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Application of artificial neural networks (ANNs) and linear regressions (LR) to predict the deflection of concrete deep beams

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Abstract. This paper presents the application of artificial neural network (ANN) to predict deep beam deflection using experimental data from eight high-strength-self-compacting-concrete (HSSCC) deep beams. The optimized network architecture was ten input parameters, two hidden layers, and one output. The feed forward back propagation neural network of ten and four neurons in first and second hidden layers using TRAINLM training function predicted highly accurate and more precise load-deflection diagrams compared to classical linear regression (LR). The ANN's MSE values are 40 times smaller than the LR's. The test data R value from ANN is 0.9931; thus indicating a high confidence level.

Keywords: deflection; deep beams; artificial neural network; high strength self compacting concrete; linear regression

1. Introduction

Design engineers for concrete structures often encounter problems where certain locations of the structures that are prone to significant shear stresses. Traditional design assumptions, specifically those involving plane sections that remain planar after deformation, do not apply to such locations.

Similar problems are encountered with deep beams and standard specifications that use ordinary beam theory are not applicable. Reinforced concrete deep beams are often 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.

Design procedure for reinforced concrete deep beams is poorly defined. Although 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, Maco 2002, Schlaich and Schäfer 1991, Ray 1980, Perera and Vique 2009, Ashour and Yang 2008, Kang *et al.*1997, Pimentel *et al.* 2008, Yun *et al.*

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2005, Mohammadhassani *et al.* 2011a, 2012a, b), no specific method has been introduced for designing of these structural elements and the prediction of serviceability is imprecise. Ray (1980) found that prior to the first crack, the beam behaves elastically, displays no non-linear distribution of strain and more than one neutral axes.

Deflection is an important serviceability limit that must be met in the designing of concrete deep beams. Although there are 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 none on the deflection prediction of HSSCC deep beams. There is only one existing studies on deep beam deflection prediction (Lu *et al.* 2010). Lu *et al*. (2010) had proposed a simplified method developed from the softened strut-and-tie model to determine the mid-span deflection and shear capacity of deep beams at ultimate state. This method of strength analysis to the extent of softening involves five unknowns and due to effect of the many different parameters on deflection prediction, the strut-and-tie model is unable to predict the exact amount of deflection.

Mohammadhassani (2011a) found that the prediction deflection as a service index is not easy due to them any effective parameters used in deep beam design which result in various failure modes and nonlinear strain distribution.

Despite many researches on the shear strength of reinforced concrete member, the exact mechanism of the load transferring system in deep beams which is dominated by shear deformation it is not fully understood. Furthermore, existing codes of practices do not cover adequately the design of deep beams. For instance, the British code BS8110 (British Standard Institution 1985) explicitly states that for design of deep beams, references should be made to specialist manual or literature. Other 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 some design instructions based on experimental investigation.

Since the process of casting and testing of concrete deep beams is very expensive and time-consuming, engineers and programmers are constantly trying to discover less costly technology to acquire the necessary information.

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 the artificial neural networks (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 attempts to simulate 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 (Bilgehan and Turgut 2010b, Atici 2011, Siddique *et al.* 2011, Mohebbi *et al.* 2011, Parichatprecha and Nimityongskul 2009), strengthening analysis (Perera *et al.* 2010), load and behaviour prediction (Pendharkar *et al.* 2010, 2011, Sonmez and Komur 2010, Chandak *et al.* 2008), damage detection (Saridakis *et al*. 2008) and non-destructive testing methods for material (Bilgehan and Turgut 2010 a, b).

Though ANN is based on simple principles, its mathematical talent is in terms of nonlinear iteration that is practical in the prediction of deep beam's deflection. ANN has been used in the prediction of load–displacement curve for concrete reinforced with composite fibres (Ashrafi *et al.* 2010) but surprisingly no such effort has been made for HSSCC deep beams.

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. ANN is able to generate output for other dimensions and parameters of a structure using a software programming that is based on practical results. Also, ANN is cost and time effective.

