*Structural Engineering and Mechanics, Vol. 45, No.3 (2013) 323-336* 323
DOI: http://dx.doi.org/10.12989/sem.2013.45.3.323

# Application of the ANFIS model in deflection prediction of concrete deep beam

Mohammad Mohammadhassani[*1], Hossein Nezamabadi-Pour[2a], MohdZamin Jumaat[1a], Mohammed Jameel[1b], S.J.S.Hakim[1c] and Majid Zargar[1d]

[1]*Department of Civil Engineering, University of Malaya, 50063, Malaysia*
[2]*Department of Electrical Engineering, Shahid Bahonar University of Kerman, Iran*

*(Received May 6, 2012, Revised November 20, 2012, Accepted December 15, 2012)*

**Abstract.** With the ongoing development in the computer science areas of artificial intelligence and computational intelligence, researchers are able to apply them successfully in the construction industry. Given the complexities indeep beam behaviour and the difficulties in accurate evaluation of its deflection, the current study has employed the Adaptive Network-based Fuzzy Inference System (ANFIS) as one of the modelling tools to predict deflection for high strength self compacting concrete (HSSCC) deep beams. In this study, about 3668measured data on eight HSSCC deep beams are considered. Effective input data and the corresponding deflection as output data were recorded at all loading stages up to failure load for all tested deep beams. The results of ANFIS modelling and the classical linear regression were compared and concluded that the ANFIS results are highly accurate, precise and satisfactory.

**Keywords:** ANFIS; deflection; deep beams; fuzzy inference system; linear regression

## 1. Introduction

The use of concrete deep beams has become more prevalent recently. Deep beams have useful applications in many structures, such as offshore structures, tall buildings, foundations, nuclear power plant and several others. Traditional design assumptions, specifically those regarding plane sections that remain the same pre and post bending are not applicable for deep beams. The behaviour and design of deep beams are completely different with normal beams. Predicting the behaviour of deep beam and deflection of its elements are important tasks for structural engineers. There is no clear guidance on deflection prediction for deep beams.

There are only few existing studies on deep beam deflection prediction. Mohammadhassani *et al*. (2013) studied the application of Artificial Neural Network (ANN) for prediction of deflection at the mid span of deep beams. They concluded a high confidence level of ANN in prediction of

∗Corresponding author, Ph.D., E-mail: mmh356@yahoo.com
[a]Professor
[b]Senior Lecturer
[c]Ph.D. Student
[d]Master

deflection at the mid span of deep beam in comparison with other methods. Lu *et al.* (2010) proposed a simplified method developed from the softened strut-and-tie model. This model determined mid-span deflection and shear capacity of deep beams at ultimate state. The suggested method of strength analysis to the extent of softening involves five unknowns. The estimation of the softening effect has been further simplified by Hwang and Lee (2002). The methods that follow strut-and-tie model (STM) are commonly used in design of deep beam but are unable to predict the exact amount of deflection.

Based on a comprehensive literature review, there are many parameters that cover deflection amount in deep beams. Amongst these parameters are concrete compressive strength, web reinforcement ratios, Young modulus, tensile reinforcement ratio, length and shear span to depth ratio (Yang *et al*. 2006).

Deep beam behaviour and its strain distributions are not linear functions of input parameters. Furthermore there has not been any effort till now to address theoretical modelling of deep beam's behaviours. Therefore, one of key problems in modelling the deflection using classical methods is the lack of a valid provision. However, the high costs involved in casting, curing and testing procedures of tough structural elements necessitates the search for inexpensive new effective tools for modelling of deep beam behaviours such as deflection, crack width, etc. This involves the use of classical and /or modern models for prediction of deep beam deflection with emphasize on behaviour and non-linear strain distribution.

Artificial intelligence (AI) system approaches such as artificial neural network (ANN), fuzzy inference systems (FIS), and neuro-fuzzy/ fuzzy-neural systems have been used successfully for modelling in many engineering applications as well as in agricultural (Mazloumzadeh *et al.* 2010 and Alavi *et al.* 2010), soil science (Yilmaz and Kaynar 2011), stability and serviceability of structures (Bilgehan 2011, Hakim *et al.* 2011, Mohammadhassani *et al.* 2013).

Fuzzy logic systems are particularly suited for modelling the relationship between variables in environments that are either ill-defined or very complex, and makes a more precise alternative. The use of qualitative variables and mathematical relationships in this technique results in a more accurate decision-making process. Fuzzy logic, which was first introduced by Zadeh (1965), is a self-learning technique that provides a mathematical tool to convert linguistic evaluation variables based on expert knowledge into an automatic evaluation strategy.

