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# Identification of a suitable ANN architecture in predicting strain in tie section of concrete deep beams

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**Abstract.** The comparison of the effectiveness of artificial neural network (ANN) and linear regression (LR) in the prediction of strain in tie section using experimental data from eight high-strength-self-compact-concrete (HSSCC) deep beams are presented here. Prior to the aforementioned, a suitable ANN architecture was identified. The format of the network architecture was ten input parameters, two hidden layers, and one output. The feed forward back propagation neural network of eleven and ten neurons in first and second TRAINLM training function was highly accurate and generated more precise tie strain diagrams compared to classical LR. The ANN's MSE values are 90 times smaller than the LR's. The correlation coefficient value from ANN is 0.9995 which is indicative of a high level of confidence.

**Keywords:** strain; deep beams; artificial neural network; STM; linear regression

## 1. Introduction

Deep beams are structural elements loaded as beams where significant load is transferred to the supports by a compression thrust joining the load and the reaction. With the ongoing progress in construction activity at the countries around the Persian Gulf, deep beam design is now an issue and problem for structural engineers due to lack of valid design code provision. The strain distribution is non linear, and the shear deformations are more significant when compared to pure flexure. Reinforced concrete (RC) deep beams are commonly used in foundations, transfer girders in high rise buildings, nuclear power plants as well as pile cap, tank, foundation walls, bins, floor diaphragms and offshore structures.

There is no clearly defined design procedure for RC deep beams. Extensive researches have been conducted on the design of deep beams (lee *et al*. 2011, Londhe 2011, Chemrouk and Kong 2004, Yang *et al.* 2007, Rigotti 2002, Schlaich and Schäfer 1991, Perera and Vique 2009, Ashour and Yang 2008, Kang *et al* 1997, Pimentel *et al.* 2008, Yun *et al.* 2005, Mohammadhassani *et al.*

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2011a), but no specific method has been introduced for their design. Mohammadhassani *et al.* (2011a) concluded that before the first crack, the beam behaves elastically, displays no non-linear distribution of strain and more than one neutral axes.

Existing design codes are lacking in the design of deep beams. The British code BS8110 (British Standard Institution 1985) states that for deep beams, references should be made to specialist manual or literature. Codes such as the ACI, the draft Euro code EC/2 (Euro code 2 1992), the Canadian code and the CIRIA guide No.2b (Construction Industry Research and Information Association 1997) present design instructions based on experimental investigation.

Currently the Strut-and-tie modelling (STM) provides design engineers more flexibility in the designing of structures that are fully or partially influenced by shear. In 1989, STM was included in the American code provisions in the AASHTO Guide Specifications for Design and Construction of Segmental Concrete Bridges. STM has since become popular in the designing and detailing of structural RC members experiencing large shear stresses. Code provisions for STM have been adopted in both ACI 318 (2002) and the AASHTO LRFD Bridge Design Specifications (1998).

STM makes allowance for the stress flows within a structure approximated with simple truss-elements that are designed using basic structural mechanics. Truss members that are in compression are known as struts and the tension force paths are known as ties. Nodes are formed when struts and/or ties intersect. The forces within a STM are calculated using static equilibrium when the truss is statically determinate. By determining strut and tie forces using basic statics and any necessary compatibility, only stresses within these elements (struts, ties, and nodes) are compared with permissible stresses. STM conforms to the lower bound theory of plasticity, which requires only equilibrium and yield conditions be satisfied. The lower bound theory of plasticity states that any load that makes it possible to find corresponding its stress distribution within the yield surface and is able to maintain internal and external equilibriums, is a load that does not result in collapse of the structure (Nielson 1971). What makes the lower bound theory appealing is its inherent conservatism. In this regard, the effects of the material used and the conservatism in STM require a precise method to predict the behaviour and design of these structural elements.

General STMs consist of concrete in struts and reinforcing steel as tie section. Despite the many researches on the use of high strength concrete (HSC) in normal and deep beams (Mohammadhassani *et al*. 2011b, lam *et al*. 2009, Danielson *et al.* 2010), there is no study specifically on the design, stress and strain distribution in the tension area of tie section in HSSCC deep beams.

The effects of longitudinal reinforcement in the tie section were discussed by as Watstein and Mathey (1958), Tan *et al.* (1997), Oh and Shin (2001). Oh and Shin (2001), Tan *et al*. (1997) concluded that the shear span-to-depth ratio effects are much more critical than the tensile reinforcement ratio effects on the shear strength of concrete beams.

In deep beams, STM is assumed to fail due to the yielding of tie, anchorage failure of the ties, the failure of nodal zone connecting the strut and ties and the crushing of the concrete. Other parameters affected by the importance of tie members in STM are the ultimate strength and ductility of deep beam. Based on Watstein and Mathey’s assumption (1958), there is constant stress along the tie in different location; thus necessary attention ought to be given to the anchorage of ties. This also implies the presence of a tied arch mechanism. If yield force of a tie is expected at any point in an STM, proper anchorage must be provided beyond this point. Thompson (2002) had studied the necessary anchorage requirement for ties.

Recent studies focus on deep beams and their behaviour (Mohammadhassani 2011a, Lu *et al.*

2010) but very few on the design or strain distribution of the tie section. To the authors' knowledge, only Whestren and Maty (1958) had studied the tension reinforcement strain variation. No work has been carried out for the bonded specification of HSSCC.