The use of the ANN technique 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. Moreover, some researchers (Rajasekharan and Pai 2003, Davis 1991) published the main principle of neural networks that are based on the aforementioned principles.

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. Due to this property, these structural elements exhibit more than one neutral axis depth (Raya 1980). Thus, the prediction of deflection is not possible using normal beam equations. Second, the behaviour of these structural elements is dominated by shear deformation. 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 deflection.

1.1 Research significant

In this study, the multi-layer feed forward neural network with back-propagation training algorithm was used to predict the HSSCC deep beam deflection. 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 a network with minimum errors and maximum correlation coefficients that will be discussed in this study.

2. Methodology

2.1 Experimental study

2.1.1 Concrete and casting

Eight deep beams were designed and cast using HSSCC. HSSCC was chosen because it is a non-segregating concrete that flows fast into the formwork and encapsulates the reinforcement without any need for compaction. The concrete mix design is given in Table 1 and the related requirements are detailed by Mohammadhassani (2011). A mix design of local aggregates with maximum 20 mm diameter was used. Ordinary Portland Cement (OPC), natural river sand, silica fume and super plasticizer were used. The specification in the design mix of HSSCC deep beam used is shown in Table 1.

The main property that defines self-compacting concrete (SCC) is its high workability which attains consolidation and specified hardened properties. Workability is the fresh concrete mix's

Table 1 High strength self-compacting concrete mix design

Compressive strength target	75 Mpa
Aggregates type	Crushed granite and natural sand
Cement type	OPC
Slump of concrete	More than 680 mm
Coarse aggregate content	553 kg/m^3
Fine aggregate content	887 kg/m^3
Cement	630 kg/m^3
Water	170 kg/m^3

Table 2 Specifications for tested concrete deep beams

Beam	f'_c (MPa)	ρ (%)	As (mm^2)
B1	91.50	0.219	191
B2	91.50	0.269	236
B3	91.10	0.410	383
B4	93.72	0.604	558
B5	79.10	0.809	760
B6	87.50	0.938	854
B7	82.24	1.050	964
B8	97.20	1.260	1165

Table 3 Bar specification

Bar (mm)	f_y (MPa)	f_u (MPa)
Φ_9	353.0	446.0
Φ_{10}	614.4	666.0
Φ_{12}	621.6	678.4
Φ_{16}	566.3	656.0

ability to fill the mould completely without affecting the concrete's quality. The beam's length, depth and thickness were kept constant with varying tensile reinforcement ratio and web reinforcement.

The properties of the hardened cementitious materials and the tensile reinforcement ratio for each deep beam are listed in Table 2. The concrete strength, f'_c, for each beam stated in Table 2 is the average strength of 3 cube samples at the time of loading.

In this table f'_c, ρ and A_s are listed as the concrete compressive strength of cube samples at the time of loading, the tensile reinforcement ratio and the corresponding area of tensile bar in each beam, respectively. The bar specifications presented in Table 3 were determined from tensile tests on a number of samples based on ASTM E8 / E8M - 09 Standard Test Methods for Tension Testing of Metallic Materials. Except for Φ9 (non-deformed), the other reinforcing bars were high tensile deformed bars. In this table f_y and f_u are the yield and ultimate stress of the bars.