Fuzzy-neural systems are part of an intelligent system which combines significant characteristics of ANNs and fuzzy inference system (FIS) to construct powerful tools for computing. ANFIS uses artificial neural network theory in order to determine the properties (fuzzy membership functions and fuzzy rules) of data samples in learning of a fuzzy inference system.

In ANFIS which is based on the Takagi-Sugeno fuzzy model (Takagi 1965), a fuzzy inference system is implemented through a feed-forward network and a hybrid learning method including back propagation theory from ANNs, recursive least square (RLS) method and clustering techniques which are used together to construct the FIS according to data appropriately. In other words, ANFIS combines fuzzy logic and ANNs, by utilizing the mathematical properties of ANNs in tuning rule based fuzzy inference system that approximates the way human brain process information. ANFIS has shown significant promise in modeling nonlinear systems where it is able to learn features of the data set and adjusts accordingly the system characteristics to a given error criterion (Jang 1993). Like ANN, ANFIS is capable of mapping unseen inputs to their outputs by learning the rules from the previously seen data. The determined values of physical parameters (input) and the real values of deflection (output) are used to train fuzzy neural network.

In structural engineering, ANFIS has been successfully applied to a various applications. These include structural analysis and design (Lee 2011, Lee *et al.* 2012) and structural damage assessment (Wilson 2012). ANFIS is applied to solve these aforementioned problems (especially modeling, curve fitting, forecasting, prediction, approximation, system identification) that are not easily by solved using conventional calculations that engineers use**.**

### 1.1 Review on related studies

In recent years, many researchers have reported using ANFIS in the field of concrete element and related fields. Bilgehan (2011) used ANFIS and ANN models for the buckling analysis of slender prismatic columns with a single non-propagating open edge crack subjected to axial loads. The main focus of his work was to study the feasibility of using ANFIS and ANN trained with the non-dimensional crack depth and the non-dimensional crack location parameters to predict the critical buckling load of different end supported condition in axially loaded compression rods. Bilgehan (2011) has concluded that the ANFIS architecture with Gaussian membership functions performed better than the multilayer feed forward ANN learning by back propagation algorithm.

### 1.2 Research significance

The main objective of this research is to establish an ANFIS model for deflection prediction of deep beams by considering main effective parameters. This paper presents the first study on the deflection prediction using ANFIS in deep beams.

The proposed model can adequately predict the mid-span deflection at ultimate state and along the loading process of deep beams at different tensile reinforcement ratio, web reinforcement ratio, compressive strengths of concrete, yield and ultimate strength of tensile and web reinforcement as well as shear span-to-depth ratios.

The rest of the paper is organized as follows: Section 2 presents methodology. Section 3 reports the results and discussion and finally the paper is concluded in Section 4.

## 2. Methodology

### 2.1 Experimental study

Experimental section of this study is presented in (Mohammadhassani 2013), as follows:

#### 2.1.1 Concrete deep beam set-up

Fig. 1 shows the adopted arrangement. The beams were levelled and placed on two steel cylinders with 5" diameters.

The load was applied with 20 KN intervals and acted on the deep beam with a same shear span from two end points. At each stage of loading, strains at both surfaces and deflection at two points along the beam length were measured. Crack widths were monitored with a hand microscope. Amounts of deflections and strains were obtained at each loading stage.

