process [18]. The limitation of input and output values within a specified range are due to the large difference in the values of the data provided to the neural network. Besides, the activation function used in the backpropagation neural network is a hyperbolic tangent function, the lower and upper limits of this function are -1 and +1 respectively. The function used to normalize the input and output is:

$$x_{i,norm.} = 2.\frac{x_i - x_{i,\min.}}{x_{i,\max.} - x_{i,\min.}} - 1$$

where:

$x_{i,norm.}$ is the normalized variable.

$x_{i,\min.}$ the minimum value of variable xi

$x_{i,\max.}$ the maximum value of variable xi

Adapted Neural Network and Analysis Approach

A *Matlab* program using *Matlab* 7.0 's built-in Neural Network Toolbox was developed to conduct the neural network analysis. With the ten input parameters given earlier, a neural network is trained to obtain the ultimate torsional strength of the beams.

The optimum solution was obtained after (262) epochs with a neural network topology as (10:25:25:1) units, as shown in figure (3).

The resilient backpropagation (RPROP) training algorithm and tan-sigmoid activation function for the each hidden layer and for output layer are used in the network for the training and testing sets and the results are shown in figure (4). The suitability of neural network model is checked by plotting the predicted values of ultimate torsional strength (the output of neural network) versus the experimental results (the target or actual values) for the training and testing sets as shown in figures (5), and (6). As can be seen, the correlation factor, r, for both sets is quite high, which proves the high accuracy of training neural network model.

Parametric Analyses based on developed Artificial Neural Network

Once the artificial neural network has been trained, a parametric analysis was conducted to study the influence of the various parameters on the ultimate torsional strength of members. These include:

(1) Influence of Concrete Compressive Strength

Figure (7) shows the effect of concrete cylinder compressive strength on ultimate torsional strength of reinforced concrete beams. It can be seen that as the concrete compressive strength increases, the ultimate torsional strength increases.

ACI-89 code, gives a reasonable agreement with the values predicted by using neural network, but ACI-05 code, does not take into account the influence of compressive strength of concrete.

(2) Influence of Ratio of Web Reinforcement

The ratio of web reinforcement (ρ_w) in this study is calculated as the ratio of volume of web reinforcement to volume of concrete in a distance of one spacing of stirrups, the amount of web reinforcement has a very important influence on the torsional strength of beams. The ACI-89 code limits the torsional reinforcement in a member by requiring the contribution of stirrups(T_S) not to exceed four times the contribution of concrete ($4T_C$). This requirement is equivalent to limiting the nominal strength of section (T_n) to $5T_C$. This is because, as long as T_S does not exceed $4T_C$, torsional failures are ductile, i.e., the stirrups and the longitudinal steel yield before the concrete crushes [19].

The artificial neural network predicts a non-linear response of beams with the amount of web reinforcement. However, the ACI-89 and ACI-05 codes give a linear response as it can be seen in figure (8). The results obtained from the neural network show that the effectiveness of stirrups becomes less as the ratio of this type of steel increases.

(3) Influence of Ratio of Longitudinal Reinforcement

The influence of the ratio of longitudinal reinforcement as predicted by artificial neural network results is analyzed here and compared with the ACI-89 and ACI-05 code equations.

Figure (9) shows that the increase of amount of longitudinal reinforcement leads to increase in the ultimate torsional strength. However, the ACI-code equations do not reveal this effect for the longitudinal reinforcement.

(4) Size effect

The increase in depth of beam leads the ultimate torsional strength to increase Fig.(10). A reasonable agreement between the results of ACI-Code equations and those of the neural network is achieved.