2.1.2 Beam details

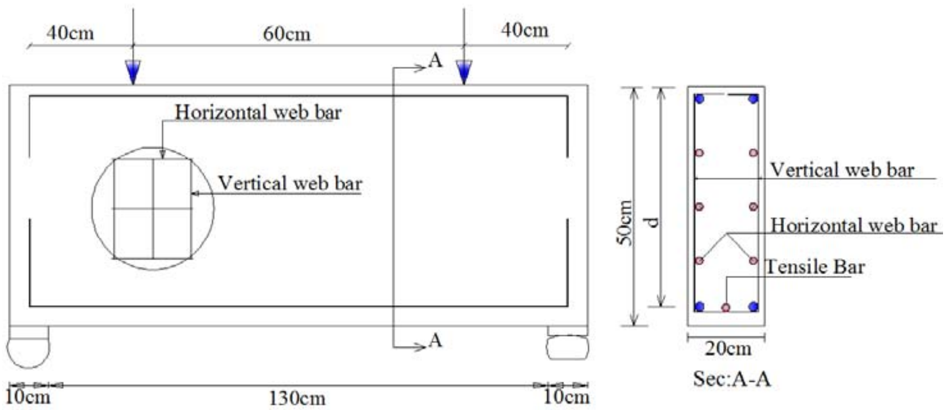


Fig. 1 Geometrical details of tested deep beams

Table 4 Bar schedule of tested beams

Beam	Tensile bar	Vertical web bar	Horizon tal web bar	*a*/*d*
B1	3Ø9	Ø9@10cm c/c	Ø9@15cm c/c	0.92
B2	3Ø10	Ø9@10cm c/c	Ø9@15cm c/c	0.91
B3	2Ø10+2	Ø9@10cm c/c	Ø9@15cm c/c	0.85
B4	2Ø10+2	Ø9@10cm c/c	Ø9@9.5cm c/c	0.86
B5	2Ø10+3	Ø10@10cm c/c	Ø10@8cm c/c	0.85
B6	1Ø8+4Ø	Ø10@10cm c/c	Ø10@8cm c/c	0.88
B7	2Ø10+4	Ø10@10cm c/c	Ø10@8cm c/c	0.76
B8	2Ø10+5	Ø10@10cm c/c	Ø10@8cm c/c	0.78

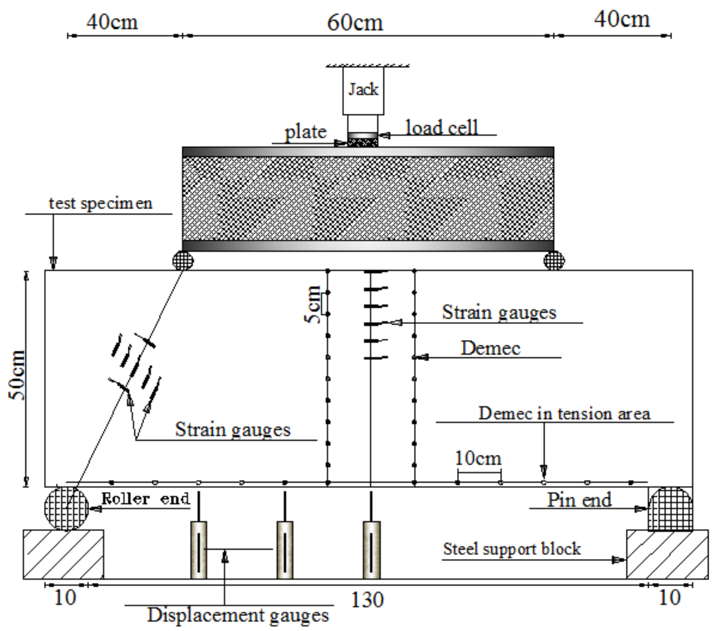


Fig. 2 Testing arrangement

All deep beams had a section of 500 mm depth, 200 mm width and 1500 mm length. The geometrical parameters of beams are schematically shown in Fig. 1, the anchorage of the main tension reinforcements was enhanced by providing 90-degree hooks at the bar's end to prevent bonding failure. The beam's details are expressed in Table 4.

2.1.3Test 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 adoption is shown in Fig. 2.

The beams were positioned on two steel cylinders with 5" diameters. After the beam was centred and levelled, the steel beam was placed on the test specimen. Load was then applied at midpoint at 20 kN intervals until the first crack. 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 deflection and strain gauge readings were taken. After each reading and observation, the next loading stage increment was repeated, until the failure or an important observation were made.