Based on the literature review, there are many parameters that affect strain in tie sections. Amongst these parameters are the concrete compressive strength, the web reinforcement percentages, and the tensile reinforcement ratios, the length and the shear span to depth ratio (Yang *et al.* 2006, Yang *et al.* 2003).

Engineers and programmers are constantly finding discover less costly technology to acquire the necessary information. Especially since, the cost casting and testing of concrete deep beams is very expensive and time-consuming. Issues such as the high cost of concrete deep beam fabrication and unknown behaviour of deep beams have increased the interest in application of computer software to predict the behaviour of these elements.

Today, neural networks and fuzzy sets are the answers to high-tech solutions. Neural networks can solve problems that cannot be solved using standard or common calculations. These networks are used when the data necessary for the interpretation is insufficient and/or not available.

Recent efforts and studies have computerized the design process, the behaviour of concrete element and their serviceability using ANN and other intelligent systems. ANN is also known as parallel distribution processor, adaptive system, self organizing system, connectionism, neurocomputer and NN (neural network).

ANN is a computational tool that emulates the human brain. It learns from existing designs and actual behaviour during the training process. ANNs are able to process incomplete and noisy data as is the case with many engineering applications. Much of ANN's achievement is due to its nonlinear and parallel processing characteristics. The use of this technology has been successful in areas of civil engineering such as concrete technology (Mohebbi *et al.* 2011, Hakim *et al.* 2011), strengthening analysis (Perera *et al.* 2010), load and behaviour prediction (Ashrafi *et al.* 2010), damage detection (Şen 2010, Saridakis *et al*. 2008, Hakim Abdul Razak 2013a, b), non-destructive testing methods for material (Bilgehan and Turgut 2010), structural element design criteria (Perera and Vique 2009, Malekly *et al.* 2010, Sasmal and Ramanjaneyulu 2008) and asphalt technology (Mirzahosseini *et al.* 2011, Tapkın *et al.* 2010).

Though ANN is based on simple principles, its mathematical talent is in terms of nonlinear iteration that is practical in the prediction of strain in tie section of deep beams.

The use of the ANN technique in civil engineering began when ANN was used to predict the ultimate shear strength of reinforced concrete deep beams (Sanad and Saka 2001). Sanad and Saka (2001) showed that the shear strengths of normal beams and deep beams are better predicted using multi-layered feed forward ANNs than other existing formulas. The recent study of using ANN in concrete structures by Mohammadhassani *et al.* (2013) reveals the best performance of ANN in deflection prediction of deep beams.

Deep beam design and failure prediction are based on two main design assumptions. First, these structural elements do not follow the ordinary beam theory in which plane sections across the beams do not remain planar after deformation. Thus, the prediction of strain in tie section is not possible using normal beam equations or beam sectional theory. Second, the behaviour of these structural elements is dominated by shear deformation that is neglected in normal beams. High economical impacts, the different deep beam behaviour and the lack of clear design procedure led to the use of computer aided intelligent technology and programs such as the ANN for the prediction of strain in tie sections.

### 1.1 Research significant

In this study, the back-propagation neural network was used to predict the strain in tie section of HSSCC deep beam. For this reason, training and testing patterns of the network were prepared using experimental data of eight HSSCC deep beams with different parameters. The number of hidden layers, neurons in each hidden layer and the type of selected function put in the information processing are the key parameters to generate architecture with minimum errors and maximum correlation coefficients; this is the main objective of this study. A comparison is made between the effectiveness of both the ANN generated and LR; this is the secondary objective of this study.

## 2. Methodology

### 2.1 Experimental study

Experimental section of this study is presented in (Mohammadhassani 2013).

Eight deep beams were designed and casted using HSSCC. The concrete mix design and the related requirements are detailed by Mohammadhassani (2011c).

### 2.2 Location of strain gauges in tie section

Two points were chosen on the tie reinforcements to study the strain distribution. One strain gauge was used at each selected points and the location of strain gauges is shown in Fig.1.

G.m represents the location of strain gauge in mid-span of tie section and G.s indicates the location of strain gauge of tie section near the support of the deep beams.

### 2.3 Test setup and loading process

All simply supported beams were subjected to two points of monotonic static load to ultimate capacity with a hydraulic jack. The arrangement adopted is shown in Fig. 2.

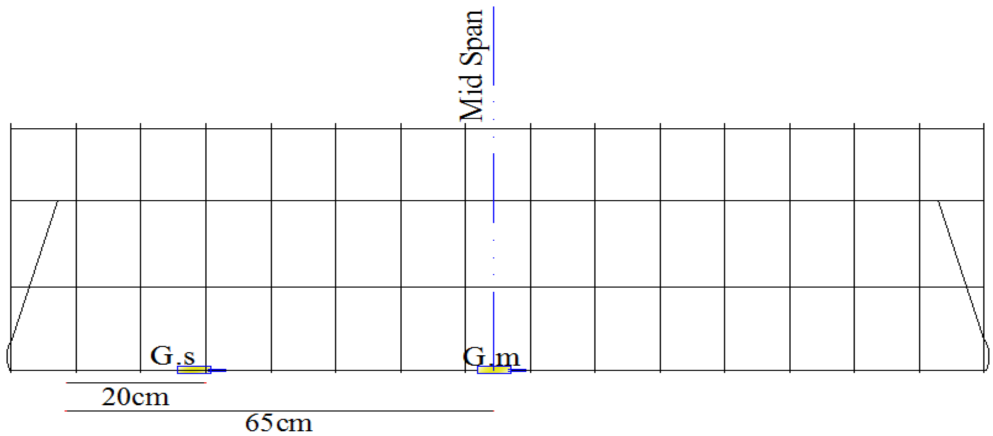


Fig. 1 Locations of strain gauges on the tensile bar (tie section) in tested deep beams