(5) Influence of Stirrups Spacing

The effect of the spacing of stirrups is depicted in figure (11). In this figure, it can be seen that the increase of spacing of stirrups, while keeping the volume percentage of stirrups for these beams identical, results in a decrease in the torsional strength. The ACI-code equations do not take into consideration the influence of stirrups spacing but they limit the maximum stirrups spacing to ($\frac{x_1 + y_1}{4}$ or 300 mm whichever is smaller) to ensure that every 45-degree crack on the wider face of the beam should be crossed by at least two stirrups. In figure (11), s =175 mm corresponds to the maximum spacing permitted by the ACI-code.

(6) Influence of Yield Point of Stirrups

In figure (12) the ultimate torsional strength of beams is plotted versus the yield stress (fsy MPa) of stirrups. In this figure, it can be seen that as fsy increases, the ultimate torsional strength is increased. A reasonable agreement between the results of ACI-code and artificial neural network is obtained.

Conclusions

This study investigates the feasibility of using the artificial neural network to evaluate the ultimate strength of reinforced concrete rectangular beams under pure torsion. The neural network is particularly useful for evaluating systems with multitude of variables. The backpropagation neural network, which is a multi-layered feedforward neural network, has been proved to accurately predicting the ultimate torsional strength of reinforced concrete beams. Neural networks can be used as a reliable alternative to costly experimental testing as well as lengthy empirical calculations for predicting ultimate strength of concrete beams.

The ultimate torsional strength of beams under pure torsion is found to be nonlinearly related to the ratio of web reinforcement.

The increasing of amount of longitudinal reinforced steel leads to increases of ultimate torsional strength.

The influence of concrete compressive strength predicted by neural network was in agreement with ACI-89 code.The results obtained from the neural network confirm the provision ofACI-89-Code which states that the contribution of stirrups should no be longer than four times the contribution of concrete.

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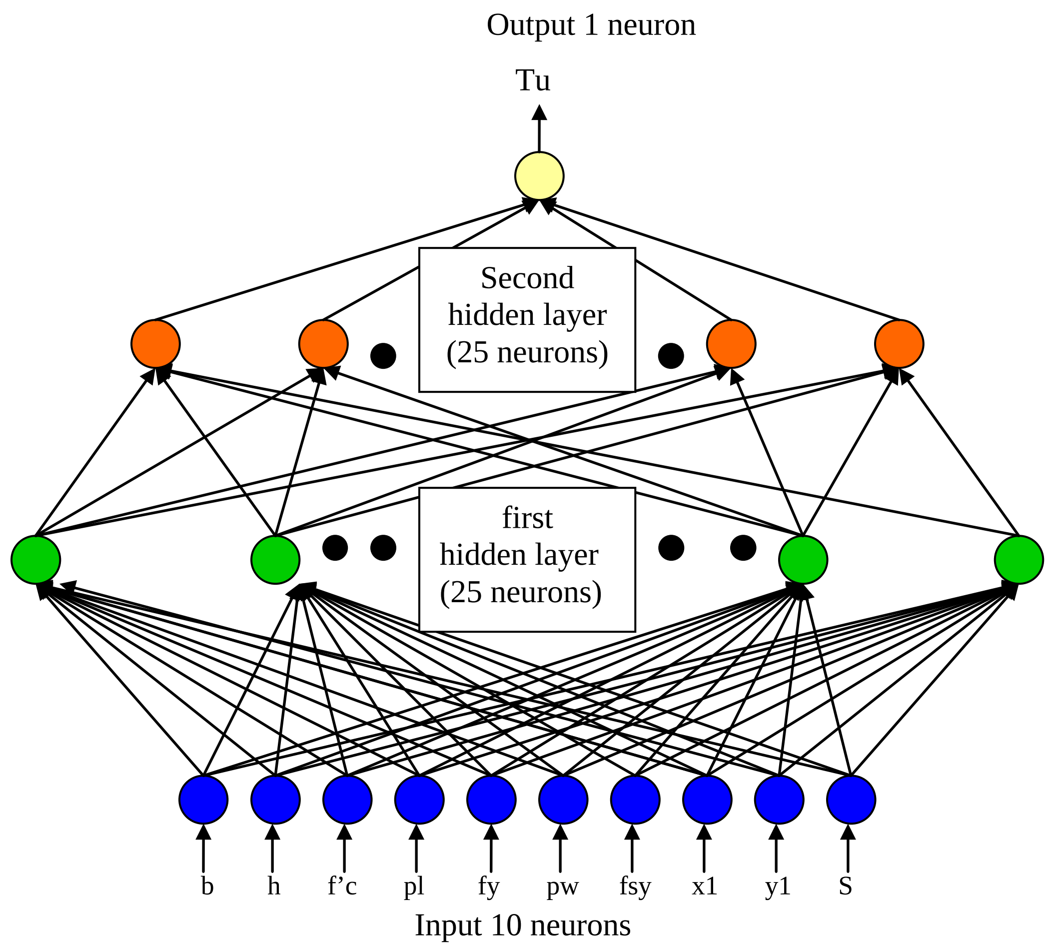


