Prediction of Structural Response for HSSCC Deep Beams Implementing a Machine Learning Approach

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ARTICLE INFO	ABSTRACT
	High Strength Concrete (HSC) is a complex type of concrete, that meets the combination of performance and uniformity at the same time. This paper demonstrates the use of artificial neural networks (ANN) to predict the deflection of high strength reinforced concrete deep beams, which are one of the main elements in offshore structures. More than one thousand test data were collected from the experimental investigation of 6 deep beams for the case of study. The data was arranged in a format of 10 input parameters, 2 hidden layers, and 1 output as network architecture to cover the geometrical and material properties of the high strength self-compacting concrete (HSSCC) deep beam. The corresponding output value is the deflection prediction. It is found that the feed forward back-propagation neural network, 15 & 5 neurons in first and second, TRAINBR training function, could predict the load-deflection diagram with minimum error of less than 1% and maximum correlation coefficient close to 1.

1. Introduction

There is no direct method for deflection prediction of deep beams. In general, the varieties of effective parameters on deep beam design are issues for applying of new method in design and prediction of deflection in these special structural elements. It is interesting and important to predict the shear behavior and loads transferring to reinforced concrete members with regards to the different load transferring system. Notwithstanding, lots of research has been done in the several last decades and the outcomes are implemented in structural design codes (e.g. ACI 318-02 Code [1], NZS [2]), it is not yet fully understood the exact mechanism of the load transferring in elements that shear deformation is dominated. Nevertheless, the code provisions do not fulfill design of elements such as deep beam and corbels. Although, in the last 50 years, extensive research has been conducted on the design and behavior of deep beams and some progress has been made [3-13], there is no exact method for designing and behavior prediction of these special structural elements. It should be noted that even in the structural design guidelines like British code BS8110 [14], ACI Codes, Euro code EC/2 [15], the Canadian code and the CIRIA guide No.2b [16], the design procedure of deep beams is not covered appropriately and the given information are mainly based on the empirical analysis.

In design and serviceability prediction of structural elements, the material properties and action, laws of mechanics, feeling and engineering judgement, past experience and analysis techniques should be considered. With regards to excessive parameters that affect on the design and behaviour of deep beams such as the concrete strength, the effect of web reinforcement, the effect of tensile reinforcement ratio, the shear span-depth ratio, the length of deep beams and the effective depth and the lack of exact design process, there is a need to search the modern and exact method for prediction of deflection and other serviceability purpose emphasizing the economical and technical justification.

In the last two decades, attempts have been made to computerize the design process, behaviour of concrete

elements and their serviceability using machine learning techniques such as artificial neural networks (ANN). The advantage of using the ANN is that it could learn from available designs during training process. ANN is a powerful knowledge surfaced from simulation of human brain and has been successfully applied in many fields of civil and structural engineering that demonstrate powerful problem solving ability [17], [18], [19], & [20]. Although, this technique is based on simple principles, its mathematical nature includes non-linear iteration that are useful in deep beam behaviour prediction. When the experimental samples consist of high dimension of elements, the data gathering to formulate the problem for other size of the structures would be difficult. Therefore, ANN could help to generate output for other dimension and parameters of structures by implementing a simulation procedure based on practical results.

In the literature, Artificial neural networks have been used to predict the ultimate shear strength of reinforced concrete deep beams (Sanad&Saka 2001)[21], design of fibre reinforced concrete beams (Hadi 2002)[22], shear design of reinforced concrete beams (Cladera & Mari 2004)[23,24], design for cable stayed bridges (Namhee Kim et al 2002)[25]. Moreover, some researchers (Rajasekharan & Vijayalakshmi Pai 2003[26], and Davis 1991[27]) have been investigating the main principals of neural networks in their studies.

In current research, the experimental results of load-deflection analysis of several High Strength Concrete (HSC) deep beams with different parameters have been applied to generate ANN for deflection prediction. The number of hidden layer, neurons in each hidden layer [28], and the type of selected function in data processing are the main parameters to simulate a network with minimum error and maximum correlation coefficient that have been discussed in this study. The outcome indicates that the ANN are capable of predicting the structural response in HSC deep beams much better compared to conventional statistical techniques, adapting its complex formulation and simulation procedure.