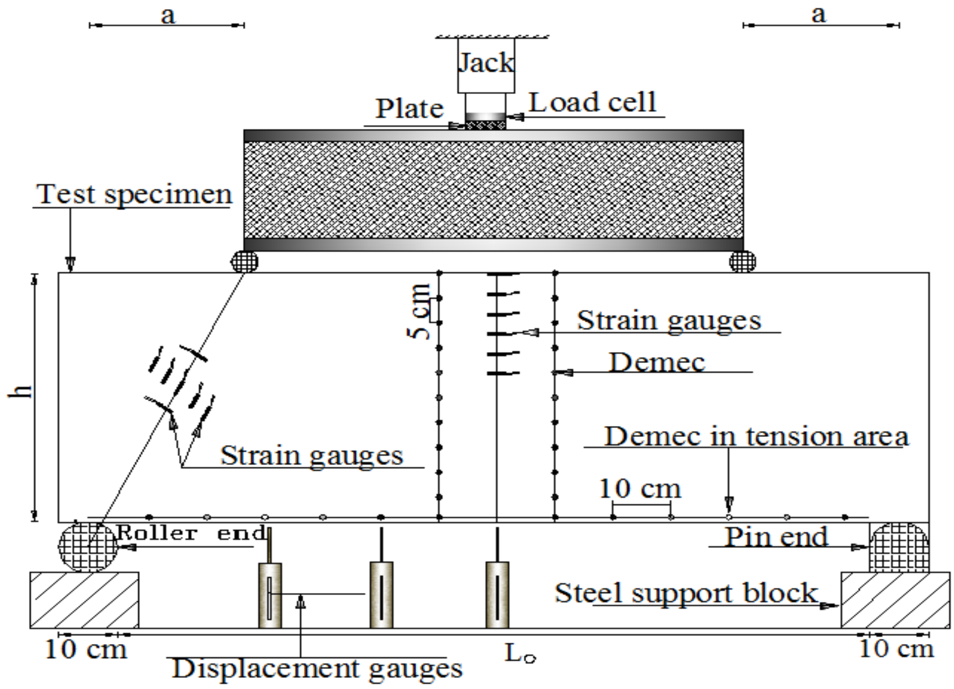



Fig. 1 Details of testing arrangement (Mohammadhassani *et al.* 2012)

### *2.2 Data availability*

The data used in this paper are based on parameters presented in Table 1. The available data set covers 3668 data points (instances) collected from tested concrete deep beams. Each instance is represented by a 10-dimensional real-valued vector and it is the input parameters shown in Table 1 with its corresponding deflection output.

Table 1 Different parameters of the eight HSSCC deep beams

| Input Parameters | | | | | | | | | | Output parameter |
|---|---|---|---|---|---|---|---|---|---|---|
| $P$ | $f_{cu}$ | $a/d$ | $l_0/d$ | $f_{yv}$ | $f_{yh}$ | $A_v/b.s_v$ | $A_h/b.s_h$ | $\rho$ | $f_y$ | $\Delta$ |

The input parameters consist of applied load ($P$), concrete cube strength ($f_{cu}$), ratio of shear span to effective depth of beam ($a/d$), ratio of effective span to effective depth of beams ($l_0/d$), yield strength of vertical web reinforcement ($f_{yv}$), yield strength of horizontal reinforcement ($f_{yh}$), area of vertical bar to distance of vertical bars ($A_v/b.s_v$), area of horizontal bar to the distance of horizontal bars ($A_h/b.s_h$), tensile reinforcement ratio ($\rho$) and strength of tensile bar at yielding condition ($f_y$) while $\Delta$ is used as the output or deflection amount at the mid span of HSSCC deep beams.

### 2.2.1 System modeling

System modeling alters the parameters of an adaptive intelligent system (like ANN, ANFIS) to suit unknown actual/engineering system transfer function. A schematic of the system modeling problem utilizing the adaptive intelligent system is shown in Fig. 2. 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, performance function, typically the mean squared error(MSE) between intelligent system's output and actual response is minimized.

The objective 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.

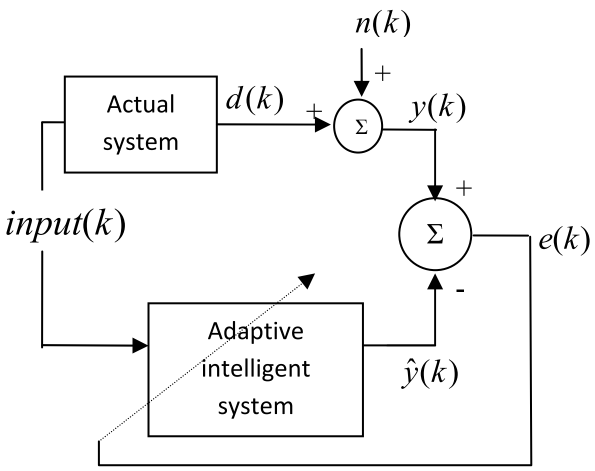



Fig. 2 System modelling using an adaptive intelligent system

### 2.3 Fuzzy expert system

Human reasoning is able to process uncertainties and vague concepts appropriately. It, however, cannot express it precisely. Fuzzy logic allows the modelling of uncertainties and the human brain's thinking, reasoning and perception (Abraham 2005). Based on the Boolean logic, we apply two concepts only, either 'True' or 'False', represented by 1 and 0 respectively. Therefore, a proposition can only be true or false. Fuzzy logic, an extension of the Boolean logic, allows intermediate values between these two values where the classical theory of binary membership in a set is extended to incorporate memberships between 0 and 1. This allows each proposition to be either True or False to a certain degree between them. With $X$ as the space of objects and $x$ as an element of $X$, a classical set $A$, $A \subseteq X$ is defined as a collection of elements $x \in X$ such that $x$ can either belong or not belong to the set $A$. In other words, the set $A$ is described in Eq. (2)

$$A = \{x | x \in X\} \tag{2}$$

where as, a fuzzy set $A$ in $X$ is defined by Eq. (3)

$$A = \{(x, \mu_A(x)) | x \in X\} \tag{3}$$

where $\mu_A(x)$ is the membership function for the fuzzy set $A$. Here, $A$ is a linguistic term (label) that is determined by the fuzzy set. The membership function maps each element of $x$ to a membership grade between zero and one ($\mu_A(x) \in [0, 1]$). For example, this set can present $x$ as 'Medium', which is a linguistic term that can be described by a fuzzy set with soft boundaries. Fig. 3 shows two sets, one based on Boolean logic and the other on fuzzy logic.