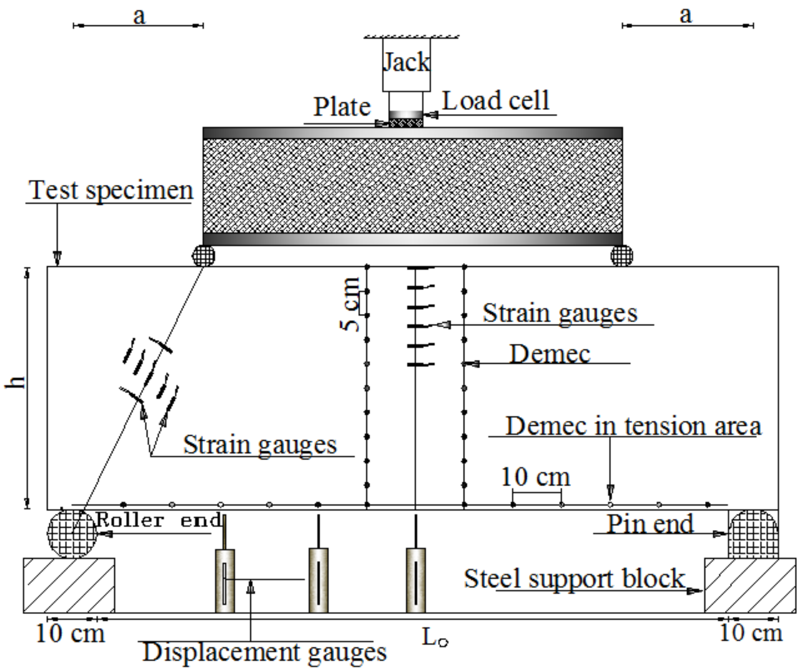


Fig. 2 Details of testing arrangement and strain gauges on the beam surface (Mohammadhassani *et al*. 2011d)

The deep beams were positioned on two steel cylinders with 5’’ diameters. After the beam was centred and levelled, the load was then applied at midspan at 20 kN intervals until the first crack appeared. In the loading process, care was taken to ascertain that the specimens were vertically aligned to reduce any possibility of other failure due to irregularity of supports. At each increment, the strain readings were taken. After each reading and observation, the next loading stage increment was repeated, until the failure or an important observation was made.

### *2.4 Numerical study*

#### *2.4.1 ANNs - structure and definition*

ANNs are modelling tools that work similar to the human brain; ANNs were, in fact, extracted from biological neural network. This intelligent information processing system consists of three main aspects including transmission, processing and storage of information.

There are three matching parts in an ANN, they are as follows:

(a) The input layer: - consists of number of nodes which receives input data of an independent variable. Therefore, the total number of nodes in the input layer is equal to the total number of the input variables of the problem.

(b): The one or more hidden layers: - receive information from the input layer, using the applied weights and pre-specified activation functions.

(c): The output layer: - receives the processed information from the hidden layer and sends the results to an external recreant.

The number of nodes in the output layer is equal to the number of output variables. The number of hidden layers and the number of nodes in each hidden layer are important factors in the design of the network, and there are generally no applicable rules to exactly determine these numbers (Flood and Kartam 1994).

The collected data for the problem is divided into training and testing data sets. Depending on the available data, about 80% of the total data is utilised as the training set. The number and distribution of training patterns affect the generalization ability of the ANN (Flood and Kartam 1994). The training pattern must cover all possible ranges of the study.

Once the topology of the ANN is determined, the training process is started by assigning values to the training parameters and specifying the activation function and learning algorithm. Different learning algorithms can be applied; amongst which is the back-propagation algorithm that is predominantly used in civil engineering applications (Adeli 2001). This algorithm looks for the minimum error function in weight space using the method of gradient descent.

### *2.5.2 System modeling*

System modeling alters the parameters of an adaptive intelligent system like ANN and other fuzzy systems to suit unknown actual engineering system transfer function. A schematic of the system modeling engineering problems using adaptive intelligent systems is shown in Fig. 3. As shown in this figure, the parameters of the estimated intelligent system are tuned using proper learning methods to ensure accurate estimation of the actual system. In other words, the performance function, typically the mean squared error (MSE) between the intelligent system's output and the actual response is minimized.