Materials and Method:
Experimental study

Six high strength self-compacted concrete (HSSCC) beams have been designed and casted. It was decided that the tensile reinforcement percentage to be variable, whilst beam's length, depth and thickness to be considered as constant parameters.

The reason for choosing HSSCC is that, it is a highly flowable, non-segregating concrete that can fill the formwork and encapsulate the reinforcement without any need for consolidation. Because of the high volume of reinforcement in a deep beam, to resolve the vibration problem use of SCC would be a

reasonable choice. The HSSCC mix design is given in Table 1 (Further details can be found in [29]). In the mix design a local aggregate with maximum 20 mm diameter. Ordinary Portland cement, natural river sand and micro silica and Super plasticizer were used. The concrete mix has the W/C ratio of 0.27, which kept constant for all beams.

Table 1: The HSSCC mix design used in this study

Parameter	Value
Characteristic cube strength	*75 MPa*
Aggregate type	*Crushed granite and natural sand*
Cement type	*Ordinary Portland cement*
Slump of concrete	*More than 600 mm*
Coarse aggregate content	*553 kg/m³*
Fine aggregate content	*887 kg/m³*
Water/binder	*0.25*
Silica fume/cement	*0.1*

The main characteristics of self-compacting concrete is its workability; as shown in Figure 1, it can be controlled for all casting in the accepted range. Further information on the HSSCC mixing process and the results of the material tests can be found in [29].

Figure 1: The flow ability of self-compacting concrete (slump=600 mm) in B1 and B2 mix design.

To reduce the risk of segregation in the used mix design, it was decided to keep the flow ability in the range of 550 to 740 mm. For each beam, nine cubes (100 mm × 100 mm × 100 mm) and three cylinders (150 mm diameter, 300 mm high) were casted as control specimens. Cubes were tested for measuring strength at 7 days, 28 days, and the age of loading and cylinders were tested for splitting tensile strength at 28 days. All cylinder and cube samples used for strength control were demoulded after 24 hours and cured for age of tested beams in humidity conditions.

The beams were casted in a steel mould and demoulded after 3 days. During this period, the test samples were covered with canvas and plastic. The

canvas was watered twice a day for 11 days, after which the framework was removed.

Figure 2: The casting arrangement and deep beam fabrication

The specifications of fabricated specimens including compressive strength (f'_c), tensile reinforcement ratio (ρ) and tensile reinforcement area (As) are given in Table 2. It should be noted, that the compressive strength given for each specimen (f''_c) is based on the average value of 3 cubic samples.

Table 2: The specification of tested beams

Specimen's Number	f'_c (MPa)	ρ (%)	As (cm²)
B1	91.5	0.219	1.91
B2	91.5	0.269	2.36
B3	91.1	0.410	3.83
B4	93.72	0.604	5.58
B5	79.1	0.809	7.60
B6	87.5	0.938	8.54

The specifications of the reinforcing bars used in this study including yield (f_y) and ultimate stress(f_u) are given in Table 3. These values are extracted based on a number of samples taken from each batch supplied. As can be seen, all the used reinforcing bars were high tensile deformed bars except the smallest size which is non-deformed ($\Phi9$).

Table 3: Bars specifications used in this study

Diameters of used bars (mm)	f_y (MPa)	f_u (MPa)
$\Phi9$	353.0	446.0
$\Phi10$	614.4	666.0
$\Phi12$	621.6	678.4
$\Phi16$	566.3	656.0

Beam Details

All deep beams had a section of 500 mm depth and 200 mm width and 1500 mm length. The beam details and geometrical parameters are presented in Table 4 and Figure 3 respectively.

Table 4: The bars specification in fabricated specimens

Beam's number	Tensile bar	d(cm)	a/d
B1	3 Φ 9	43.55	0.92
B2	3 Φ 10	43.85	0.91
B3	2 Φ 10+2 Φ 12	46.90	0.85
B4	2 Φ 10+2 Φ 16	46.20	0.86
B5	2 Φ 10+3 Φ 16	47.00	0.85
B6	1 Φ 8+4 Φ 16	45.50	0.88

As shown in Figure 3, the anchorage of the main tensile reinforcements was enhanced by providing 90-degree hooks at the bar ends to prevent bonding failure.