2.1 Numerical study

2.1.1 ANNs structure and definition

Artificial Neural Networks (ANNs) are modelling tools that work similar to the human brain; ANNs were, in fact, extracted from biological neural network. ANN is an intelligent information processing system and consists of three main aspects included transmission, processing and storage of information.

The matching parts of an ANN are three parts as:

(a) The input layer which 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 which receive information from the input layer, using the applied weights and pre-specified activation functions.

(c) The Output layer which 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 no generally 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 predominant used in civil engineering applications (Adeli 2001). This algorithm looks for the minimum error function in weight space using the method of gradient descent.

2.2.2 System modeling

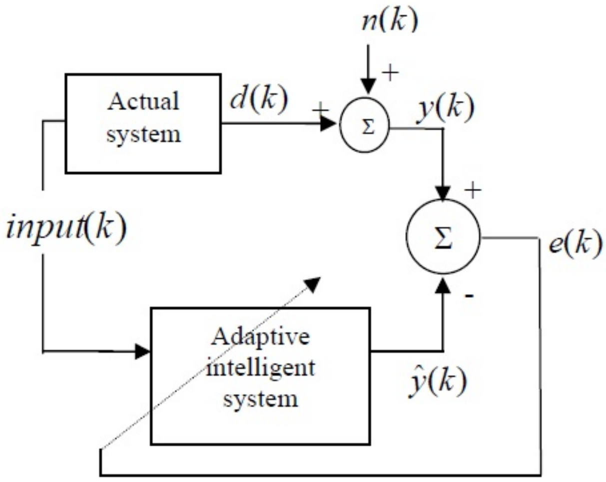


Fig. 3 System modelling using adaptive intelligent system

System modeling alters the parameters of an adaptive intelligent system e.g. ANN and fuzzy systems to suit unknown actual engineering system transfer function. A schematic of the system modeling problem utilizing the adaptive intelligent system 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 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 system tools to model the deflection of deep beams.

2.2.3 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. R is the degree of success in reducing standard deviation (SD). It is widely used in the sciences as a measure of the strength of linear dependence between two variables. Eq. (2) presents the *R* value 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.

2.2.4 Training and testing of neural networks

Training means to present the network with the experimental data and have it learn, or modify its weights, so that it correctly predicts the mid-span deflection 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 relationships between the experimental data. The mathematical neuron model is shown in Fig. 4.