Fig.(3) The structure of the proposed NN model

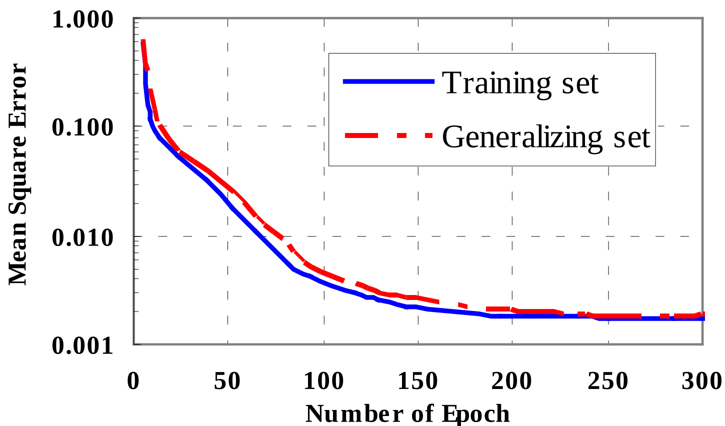
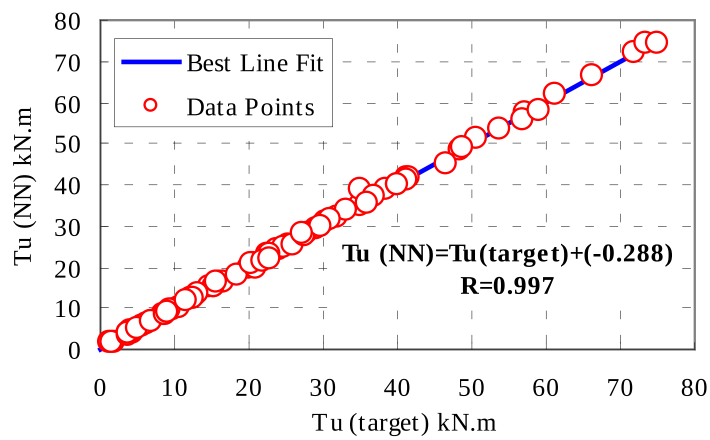


Fig.(4) Convergence of the NN for training and testing sets based on the RPROP algorithm



Fig(5) Comparison between NN results and target results for training patterns based on RPROP algorithm

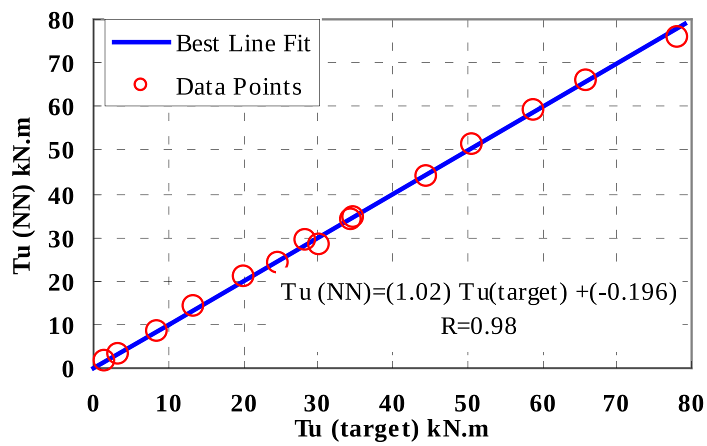


Fig.(6) Comparison between NN results and target results for testing patterns based on RPROP algorithm