Test Setup and Loading Process

All tested specimens were simply supported and a 2 points monotonic static loading protocol was applied on with a hydraulic jack. The arrangement of test setup is illustrated in Figure 4.
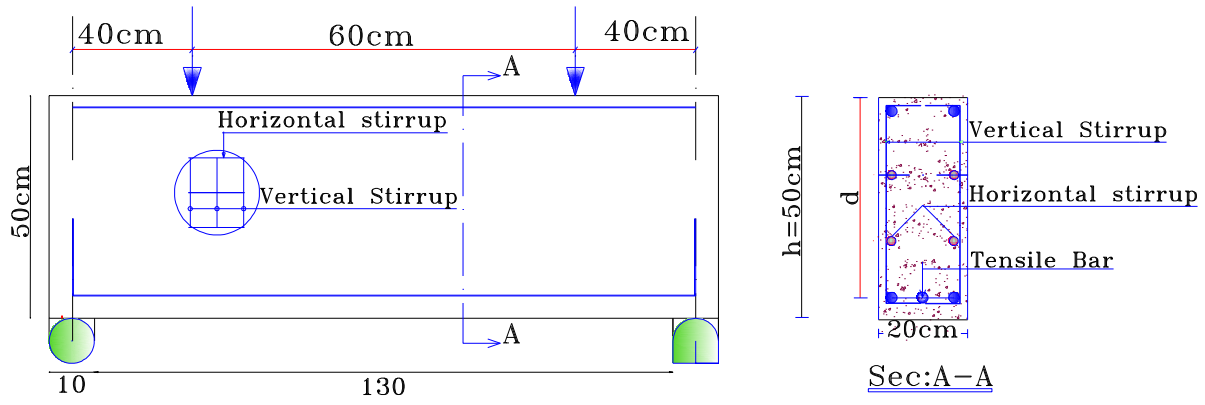

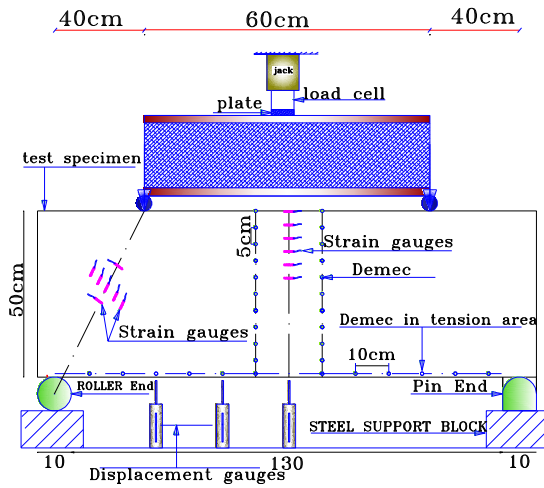**Figure 3: schematic representation of one of the tested specimen**

Figure 4: Test Setup arrangement

Figure 5: Neuron model with R-element in input model

The effect of (P) on (a) is defined by the weight (W). The other input is 1 (the constant amount) that was multiplied in bios (b) and then added with WP.

Based on the complexity of the problem, the architecture of the proposed ANN model can be a single or multi-layer network. The structure of the single and multilayer ANNs are shown in Figure 6. A typical multi-layer artificial neural network (MNN) includes an input layer, output layer and hidden layers of neurons. MNNs are sometimes known as layered networks.

Figure 6: Single and multilayer network

The beams were positioned on two steel cylinders with 5" diameters to simulate the simply supported boundary conditions. After the beam was centred and levelled, the steel beam was placed on the test specimen, and the loading was applied at midpoint at 20 KN intervals until the first crack occurred.

During the loading process, care has been taken into account to make sure that the supports will remain regular and other types of failure would not happen. At each increment, the deflection values 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 was made.