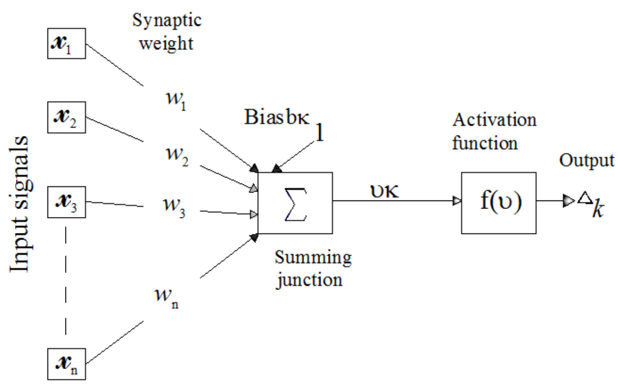


Fig. 4 Neuron model with n-element in the input model

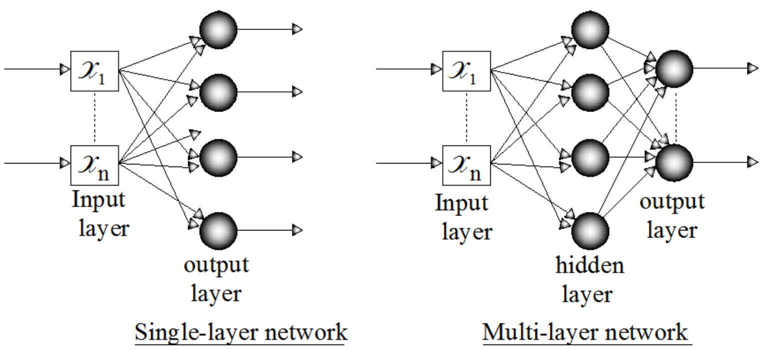


Fig. 5 Single-layer and Multi-layer networks

Table 5 Different parameters of eight deep beams

Input parameters										Out put
P	f	$\frac{\alpha}{d}$	$\frac{l_0}{d}$	f_{yv}	f_{yh}	$\frac{A_v}{bs_v}$	$\frac{A_h}{bs_h}$	ρ	f_y	Δ

The effect of input vector (x) on output (Δ) 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 W^TX.

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 are sometimes known as layered networks.

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 this present research, the load-deflection analysis of eight HSSCC deep beams with different parameter indicated in Table 5 are discussed and an ANN is built and applied for the deflection prediction of deep beam.

It is worth mentioning that the parameters in Table 5 are as follows:

P =applied load in each incremental loading stage

f_{cu} =28 days cylindrical 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

ρ=the tensile reinforcement ratio

f_y= the tensile bar yield strength

A total of 3668data samples are used to train the network. The rest 20% of data samples are applied for network testing. In all survived net, ten neurons are used in the input layer (P, f_{cu}, $\frac{a}{d}$, $\frac{l_0}{d}$, f_{yv}, f_{yh}, $\frac{A_v}{bs_v}$, $\frac{A_h}{bs_h}$, ρ, f_y) and only one neuron in the output layer (Δ). A multi-layered feed-forward neural network (MLFFNN) equipped with back-propagation (BP) learning algorithm is constructed.

2.2.5 Variants of back-propagation learning algorithm

To train the MLFFNN, five variant of BP algorithms are examined. More precisely, the Levenberg-Marguardt BP (Trainlm), Gradient descent with momentum (Traingdm) and (Traingda), Basic gradient descent (Traingd) and Adaptive learning rate (Traingdx) were used for network training at the end of analysis. Descriptions of these algorithms are presented in Table 6.

3. Results and discussion

In relation to the failure mode of deep beams, serviceability of a structure is determined by observing its deflection and cracking. In addition, it was observed that the stiffness of the beams increases with the increase in section height and this leads to brittle failure. In this study, the experimental load–deflection graphs are presented in Fig. 6.

As noted in Fig. 6, all the beams demonstrated a nearly linear response up to about more than 85% of the ultimate load. As illustrated in some cases, failure occurred closer to the peak of the applied loads. This is the result of the failing of the members where shear deformation is a predominated behaviour.

Table 6 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
Traingdm	Gradient descent with momentum. Generally faster than Traingd. Can be used in incremental mode training.
Traingda	Updates weight and bias values according to gradient descent with adaptive learning rate, can train any network as long as its weight, net input, and transfer functions have derivative functions. Gradient descent with adaptive lr back-propagation
Traingd	Basic gradient descent. Slow response, can be used in incremental mode training.
Traingdx	Adaptive learning rate. Faster training than Traingd, but can only be used in batch mode training.