The objective of the function in system modelling problems is expressed as follows

$$MSE = \frac{1}{L}\sum_{k=1}^{L}(\hat{y}(k) - y(k))^2 \tag{1}$$

where $y(k)$ is noisy output of the actual system (measured or observed output), $\hat{y}(k)$ is the adaptive

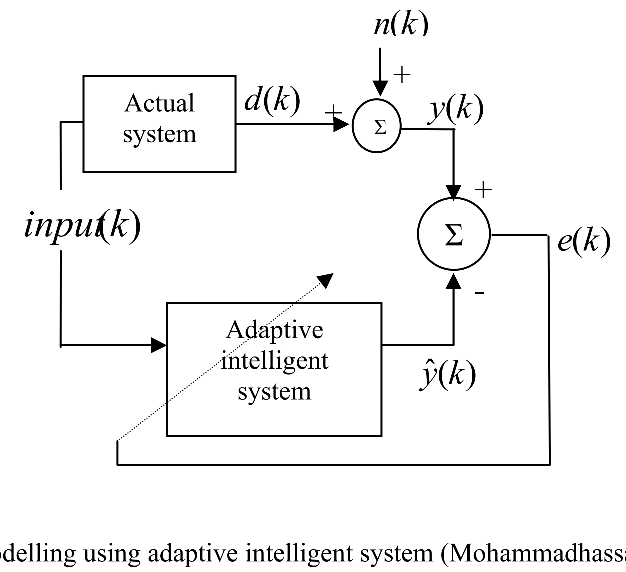


Fig. 3 System modelling using adaptive intelligent system (Mohammadhassani *et al*. 2013)

intelligent system output and $L$ is the number of instances. Some cases are noise free where $y(k)$ is equal to $d(k)$ which is the desired output. When noise is present, $\hat{y}(k)$ is the estimation of desired output or semi desired output. Multilayer feed forward neural network is used in this study as an adaptive intelligence tools to predict the strain in tie section of deep beams.

### 2.5.3 Evaluation

To evaluate the comparative methods, the MSE and Correlation Coefficient / Pearson Coefficient (R) values are used in this study. MSE is a risk function which corresponds to the expected value of the squared error loss or quadratic loss. Correlation Coefficient is the degree of success in reducing standard deviation (SD). It is widely used in the sciences as a measure of strength of linear dependence between two variables. Eq. 1 presents the MSE and R is calculated as follows.

$$R^2 = 1 - \frac{\sum_{k=1}^{L}(y(k)-\hat{y}(k))^2}{\sum_{k=1}^{L}(y(k)-y_{ave})^2} \tag{2}$$

where $\hat{y}(k)$ is the output predicted by ANN, $y(k)$ is the actual (observed) output, $y_{ave}$ is the averaged actual output and $L$ is the total number of training/testing instances.

### 2.5.4 Training and testing of neural networks

Training means to present the network with the experimental data and have it learn, or modify its weights to correctly predict the strain in tie section of HSSCC deep beams. However, training the network successfully requires many choices and training experiences.

The master unit of the network is a complex network of neurons that act parallel and work as a numerical processing unit. The effect of the connection between neurons is referred to as the weight of the internal connection. In the generation process, the network gets random amount of the weight to find the optimum relationship between the experimental data. ANN learns to solve the problems based on the relationship between the experimental data. The mathematical neuron model is shown in Fig. 4.

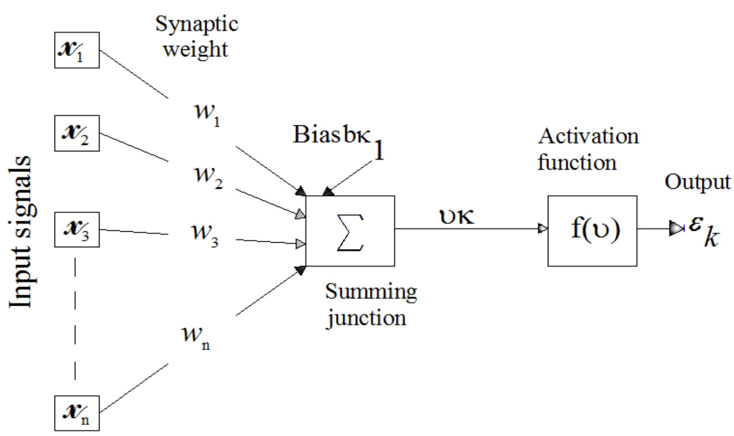


Fig. 4 Neuron model with *n*-element in the input model (Mohammadhassani *et al.* 2013)

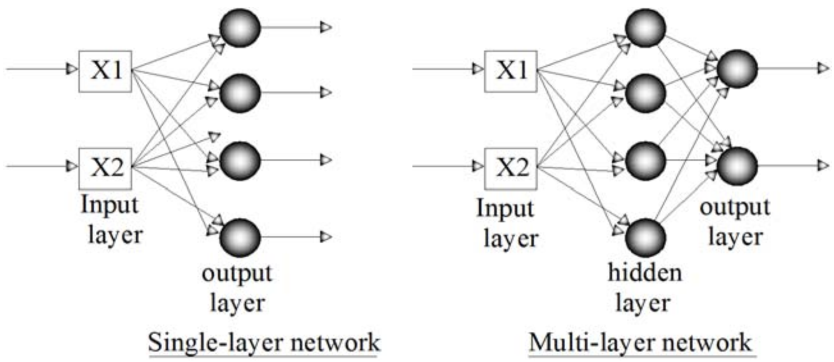


Fig. 5 Single-layer and Multi-layer networks (Mohammadhassani *et al*. 2013)

Table 1 Different parameters of eight deep beams

| Input Parameters | | | | | | | | | | Out put |
|---|---|---|---|---|---|---|---|---|---|---|
| $P$ | $f_{cu}$ | $a/d$ | $l_0/d$ | $f_{yv}$ | $f_{yh}$ | $A_v/bs_v$ | $A_h/bs_h$ | $\rho$ | $f_y$ | $\varepsilon$ |

The effect of input vector ($X$) on output ($\varepsilon$) is defined by the weights ($W$). The other input is the constant value of 1 that is multiplied by bias ($b_k$), and then added with WX.