Numerical Study

Artificial Neural Network (ANN) is a machine learning technique that works like human brain. The main units of the network are neurons that are connected together in a complex manner. They act parallelly and work as numerical processors. All machine learning algorithms including ANN learns to solve the problems based on relationship between experimental data. The effect of connections between neurons indicates the weight of each connection. The schematic structure of an ANN is shown in Figure 5.
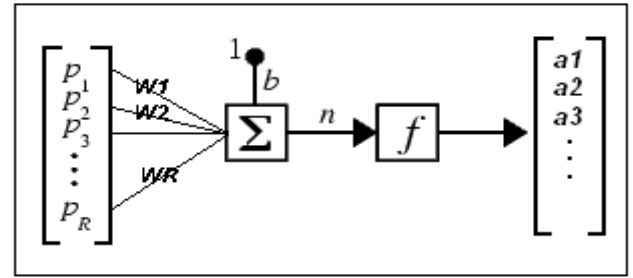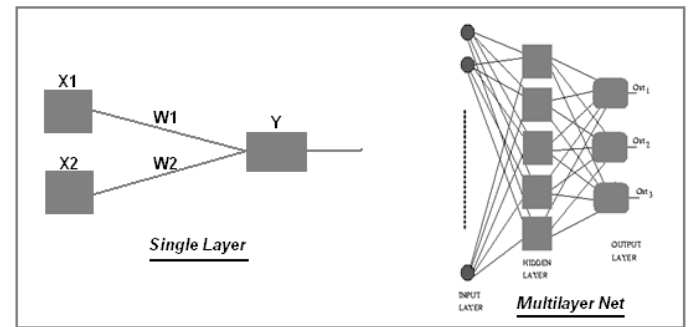
In case of using MNNs, the computational ability will be significantly improved compared to a single layer ANN. In current study, the load-deflection analysis of six HSSCC deep beams with different parameter indicated in Table 5 has been discussed and the produced ANN model has been applied for deflection prediction of the deep beam.

model has been applied for deflection prediction of the deep beam.

Table 5: Different parameters of tested specimens in this study

Item	Parameters								
	f_{cu}	a/d	L_0/d	f_{yv}	f_{yh}	A_v/bs_v	A_h/bs_h	ρ	f_y
DB1	91.5	0.804	2.985	353.0	353.0	0.00640	0.00424	0.002191	353.00
DB2	91.5	0.798	2.965	353.0	353.0	0.00640	0.00424	0.002690	614.40
DB3	91.1	0.746	2.772	353.0	353.0	0.00640	0.00424	0.004090	618.00
DB4	93.7	0.757	2.810	353.0	353.0	0.00636	0.00669	0.006040	590.35
DB5	79.1	0.851	2.979	614.4	614.4	0.00785	0.00982	0.008088	585.54
DB6	87.5	0.769	2.857	614.4	614.4	0.00785	0.00982	0.009380	523.64

Table 6: Properties of the selected network (five best architectures)

Net. Market.	Neurons in Hidden Layer			Training Function	Adaption Learning Function	Training Transfer Function In hidden layer			Transfer Function in output layer
	H1	H2	H3			H1	H2	H3	
Net.1	10	1	-	TRAINBR	LEARNGDM	Tansig	Logsig	-	Purelin
Net.2	10	10	-	TRAINBR	LEARNGDM	Tansig	Logsig	-	Tansig
Net.3	10	5	-	TRAINBR	LEARNGDM	Tansig	Logsig	-	Purelin
Net.4	15	5	-	TRAINBR	LEARNGDM	Tansig	Logsig	-	Purelin
Net.5	15	5	-	TRAINBR	LEARNGD	Tansig	Logsig	-	Purelin

The parameters given in Table 5 are as follows:

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_{vy} = the yield strength of vertical web reinforcement

f_{hy} = 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 bar percentage

f_y = the tensile bar yield strength and

The output load-deflection of B2 specimen was applied for network testing and the other deep beam outputs were used for verification and training stages. A total of 1084 data have been utilized to simulate the proposed network, 954 data for training process, 99 data for verification, and 31 data for testing stage. The architecture of the proposed ANN model includes ten neurons in input layer (f_{cu}, a/d, L_0/d, f_{vy}, f_{hy}, A_v/bs_v, A_h/bs_h, ρ, f_y, & *loading*) and one neuron in output layer (*deflection*). Feed-forward back propagation (FFBP) was constructed at the end of ANN. Twenty network architectures with different hidden layers and network functions have been selected from the five best networks as indicated in Table 6.