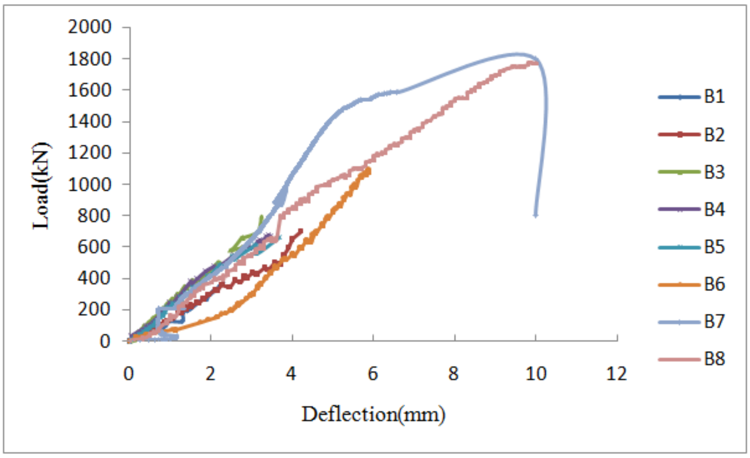


Fig. 6 Deflection of tested HSSCC deep beams at mid span

3.1 The best learning function and optimum architecture of MLFFNN

To optimize the architecture of the network, we examined 50 nets. First we constructed a MLFFNN including two hidden layers in which 20 and 15 neurons were considered for the first and second layers, respectively. Also, we used the tangent hyperbolic (tansig) and linear (purlin) transfer functions 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”, “traingd”, “traingdm”, “traingda” and “traingdx”, the network was trained in 25 independent runs with initial random weights. Each run is performed with maximum 1000 epochs of training. The results of the above mentioned experiments are summarized in Table. 7. In this table, for each of the trained network, we have computed the MSE and correlation coefficient “R” 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 7.

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, we tested an MLFFNN with one hidden layer to determine the best number of neurons; various numbers of neurons between 1 to 30 are examined. Figs. 7 and 8 summarize the results of MSE and *R* values for this step.

These figures show that having more than 5 neurons results in acceptable model. However, among them the highest *R* and lowest MSE is obtained by 10 neurons in the first layer. 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.

Table 7 Comparison of performance of different type of BPs on prediction of deflection

		Traingdm		Traingda		Traingd		Traingdx		Trainlm	
		learn	test	Learn	test	learn	test	Learn	test	learn	test
MSE	Max	47.347	46.46	0.46	0.457	7.751	6.952	174.860	172.946	0.0257	0.0123
	Min	0.8498	0.855	0.122	0.132	0.068	0.045	0.7970	0.7972	0.0181	0.0047
	Avg	14.762	15.42	0.216	0.216	0.895	0.838	35.526	35.598	***0.0202***	***0.0064***
Correlation(R)	Max	0.9283	0.913	0.987	0.985	0.993	0.995	0.9360	0.9312	0.9980	0.9995
	Min	0.4133	0.413	0.950	0.947	0.002	0.050	0.1510	0.1974	0.9972	0.9986
	Avg	0.1227	0.113	0.977	0.975	0.910	0.913	0.3601	0.3433	***0.9978***	***0.9993***
Time		3.7060		21.7297		101.5654		4.8909		73.043	

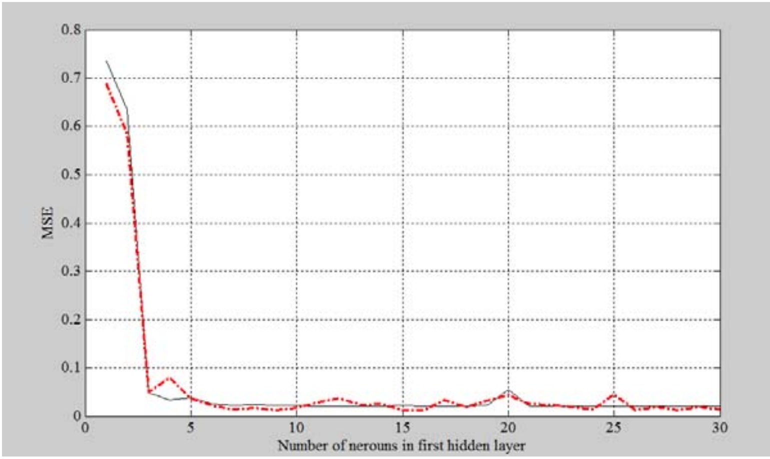


Fig. 7 The MSE value for different number of neurons in first hidden layer. The dashed line represents the test data while the solid line is the learning data