In general, ANN can be structured in either a single layer or a multilayer networks. The structure of a single and a multilayer ANNs are shown in Fig. 5. A typical multi-layer artificial neural network (MLNN) includes an input layer, output layer and at least one hidden layer of neurons.

MLNNs supply an improvement in computational ability over a single-layer neural network unless there is a nonlinear relationship between layers. Many of neural network abilities, such as learning, nonlinear functional approximation, generalization etc are in fact completed because of the nonlinear activation function of neurons. In present research, the strain analysis along the tie section of eight HSSCC deep beams with different parameter indicated in Table 1 are discussed and an ANN is built and applied for the strain prediction in tie section of deep beam.

It is worth mentioning that the parameters in Table 1 are as follows:

$P$ =applied load in each incremental loading stage
$f_{cu}$ =28 days cube strength of concrete
$a$ =shear span
$d$ =effective depth
$l_0$ =overall length of tested beams
$b$ =the beam width
$f_{yv}$ =the yield strength of vertical web reinforcement
$f_{yh}$ =the yield strength of horizontal web reinforcement
$A_v$ =the area of vertical web reinforcement
$s_v$= the distance of vertical web reinforcement
$A_h$ =the area of horizontal web reinforcement
$s_h$ =the distance of horizontal web reinforcement
$\rho$ =the tensile reinforcement ratio
$f_y$ =the tensile bar yield strength

Table 2 BP learning functions used in this study

| Function | Description |
|---|---|
| Trainlm | Trainlm Levenberg-Marquardt BP algorithm. Fastest training algorithm for networks of moderate size. Has memory reduction feature for use when the training set is large |
| trainoss | The one step secant (OSS) method is an attempt to bridge the gap between the conjugate gradient algorithms and the quasi-Newton (secant) algorithms. This algorithm does not store the complete Hessian matrix; it assumes that at each iteration, the previous Hessian was the identity matrix. This has the additional advantage that the new search direction can be calculated without computing a matrix inverse. |
| traincgf | Fletcher-Reeves conjugate gradient algorithm. Have smallest storage requirements of the conjugate gradient algorithms. |
| trainrp | Resilient backpropagation. Simple batch mode training algorithm with fast convergence and minimal storage requirements. |

A total of 3773 data is utilized to create the network. 20% of output data is applied for network testing and the other outputs are used for verifying and training. A multi-layered feed-forward neural network (MLFFNN) equipped with back-propagation (BP) learning is constructed.

#### *2.5.5 Variants of back-propagation learning algorithm*

To train the MLFFNN, eight variant of BPs are examined. More precisely, the Levenberg-Marguardt BP (Trainlm), Gradient descent with momentum (Traingdm) and (Traingda), Basic gradient descent (Traingd), Adaptive learning rate (Traingdx), Fletcher-Reeves conjugate gradient algorithm , one step secant  and Resilient backpropagation were used for network training at the end of analysis. Description of the trainings are presented in Table 2.

## 3. Results and discussion

Ties are the elements within a strut-and-tie model that carry tension, and are generally confined to reinforcing or pre-stressing steel. The geometry of a tie is therefore much simpler. The tie is geometrically confined to elements that can carry high tensile forces, and the allowable force is generally given as a fraction of the yield force.

In the ACI 318-08 provision the main load-carrying mechanism in the STM approach consists of single diagonal struts between the loading and the support point (refer to Fig. 6).

The most commonly accepted STM used in deep beam design are the tied arch or truss models depending on the *a/d* of the beam. The horizontal component of each strut at the support is set in equilibrium by a horizontal tie extending the full length of the beam (Fig. 6); it is assumed that the tie force in the model is constant throughout the span. To ensure this constant tie force, the longitudinal bar forming the ties must be anchored at the face of the node over each support. This is to develop the yield stress and prevent bond failure.

Figs. 7 to 8 show the strain distribution along the tie section of the deep beam tested. G.m represents the amount of strain in mid-span of tie section and G.s indicates the amount of tie strain near the support of the deep beams.