Training Algorithms

Bayesian Regularization (TRAINBR) & Levenberg-Marguardt Backpropagation (TRAINLM) algorithms were used for network training at the final stage. TRAINBR algorithm indicated the best compatibility with the given problem.

The Best Training and Transfer Function

Various type of functions with different architectures were investigated. The tray consisted of TONSIG for the first hidden layer, LOGSIG for the second hidden layer, and PURLIN for the output were indicated as the best training and transfer functions.

The Best Network Architecture

The best architecture was calculated by testing of different number of neurons in hidden layers. To this end, SSE and MSE method were used to determine the minimum error. The (10-15-5-1) architecture indicating 10 inputs, 15 neurons in the first hidden layer, 5 neurons in second hidden layer, and 1 output was selected as the optimum architecture.

Training

954 of 1084 normalized data in [0,1] have been utilized for training procedure.

Verification

In the proposed model, the stopping time of calculation has been applied to 99 data to determine the network structure that has not been used in training. data verification has been checked frequently in training stage. The operation function will run till an increment in error percentage occurred in the verification process.

Testing

Final step will be the testing process. To this, 31 data were used for testing procedure after training and verification stages.

Results and Discussion:

Serviceability of a structure/infrastructure is normally determined by its deflection and cracking. In general, the deflections of deep beams are small compared to those of normal beams and it was also indicated that the stiffness of the beam elements will be enhanced with increase in the section height leading to brittle failure. In this study, the experimental deflection's amount versus the load graphs are presented in Figure 7.
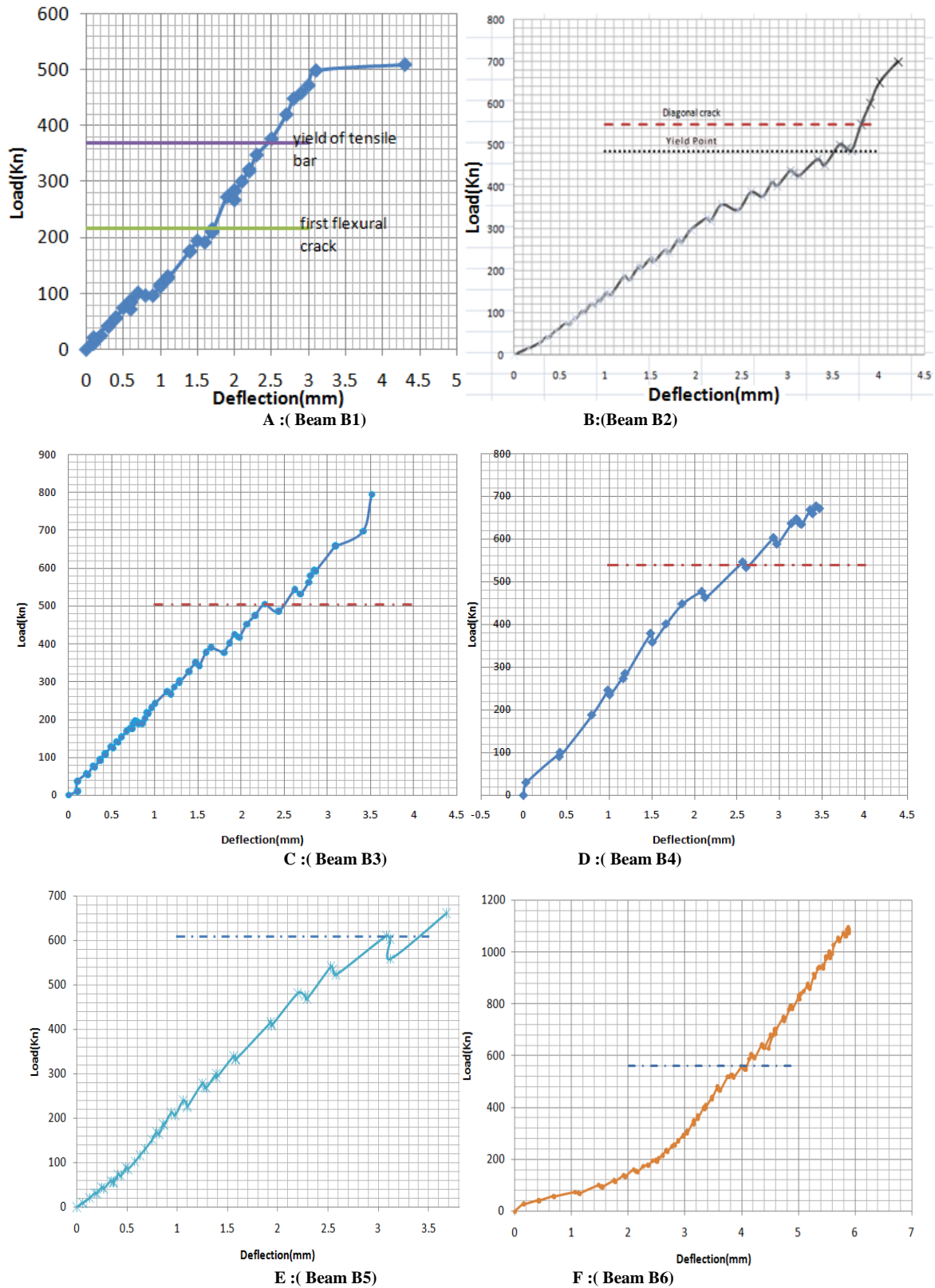
Figure7: The deflection of tested beams at the mid span