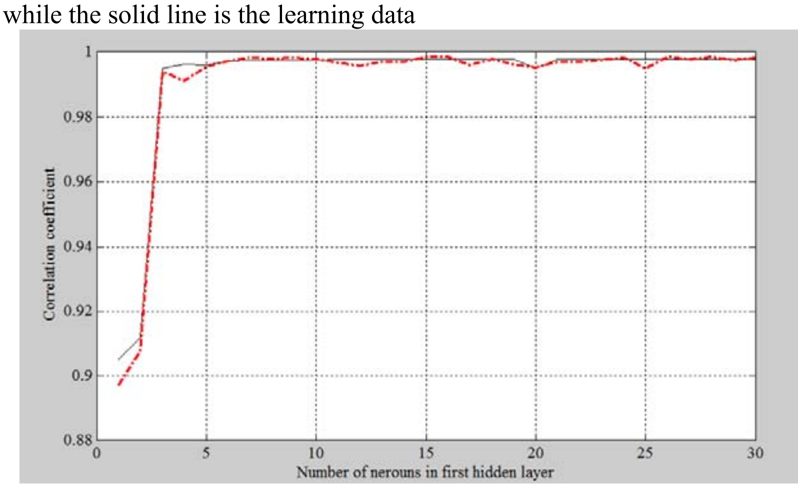


Fig. 8 The *R* value for different number of neurons in first hidden layer

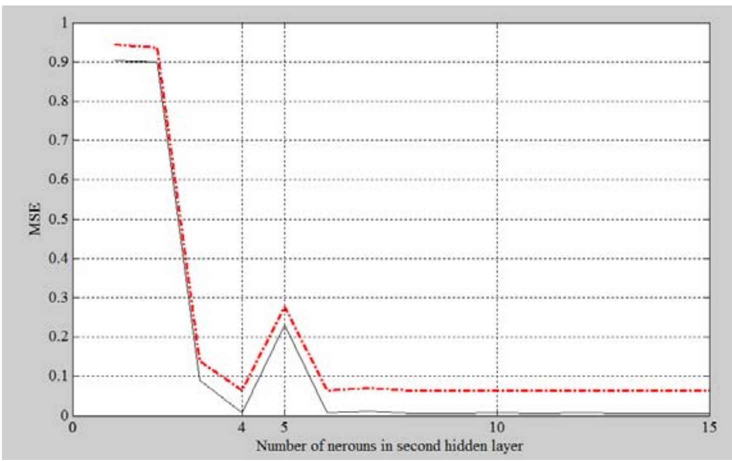


Fig. 9 The MSE values for different number of neurons in second hidden layer

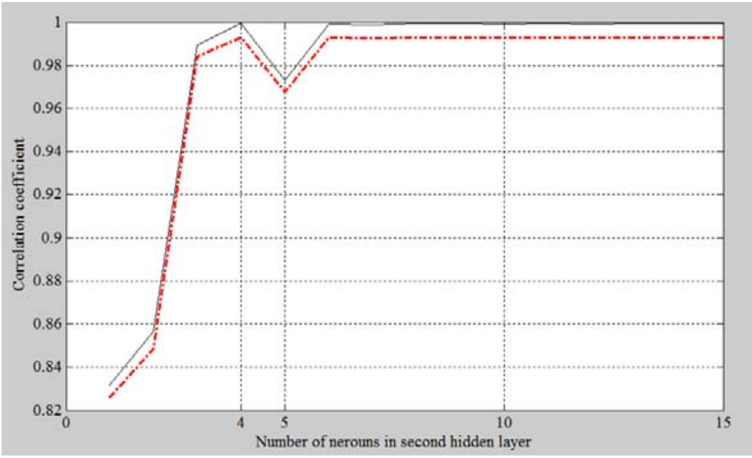


Fig. 10 The *R* values for different number of neurons in second hidden layer

Table 8 The optimum network specification

Subject	Definition
Structure	10-10-4-1
Transfer function (hidden-layer)	Tangent hyperbolic (tansig)
Transfer function (output-layer)	Linear (purlin)
Learning function	trainlm