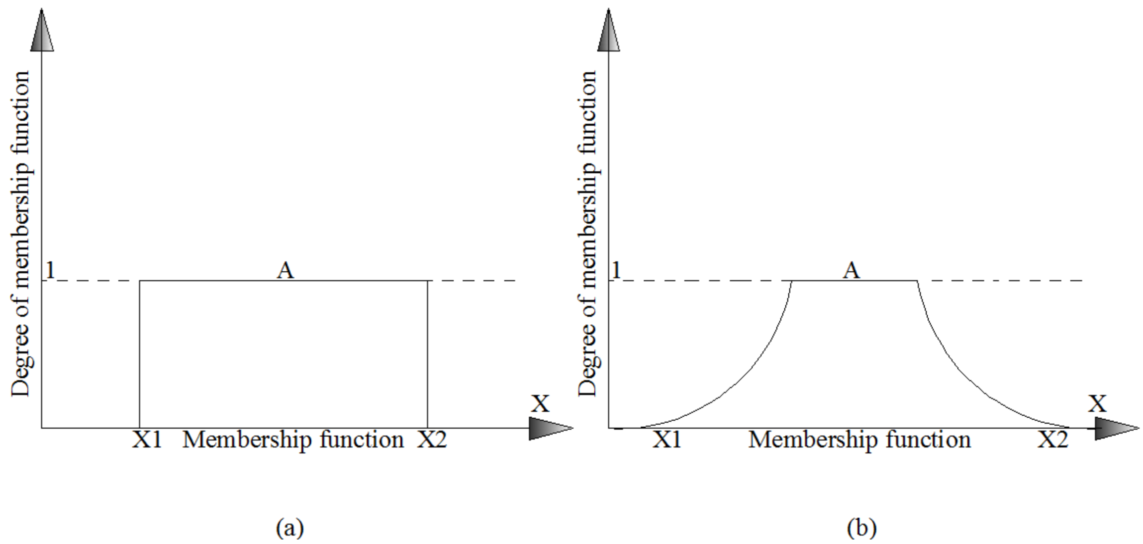



Fig. 3 An example of (a) classical boolean set, and (b) fuzzy logic set

### 2.4 Fuzzy inference system (FIS)

Fuzzy systems provide the means of representing the expert knowledge of the human about the process in terms of fuzzy (IF–THEN) rules which is the basic unit for capturing of knowledge in a fuzzy system. Similar to a conventional rule in artificial intelligence, a fuzzy rule has two components: an 'IF' part and a 'THEN' part which are also referred to as antecedent and consequent, respectively. The main structure of the fuzzy rule is shown in Eq. (4)

$$IF \ \langle\text{antecedent}\rangle \quad THEN \ \langle\text{consequent}\rangle \tag{4}$$

The antecedent of a fuzzy rule can conditionally be satisfied to a degree. Similar to conventional rules, the antecedent of a fuzzy rule may combine multiple simple conditions into a complex string using AND, OR and NOT logic operators. The consequence of a fuzzy rule can be classified into two main categories:

a) Fuzzy consequent (Eq. 5) where $C$ is a fuzzy set.

b) Functional consequent (Eq. 6) where $p$, $q$ and $r$ are constant.

$$IF\ \ x\ is\ \ A\ \ and\ \ \ y\ is\ \ B\ \ THEN\ \ \ f\ \ is\ \ C \tag{5}$$

$$IF\ \ x\ is\ \ A\ \ and\ \ \ y\ is\ \ B\ \ THEN\ \ \ f = px + qy + r \tag{6}$$

Basically, fuzzy inference systems incorporates an expert's experience into the system design and are composed of 4 blocks (Fig. 4). A FIS comprises a 'fuzzifier' that transforms the 'crisp' inputs into fuzzy inputs by membership functions that represent fuzzy sets of input vectors. It also contains a knowledge-base that includes the information given by the expert in the form of linguistic fuzzy rules. An inference-system (Engine) uses them together by a method of reasoning and a 'defuzzifier' that transforms the fuzzy results of the inference into a crisp output using a 'defuzzification' method (Herrera and Lozano 2003).