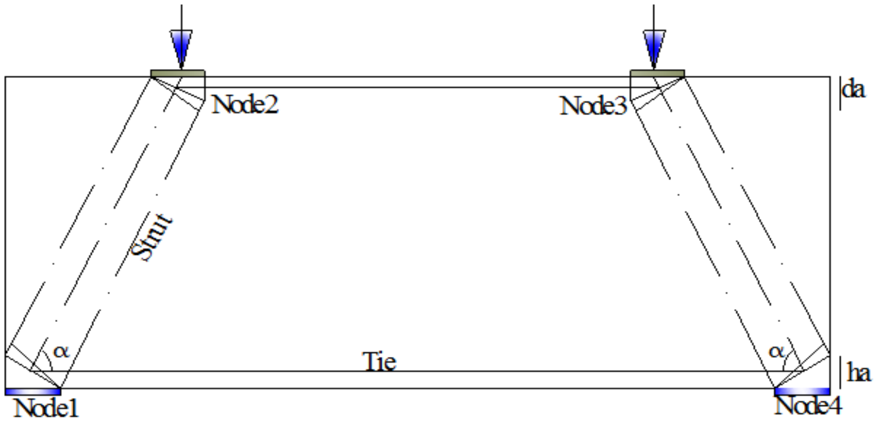


Fig. 6 Strut and tie model using ACI code

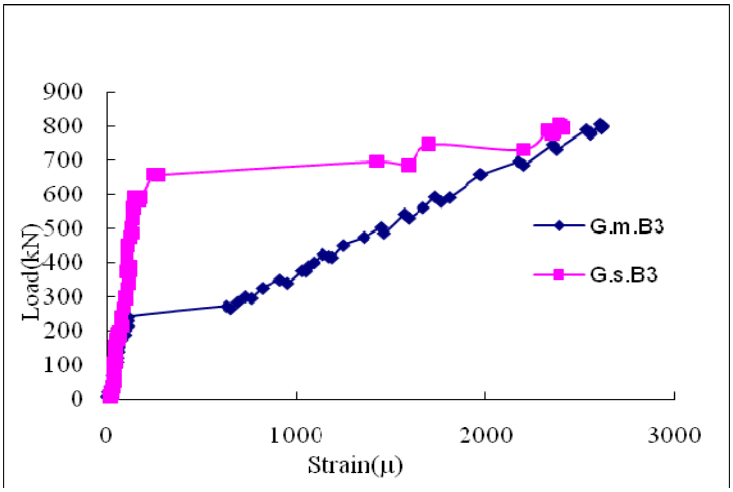


Fig. 7 Strain variation along the Tie section of B3

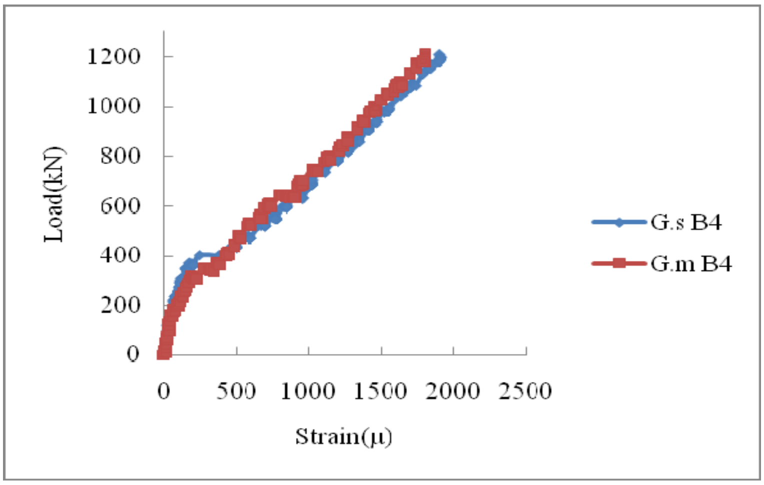


Fig. 8 Strain variation along the tie section of B4

Table 3 Comparison of performance of different type of BP on prediction of tie strain

| | | Trainrp | | Traincgf | | Trainoss | | Trainlm | |
|---|---|---|---|---|---|---|---|---|---|
| | | learn | test | learn | test | learn | test | learn | test |
| MSE | Max | 1.13e4 | 1.35e4 | 4.36e4 | 4.16e4 | 4.0e4 | 6.54e4 | 2704.9 | 5038.4 |
| | Min | 1.94e3 | 1.93e3 | 6.18e3 | 7.59e3 | 5.29e3 | 7.37e3 | 431.8 | 669.5 |
| | Avg | 5.20e3 | 5.90e3 | 1.32e4 | 1.39e4 | 1.59e4 | 2.14e4 | 936.6 | 1606.6 |
| Correlation(R) | Max | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | Min | 1 | 1 | 1 | 1 | 1 | 1 | 0.9987 | 0.9977 |
| | Avg | 1 | 1 | 1 | 1 | 1 | 1 | 0.9996 | 1 |
| Time | | 31.998 | | 33.67 | | 28.18 | | 84.37 | |

As seen the strain variation along the tie section of deep beam is not linear and show complexities in behaviour that converge with increasing the applied load.

### 3.1 The Best learning function and optimum architecture of MLFFNN

To optimize the architecture of the network, 50 nets were examined. First a MLFFNN was constructed with two hidden layers in which 20 and 15 neurons were considered for the first and second layers respectively. Also, the tangent hyperbolic (tansig) and linear (purlin) transfer functions were used for the hidden layers and the output layer respectively. This MLFFNN structure was trained 5 times independently to find the best type of BP. In the experiments, for each type of BP including “trainlm”, “traincgf”, “trainoss” and “trainrp”, the network was trained in 25 runs with initial random weights. The results of the above mentioned experiments are summarized in Table 3. In these tables, for each of the trained network, the MSE and R were computed for learn and test sets. The average of MSE and R values over 25 independently initialized networks, the maximum and minimum values of MSE and R, and the average training time for each type of BP function are summarised and compared in Table 3.