As depicted in Figure 7, a linear trend existed up to the yielding point of longitudinal bars and the ultimate strength at failure in the beams. As illustrated, failures mainly occurred at the points where peak loadings are applied Such the phenomenon is the result of shear deformation and brittle failures in deep beam structural elements. The area under the entire load-deflection diagram represents the absorbed energy during failure. The amount of this energy is a critical parameter for determining the structure's ductility. In general, ductility of a structure is characterized by the deformation at which the structure fails under a given type of loading. As can be seen in Figure 7, the absorbed energy increased with increment in tensile bar percentage.

As stated in the literature, high economical expenses and the different behavior of deep beams led to behavior prediction of these elements; however, the use of ANN based models as an innovative approach is not yet investigated by others. Deep beam design and failure prediction are impressed by two main assumptions in design. Firstly, these structural elements do not follow the Bernoulli assumptions that suppose section of bending plate remains plain after loading. Due to this property, these structural elements exhibit more than one neutral axis depth (Mohammadhassani [29], Raya [8]). Thus, the prediction of deflection is not possible by the equation used for normal beams.

Secondly, the shear deformation is dominated by failure in these structural element that lead failure in compression strut trajectories when the minimum tensile bar by codes are satisfied.

To this, the use of ANN based model can be a rational approach to predict the structural response of these complex structural elements. Table 7 gives the specification of simulated ANNs.

Table 7: The specification of input and procedure of networks

|	
The deep beams used to generate ANNs	6 (B1, B2, B3, B4, B5, & B6)
The deep beams used for training & verification	5 (B1, B3, B4, B5, & B6)
The deep beams used for testing	1 (B2)
Number of data used for training, verification & testing	954, 99, & 31
The selected network architecture	10-15-5-1 (output-hidden1-hidden2-output)
Training & learning function	TRAINBR & LEARNGDM
Training transfer function in 1st & 2nd hidden layers	TONSIG & LOGSIG
Training transfer function in output	PURLIN

The training error for the five best networks, as shown in Table 6, was calculated and two important parameters [30]; the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) are presented in Figure 8. All network errors are in acceptable range and the Net.4 has the minimum error based on MSE & RMSE calculated values. The correlation coefficients for the 5 networks, are as well presented in Table 8, and were acceptable and closed to 1.
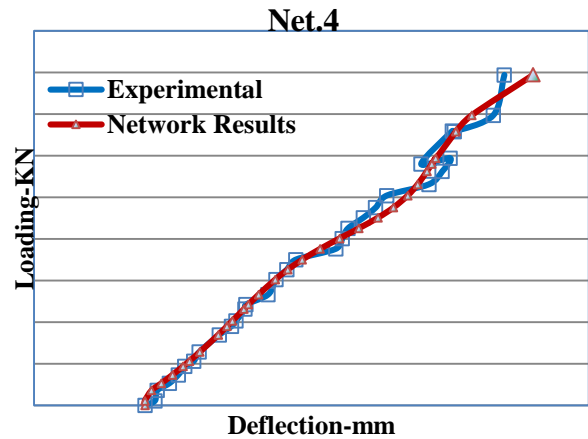
Table 8: Network Correlation Coefficient