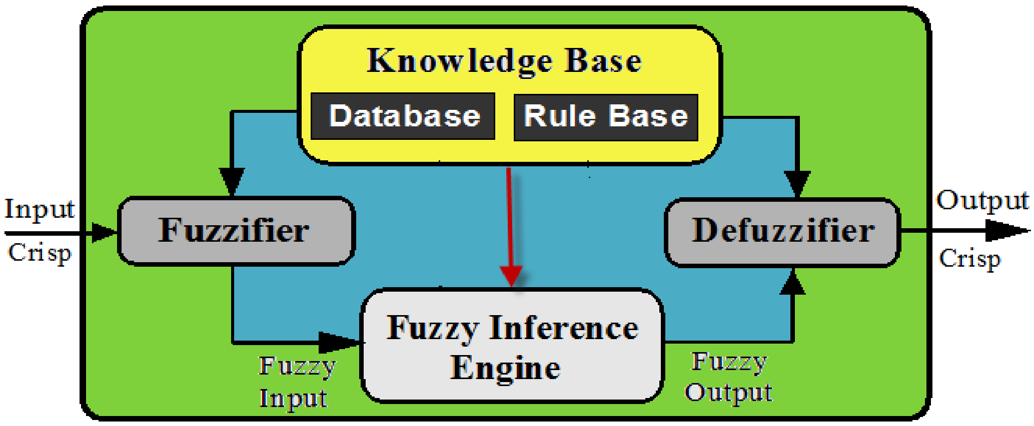



Fig. 4 A flow diagram of a fuzzy inference system (FIS)

The knowledge-base comprises two components: a data-base, which is the membership functions of the fuzzy sets used in the fuzzy rules, and a rule-base which comprises a collection of linguistic rules that are combined by a specific operator. The generic structure of a FIS is shown in Fig. 4. The two common types of FIS vary according to differences between the specifications of the consequent part of fuzzy rules (Eqs. 5 and 6). The first fuzzy system uses the inference method proposed by Mamdani in which the rule consequent is defined by fuzzy sets and has the structure of Eq. 5 (Mamdani and Assilian 1975).

The second fuzzy system proposed by Takagi, Sugeno and Kang (TSK) contains an inference engine where the conclusion of a fuzzy rule is made up of a weighted linear combination of the crisp inputs rather than a fuzzy set (Takagi and Sugeno 1985). The TSK system has the structure shown in Eq. 6. The TSK models are suitable for approximating large non-linear systems.

The knowledge-base containing the database and rule-base of a FIS can be constructed from an expert's knowledge. For this, the expert selects the membership functions and rules. In this way, fuzzy models can help in extracting expert knowledge at an appropriate level. Fuzzy systems can also be constructed from data and this alleviates the problem of knowledge acquisition. Various techniques have been used to analyze the data with the best possible accuracy. There are two common approaches for constructing a FIS using available data. The first approach is where the rules of the fuzzy system are often designated *a priori* and the parameters of the membership functions are adapted during the learning process from input to output data using an evolutionary algorithm (e.g., genetic algorithm). In the second approach, the fuzzy system can be generated using hybrid neural nets. The neural net defines the shape of the membership functions of the premises; this architecture and learning procedure is called an adaptive network-based fuzzy inference system (Jang 1993).

### *2.5 Adaptive network-based fuzzy inference system (ANFIS)*

ANFIS is a multilayer feed-forward network in which each node performs a particular function on incoming signals as well as a set of parameters pertaining to this node (Jang 1993). Similar to ANN, ANFIS is capable of mapping unseen inputs to their outputs by learning the rules from the previously seen data. A simple structure of this type of network having just two inputs of $x$ and $y$ and one output off is shown in Fig. 5.

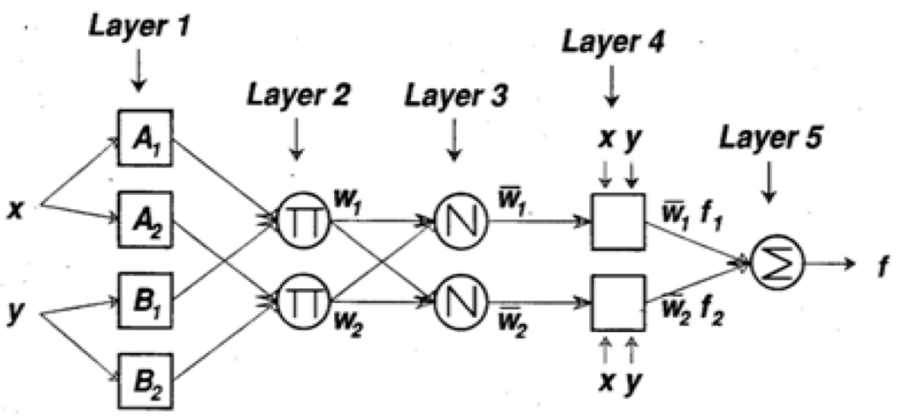



Fig. 5 ANFIS architecture

As can be seen from the figure, ANFIS contains five layers in its architecture including, the fuzzify layer, product layer, normalized layer, defuzzify layer, and total output layer. It is highlighted here that by assuming just two membership functions for each of the input data $x$ and $y$, the general form of a first-order TSK type of fuzzy if–then rule has been given by Eq. 7. Here, we re-write the rule $i$ of the ANFIS as