Table 9 Comparison of MSE and *R* values from ANN and linear regression

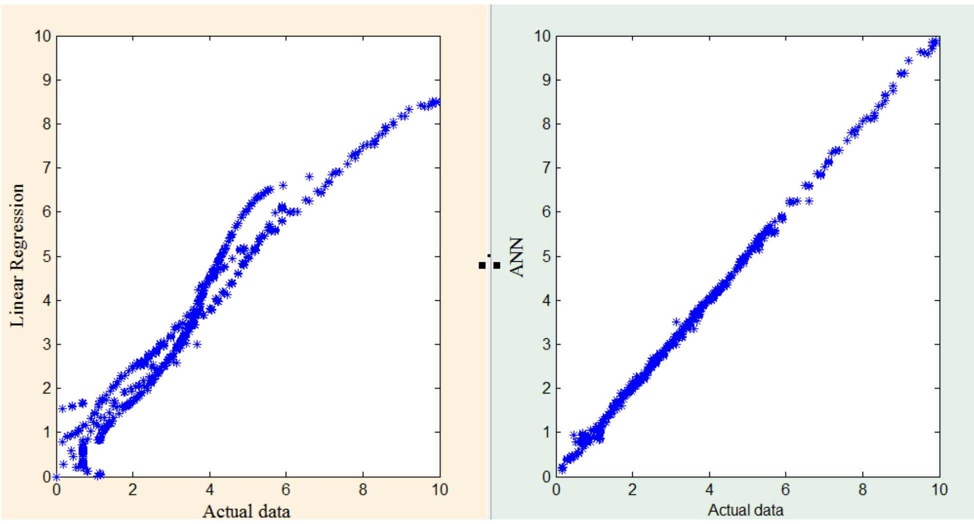
	Training set			Testing set		
Methods	Instances	MSE	*R*	Instances	MSE	*R*
Linear regression	2934	0.2275	0.9745	734	0.2148	0.9766
ANN	2934	0.0054	0.9999	734	0.0641	0.9931

In the sequel, to find the best number of neurons for the second layer, we constructed an MLFFNN with two hidden layers in which the numbers of neurons in the first hidden layer is fixed at 10 and the numbers of neurons in the second hidden layer varies from 1 to 15. Figs. 9 and 10 summarize the MSE and R values for this step.

The dashed line represents the test data while the solid line is the learning data in Figs. 7 to 10. These figures show that the architecture including 4 neurons results from the second hidden layer provides the best results. Therefore the optimum network is described in Table 8.

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 9 summarizes the MSE and R results obtained using the proposed method and the linear regression 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 9.



(a) (b)

Fig. 11 Deflection prediction performance from: (a) LR and (b) ANN

As noted, the MSE values from ANN is approximately 40 times smaller than values from classical linear regression. Furthermore, the *R* values from ANN for test data is 0.9931 which is an exciting value to a scientist beacuse 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. Figure 11Shows the deflection 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. Figure 11 reveals that the proposed ANN method is highly accurate and precise compared to the classical LR for the deflection prediction of HSSCC deep beams.

4. Conclusions

As seen in this paper, modelling of deep beams using a linear tool like linear regression cannot lead to an accurate model. It is due to complex behaviour of deep beams. The experimental results provided in this study shows that the multi-layer ANN due to its ability in modelling of nonlinearity can predict and model the deep beam complex behaviour with an acceptable precision.

The results show that for deflection prediction of deep beams the function Levenberg-Marguardt BP (Trainlm) is found to be best function for training multi-layered feed-forward neural network.

Based on the analysis of networks in the current study, the ANN model with 10 inputs, 10 neurons in first hidden layer, and 4 in second hidden layers is selected for the deflection prediction in deep beams. The result shows that the MSE values from ANN are approximately 40 times smaller than values from classical linear regression. The R value from ANN is 0.9931 for test data, which indicate a high confidence level.

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