The results are reported for 25 independently initialized weights. The best selection is based on the maximum average correlation coefficient value or the minimum average MSE value. Therefore by this definition, the function “trainlm” is selected as the best function for the training of MLFFNN for the rest of the experiments.

The best architecture was found out by testing the different number of hidden layers and neurons in each hidden layer. In this order, R and MSE measures were used to determine the best architecture. First, an MLFFNN was tested with one hidden layer to determine the best number of neurons; various numbers of neurons between 1 to 30 are examined. Figs. 9 and 10 summarize the results of MSE and R values for this step.

Figs. 9 and 10 show that having more than 11 neurons results in acceptable model. It should be noted that increasing the number of neurons in the hidden layer through decreasing the MSE of the training set may lead to network over-fitting or over training. This means that the network losses its generalization capability and cannot provide a good response to unseen data.

In the sequel, to find the best number of neurons for the second layer, an MLFFNN was constructed with two hidden layers in which the numbers of neurons in the first hidden layer is fixed at 11 and the numbers of neurons in the second hidden layer varies from 1 to 15. Figs. 11 and 12 summarize the MSE and R values for this step.

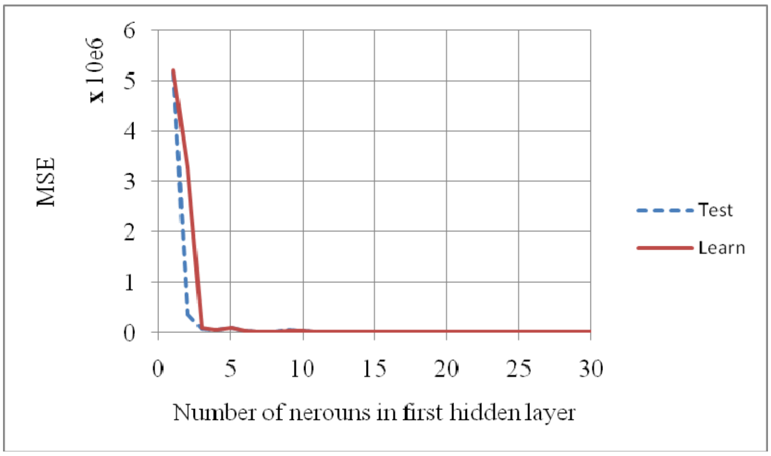


Fig. 9 The MSE value for different number of neurons in first hidden layer

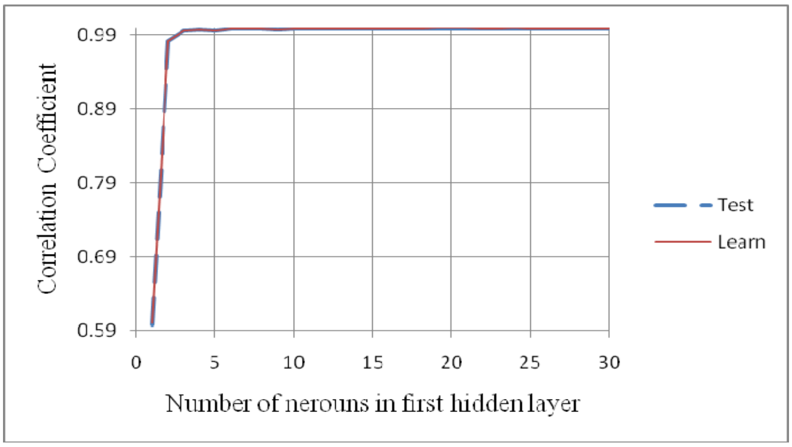


Fig. 10 The *R* value for different number of neurons in first hidden layer

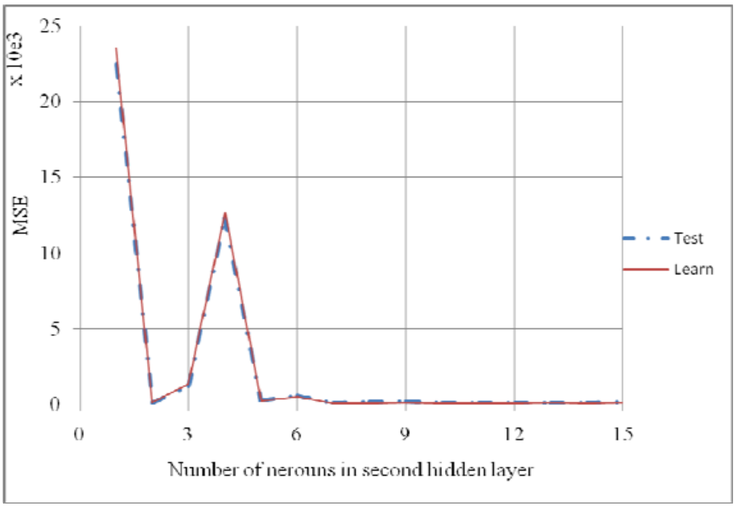


Fig. 11 The MSE values for different number of neurons in second hidden layer

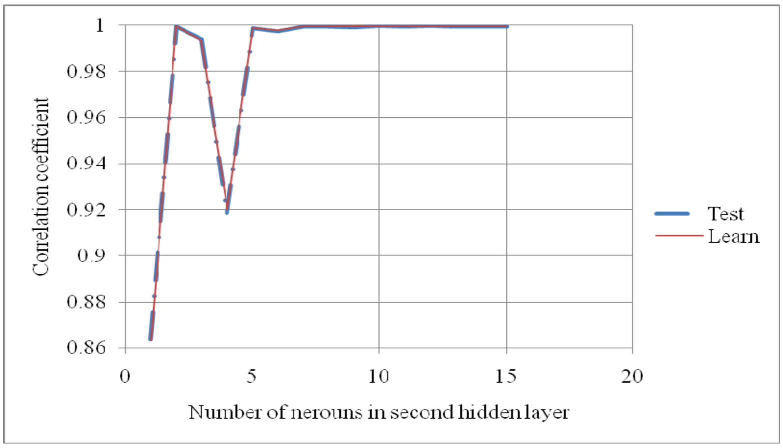


Fig. 12 The *R* values for different number of neurons in second hidden layer

Table 4 The optimum network specification

| Subject | Definition |
|---|---|
| Structure | 10-11-10-1 |
| Transfer function (hidden-layer) | Tangent hyperbolic (tansig) |
| Transfer function (output-layer) | Linear (purlin) |
| Learning function | trainlm |

Table 5 Comparison of *MSE* and *R* values from ANN and linear regression

| | Training Set | | | Testing set | | |
|---|---|---|---|---|---|---|
| Methods | Instances | MSE | R | Instances | MSE | R |
| Linear regression | 3018 | 82252 | 0.9605 | 755 | 89898 | 0.9550 |
| ANN | 3018 | 874.86 | 0.9996 | 755 | 977.49 | 0.9995 |