$$\text{Rule } i\text{: } IF\ x\ is\ A_i\ and\ \ y\ is\ B_i\ THEN\ \ f_i = p_i x + q_i y + r_i\text{, } i = 1,2,...,n \tag{7}$$

where $n$ is the number of rules and $p_i$, $q_i$ and $r_i$ are the parameters determined during the training process. At first stage of the learning process, the membership function ($\mu$) of each of the linguistic labels $A_i$ and $B_i$ are calculated as follow

$$O_i^1 = \mu_{Ai}(x), \quad i = 1, 2, \ldots, n \tag{8}$$

$$O_i^1 = \mu_{Bi}(y), \quad i = 1, 2, \ldots, n \tag{9}$$

At the second layer which is the product layer, the previously calculated membership degrees of linguistic variables are multiplied as shown in Eq. 10

$$O_i^2 = w_i = \mu_{Ai}(x)\, \mu_{Bi}(y), \quad i = 1, 2, \ldots, n \tag{10}$$

The third layer, the normalized layer, where the ratio of each weight to the total weights is calculated

$$O_i^3 = \overline{w}_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \quad i = 1, 2, \ldots, n \tag{11}$$

The fourth layer is the defuzzification layer with adaptive nodes where their outputs depend on the parameter(s) pertaining to these nodes and the learning rule specifies how these parameters are altered to minimize the measure of prescribed error (Jang 1993). The relationship for these nodes is as follows

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \quad i = 1, 2, \ldots, n \tag{12}$$

Finally in the fifth layer, the summation of all the incoming signals is performed where the output of the system is the final result

$$O_i^5 = \sum_{i=1}^{n} \overline{w_i} f_i \quad i = 1, 2, \ldots, n \tag{13}$$

## 3. Result and discussion

### *3.1 Experimental results*

This work presents the use of ANFIS modelling to generalize empirical data and predict mid span deflection amount of HSSCC deep beams. Firstly the variations of experiment load-deflection graphs at mid span of beam length are presented in Fig. 6, which indicates different function of behaviour.

This figure shows that the load deflection relationship is nearly nonlinear for each of tested HSSCC deep beam. As stated before, the main failure mode of deep beam is failure under shear deformation although other failures are expected. By domination of shear failure real behaviour of deep beams is not easy to understand (Mohammadhassani *et al.* 2011). Each graph indicates different load deflection behaviour which is either near linear, exponential or parabolic. These unique behaviours indicate that the shear strength, the redistribution of internal forces before failure, and the internal force mechanisms in deep beams are very different from those in normal beams.

### *3.2 Development of ANFIS model for the prediction of deflection of deep beam*

Firstly, the data is normalized. To normalize the data, a Gaussian normalization technique is used. Then, 80% of the normalized data are randomly chosen as training data and the remainder 20% as testing data. Then the ANFIS models with different parameters (total ten) as input are implemented with regard to Fig. 3. To implement ANFIS the MATLAB programming language version R2010a is used.Genfis2 function based on subtractive clustering method is used to generate the FIS structures.

Finding the best structure with the appropriate membership function parameters involved two processes: Learning and Testing. Through the learning process first the membership functions of the inputs are generated using subtractive clustering. Then, the membership function parameters are tuned using a back propagation algorithm in combination with a recursive least squares method followed by the testing step where the generalization capability of the generated model is checked. To decrease the Mean Square Error (MSE) obtained by this method, the number of membership functions was gradually increased by lowering the range of influence of cluster centres in a step by step and trial and error manner.