Network	Net.1	Net.2	Net.3	Net.4	Net.5
Correlation Coefficient	0.986	0.990	0.985	0.992	0.990
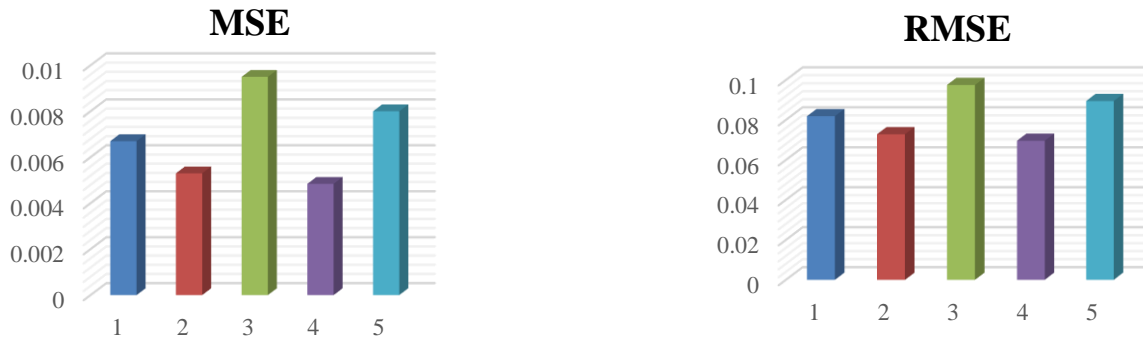
Figure 8: Calculated MSE & RMSE for the five best networks

Predicted Def = 1.020
Target - 0.033
R² = 0.992
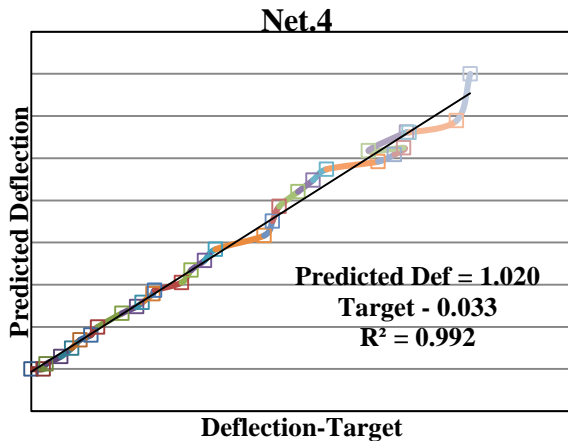
Figure 9: ANN response in deflection prediction

Figure 10: Evaluation of target and deflection prediction by ANN

As can be seen in figures 9 and 10, the feed forward back-propagation neural network, 10-15-5-1 (10 inputs, 15 neurons in first hidden layer, 5 in second hidden layer and 1 output) was set as optimum network architecture. TRAINBR training function, LEARNGDM learning function, TANSIG and LOGSIS were set as training functions in the first and second hidden layer. PURLIN transfer function in output layer can predict the load-deflection diagram with minimum error of less than 1% and maximum correlation coefficient closed to 1.

Conclusion

In regard to the different survived ANNs in current study, the (Net. 4) architecture has been selected for deflection prediction in HSSCC deep beams. The below results indicated that the proposed simulated network is very efficient for load-deflection prediction of these complex structural elements.

Training

The training RMSE for the generated network calculated as 0.979%

Verification

The verification RMSE for the generated network calculated as 0.962%

Testing

The testing RMSE and correlation coefficient for the generated network calculated as 0.696% and 0.992 respectively.

Finally, the results of this study reinforce the notation that machine learning techniques including artificial intelligence based models are practicable for establishing relations between loads and structural responses for the HSSCC deep beams.

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