The dashed line represents the test data while the solid line is the learning data in Figs. 9 to 12. Figs. 11 and 12 show that the architecture including 10 neurons results from the second hidden layer provides the best results. Therefore the optimum network is described in Table 4.

Linear Regression (LR) is an excellent, simple and yet effective scheme used for prediction of domains with numeric attributes. The linear models function as building blocks for more complex learning tasks. Linear regression analysis is carried out to establish a relationship between the output and input data for the proposed ANN modelling.

Table 5 summarizes the MSE and R results obtained using the proposed methods separately for training and testing data. The neural network was trained 25 times using independent initial weight values and the average values of MSE and R have been shown in Table 5.

As noted, the MSE values from ANN are approximately 94 times for training data and 92 times for test data smaller than values from classical linear regression. Furthermore, the R values from ANN for test data is 0.9995 which is an exciting value to a scientist becasuse it is very close to the value 1 which is indicative of very high degree of confidence.

The results obtained by the experiments show that the difference between these two comparative methods is more obvious for the test set.

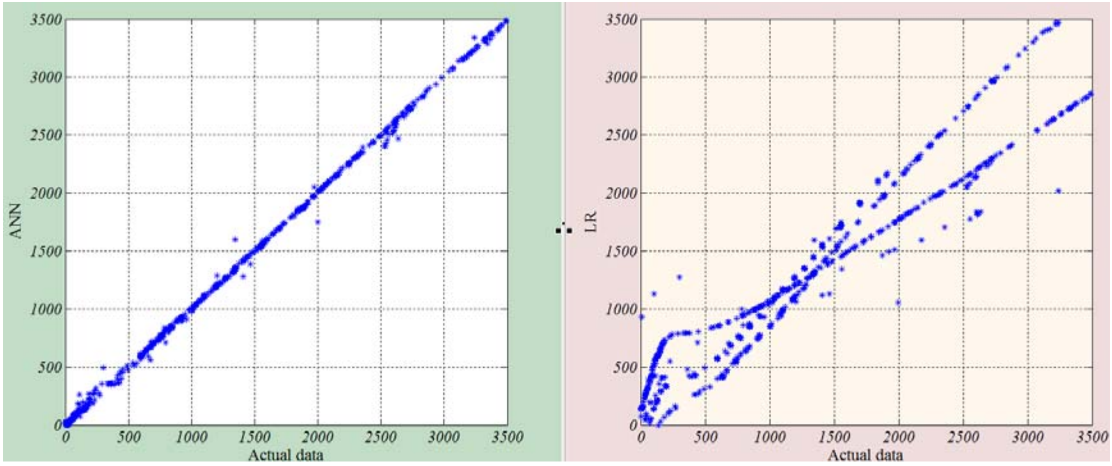


Fig. 13 Tie strain prediction performance from (a) ANN, (b) LR

Fig. 13 shows the tie strain prediction performance provided by LR and ANN for the test data. The horizontal and vertical axes present the actual and predicted data respectively.

A precise modelling should result in a direct linear relation between the actual and predicted data. Fig. 13 reveals that the proposed ANN method is highly accurate and precise compared to the classical LR for the strain prediction in tie section of HSSCC deep beams.

## 4. Conclusions

Based on the analysis of networks in this study, the ANN architecture with 10 inputs, 11 neurons in first hidden layer and 10 in second hidden layer is selected for the strain prediction in Tie section of deep beams. The result shows that the MSE values from ANN are 94 times lesser for training data and 92 times lesser for test data compared to corresponding values from LR. The R value from ANN is 0.9995 for test data, which is indicative of a high confidence level.

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