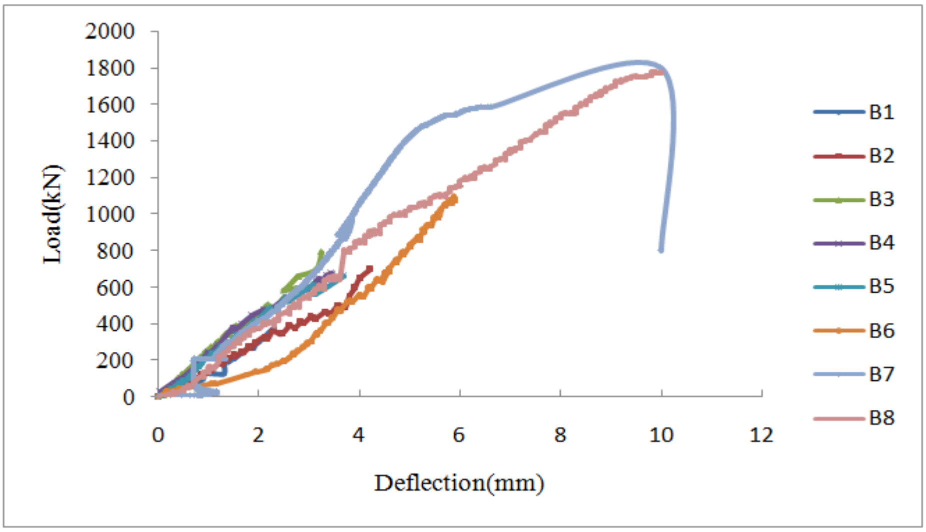



Fig. 6 Deflection of tested HSSCC deep beams at mid span (Mohammadhassani 2012a)

### *3.3 Results of numerical analysis*

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 ANFIS modelling.

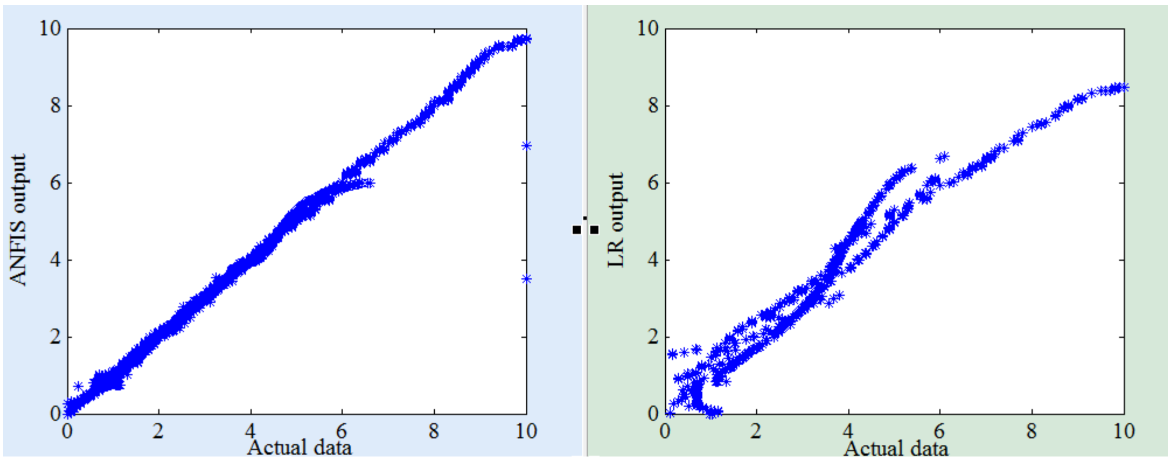
To evaluate the comparative methods, the MSE and Correlation Coefficient / Pearson Coefficient (R) values are used in this study. MSE is a risk function which corresponds to the expected value of the squared error loss or quadratic loss. R is the degree of success in reducing standard deviation (SD).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

$$R^2 = 1 - \frac{\sum_{k=1}^{L} (y(k) - \hat{y}(k))^2}{\sum_{k=1}^{L} (y(k) - y_{ave})^2} \tag{14}$$

where $\hat{y}(k)$ , $y(k)$ and $y_{ave}$ are the output predicted by ANFIS, actual (observed) output and averaged actual output, respectively, and $L$ is the total number of training/testing instances. Table 2 summarizes the MSE and R results obtained using the proposed method and the linear regression separately for training and testing data.

Table 2 Comparison of MSE and R values from ANFIS 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 |
| ANFIS | 2934 | 0.0217 | 0.9976 | 734 | 0.0087 | 0.9991 |




(a) (b)

Fig. 7 Deflection prediction performance from (a) ANFIS (b) LR

As noted, the MSE values from ANFIS is approximately 10 times smaller than values from classical linear regression. Furthermore, the R values from ANFIS for test data is 0.9991 which is an exciting value nearest to 1 for a scientist. The results obtained by the experiments show that the difference of two comparative methods is more obvious for test set. Fig. 7 shows deflection prediction performance provided by linear regression and ANFIS 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. 7 reveals that the proposed ANFIS method is highly accurate and precise compared to the classical linear regression for the deflection prediction of HSSCC deep beams. The relation between input variables and deflection output variable can be visualized with the modelled fuzzy surfaces shown in Figs. 8 and 9.