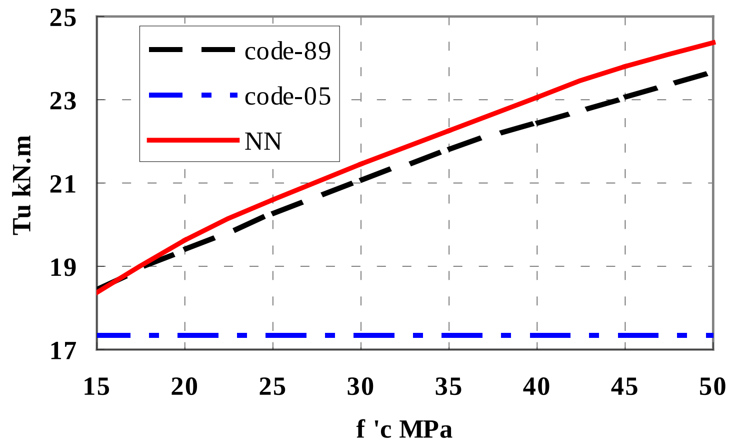


Fig.(7) Influence of the concrete compressive strength as related to ratio of transverse reinforcement (pw=0.5%)

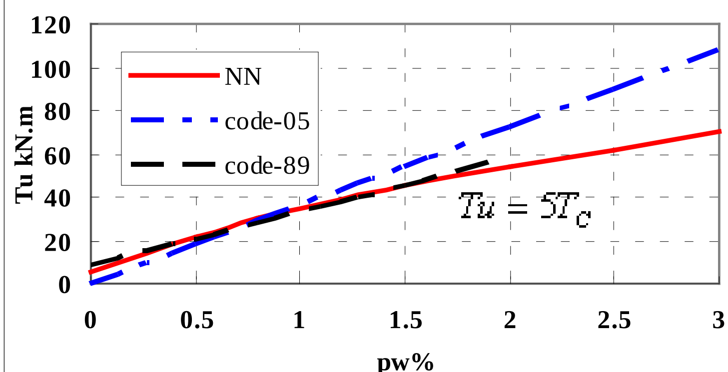


Fig.(8) Influence of transverse reinforcement in relation to the concrete compressive strength (f 'c =25 MPa)

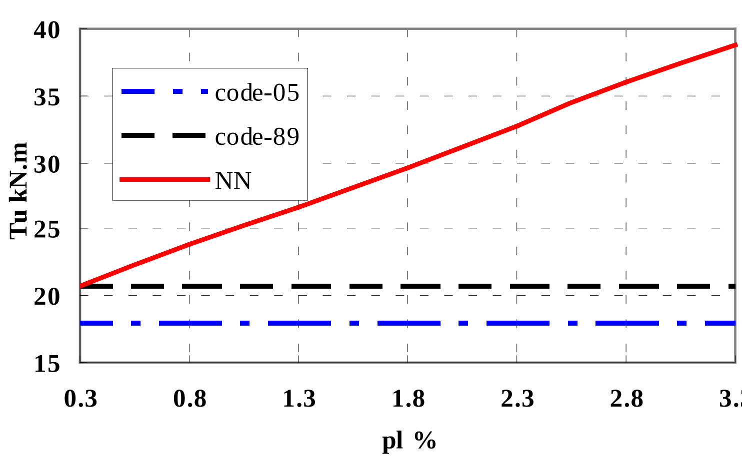


Fig.(9) Influence of the amount of longitudinal reinforcement in relation to the amount of transverse reinforcement (pw=0.5%)

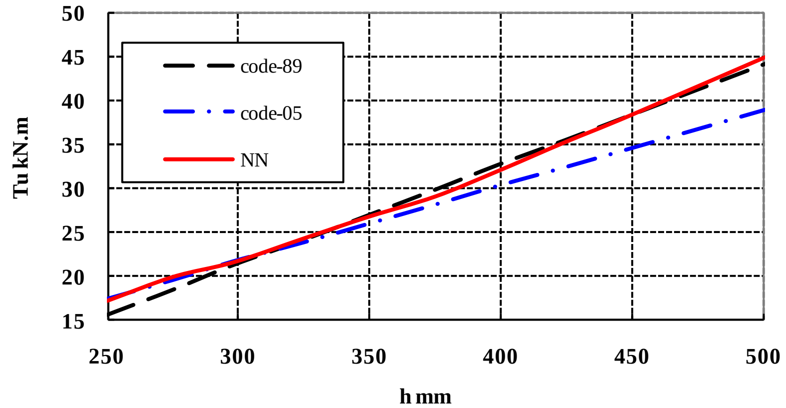


Fig.(10) Influence of size effect on the ultimate torsional strength

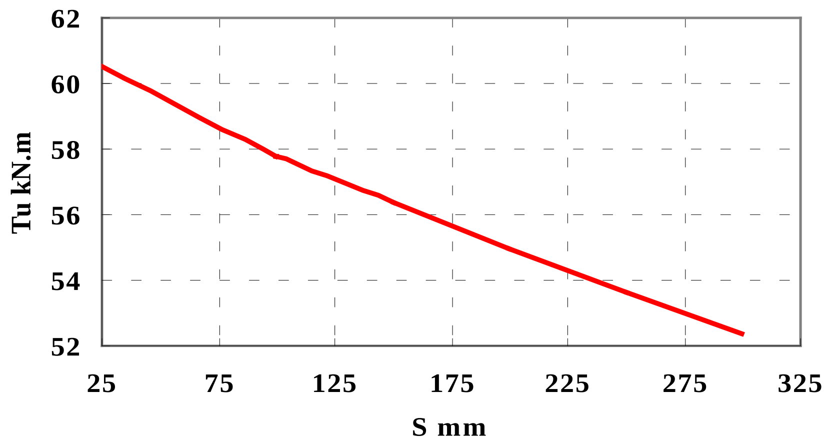


Figure (11) Influence of spacing of stirrups on ultimate torsional strength

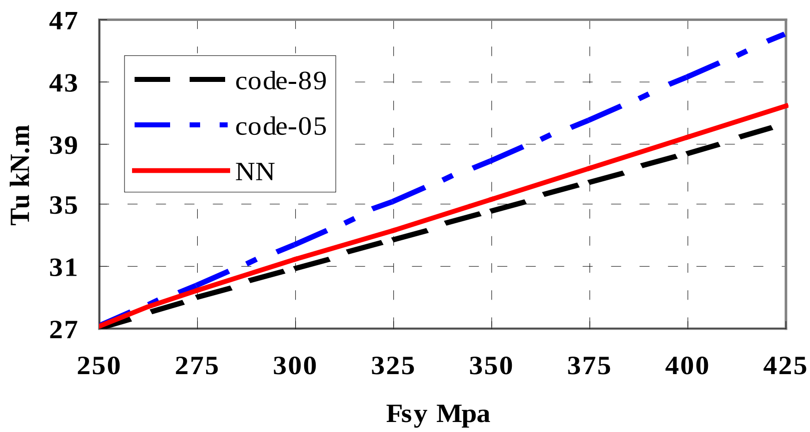


Figure (12) Influence of yield stress of transverse reinforcement on ultimate torsional strength