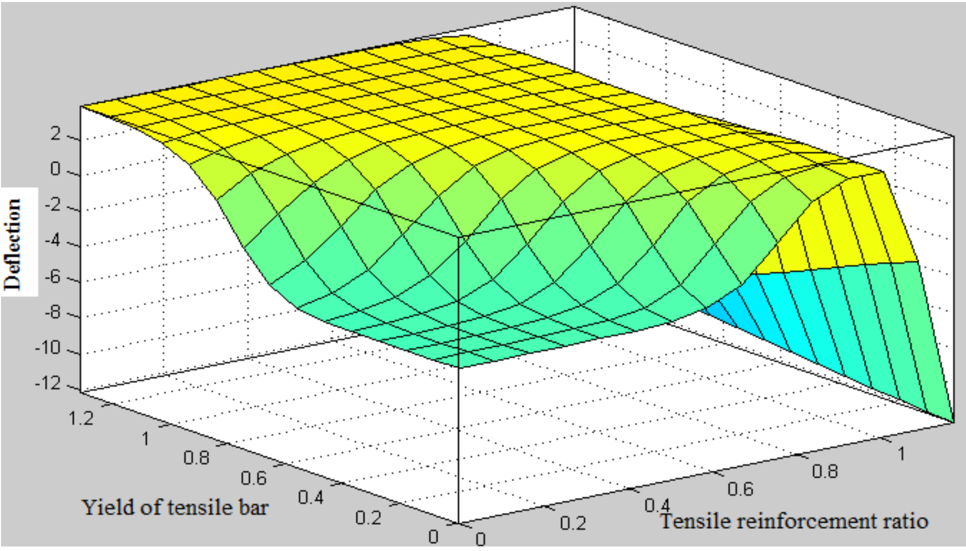



Fig. 8 Fuzzy surface: Tensile reinforcement ratio and yield strength of tensile bar versus Deflection prediction

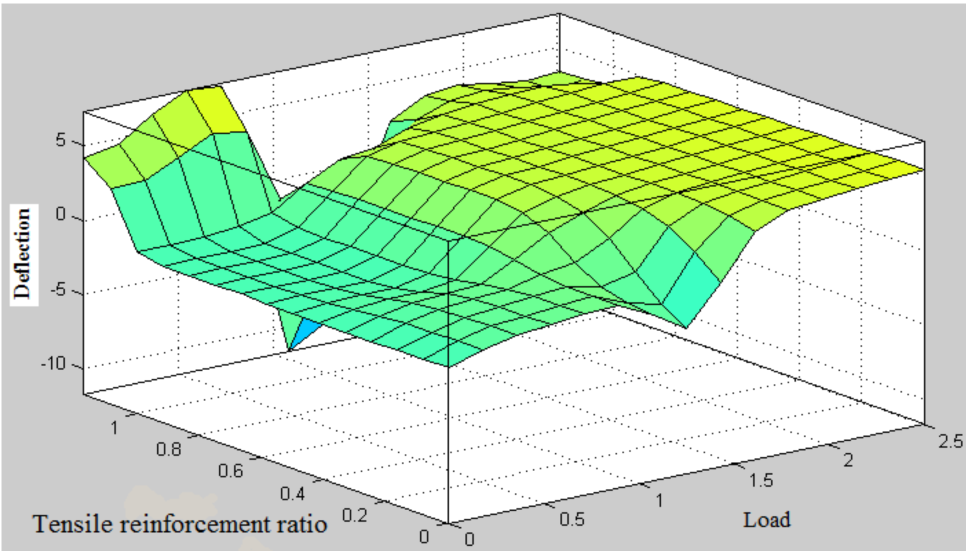



Fig. 9 Fuzzy surface: Tensile reinforcement ratio and load versus Deflection prediction

Graphical User Interface (GUI) tool allows the examining of the output surface of a FIS model. GUI provides a visual impression of the possible combinations of the two input variables and the output in 3-D. This is a fast visual method to analyse the deflection amount in deep beams. The FIS gives mathematical solution to determine deflection based on data such as tensile reinforcement ratio vs yield strength and tensile reinforcement ratio vs load.

## 4. Conclusions

The applications of ANFIS and linear regression models for deflection prediction of HSSCC deep beams have been demonstrated in the present study. ANFIS showed relatively higher accuracy and precision compared to the linear regression. The MSE from ANFIS is approximately 10 timeslesser for training set and 20 times lesser for testing setand therefore is more accurate than those from classical linear regression. Comparison of performance of deflection prediction performance of both linear regression and ANFIS for the test data shows that the proposed ANFIS method is more accurate than the classical linear regression in deflection prediction for any type of deep beams.

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