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Prediction of shear capacity of channel shear connectors using the ANFIS model

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Abstract. Due to recent advancements in the area of Artificial Intelligence (AI) and computational intelligence, the application of these technologies in the construction industry and structural analysis has been made feasible. With the use of the Adaptive-Network-based Fuzzy Inference System (ANFIS) as a modelling tool, this study aims at predicting the shear strength of channel shear connectors in steel concrete composite beam. A total of 1200 experimental data was collected, with the input data being achieved based on the results of the push-out test and the output data being the corresponding shear strength which were recorded at all loading stages. The results derived from the use of ANFIS and the classical linear regressions (LR) were then compared. The outcome shows that the use of ANFIS produces highly accurate, precise and satisfactory results as opposed to the LR.

Keywords: shear connector; channel; composite beam; shear strength; ANFIS; LR

1. Introduction

Recently, the use of channel shear connectors has become a preferred alternative over common shear connectors such as studs (Maleki and Mahoutian 2009). Among the many advantages of a channel connector are that it has a higher load carrying capacity, it allows the use of the reliable conventional welding system, and it does not require inspection such as the bending test which is needed in the use of stud connectors. Furthermore, the use of only a few channel shear connectors would suffice to replace the need for a huge number of headed stud shear connectors (Maleki and Bagheri 2008a).

Slutter and Driscoll (1965), Pashan (2006) and Viest (1952) presented the test results of preliminary studies on channel shear connectors to determine these connectors' behaviour and to evaluate the possibility of the use of channel profiles as shear connectors. Several equations were derived from the aforementioned studies to determine the capacity of channel shear connectors

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embedded in a solid concrete slab. These equations were adopted from the building codes, such as the National Building Code of Canada (NBC 2005) and American Institute of Steel Construction (AISC) specification (AISC 2005).

Maleki and Bagheri (2008a, b) have recently conducted strength tests on channel connectors embedded in different concrete materials under monotonic and low cycle fatigue loading. Moreover, Maleki and Mahoutian (2009) have recommended modified equations in predicting the capacity of channel shear connectors that are embedded in polypropylene (PP) concrete, while Shariati *et al*. (2010, 2011) have proposed such equations for channel shear connectors embedded in light weight aggregate concrete (LWAC). In addition, Hosain and Pashan (2009) have suggested two equations to determine channel capacity in solid and metal deck slabs. Current research has been carried out on channel shear connectors to determine their behaviour and to make comparisons with other type of connectors Shariati *et al*. (2012a, b, 2013).

This paper aims at examining the behaviour of channel shear connectors and the effects of their different sizes in concrete with varying strength levels, with and without reinforcement bars under monotonic and low cycle fatigue loading.

However, since the casting, curing and testing procedures of channel shear connectors involved high costs, the search for new effective tools which are economical is required in designing shear connectors with modelling. Moreover, it is essential in determining the shear strength of shear connectors with varying dimensions and in different levels of concrete strength. This involves the utilization of modern models in predicting the channel connectors' shear capacity, emphasizing on their behaviour.

1.1 Why use artificial intelligence (AI) system approaches

Numerous engineering applications such as nuclear energy (Lali and Setayeshi 2011), concrete technology (Hakim *et al*. 2011), stability of structures (Bilgehan 2011), soil science (Yilmaz and Kaynar 2011), Structural damage detection (Hakim and Razak 2013a, b) and deep beam element (Mohammadhassani *et al*. 2013a) has successfully applied the Artificial intelligence (AI) system approaches for modelling purposes. This includes the Artificial Neural Network (ANN), Fuzzy Inference Systems (FIS), and Neuro-fuzzy / fuzzy-neural systems among others.

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

As part of an intelligent system that combines the ANNs and Fuzzy Inference System (FIS) significant characteristics, the fuzzy neural systems are normally used to create powerful tools for computing. The properties (fuzzy rules and fuzzy membership functions) of data samples in the learning of a fuzzy inference system are determined by ANFIS through the use of the ANN theory. In this research, for the purpose of modeling and predicting the shear capacity of channel shear connectors, the ANFIS which is based on the Takagi-Sugeno fuzzy model is applied.

A fuzzy inference system is applied using a feed-forward network and a hybrid learning method. This includes the recursive least squares (RLS) method, back propagation theory from ANNs and clustering techniques which are combined to appropriately construct the FIS according to the data. Concisely, the ANFIS combines ANNs and Fuzzy logic. The ANFIS uses the mathematical properties of ANNs in tuning rule based on fuzzy inference system which approximates the way that human brain process information. In modeling nonlinear systems, the use of ANFIS has proved to be reliable due to the ability to study features of the data set and adjust the system characteristics accordingly to a given error criterion. Moreover, through learning the rules from previously seen data, the ANFIS is capable of mapping unseen inputs to their outputs. The use of ANFIS and ANN models have been applied by Bilgehan (2011) for the buckling analysis of slender prismatic columns with a single non-propagating open edge crack subjected to axial loads. Through this study, Bilgehan concluded that as oppose to the multilayer feed forward ANN learning by back propagation algorithm, the ANFIS architecture with Gaussian membership functions performed better.

1.2 Research significance

Due to expensive experimental tests and lengthy procedure of the nonlinear finite element analysis, the prediction of shear capacity of channel connectors in composite beam is rather difficult. In this research, the application of ANFIS as a non-linear tool and linear regression (LR) as a linear tool in predicting the shear capacity of channel connectors in composite beam are being examined and compared. The proposed model offers an adequate prediction of the shear capacity of channel connectors with varying dimensions and in concrete with different strength level, with and without reinforcement bars.

2. Experimental test program

2.1 Specimen details and test setup

Based on the strength of concrete and the size of channel shear connector in the concrete slabs, push-out specimens that consist of a steel I beam with two slabs attached to each flange of the beam were prepared. To each beam flange, one channel was welded and for all slabs, two layers of steel bars with four 10 mm diameter steel bar hoops were applied in two perpendicular directions. All the details of the push-out specimens are in accordance with those of Maleki and Bagheri (2008a, b). Fig. 1 illustrates the details of a typical specimen.

Four types of channels – 100 and 75 mm in height and 30 and 50 mm in length – were used. The channels with 100 mm height had a flange thickness of 6 mm and web thickness of 8.5 mm while the channels with 75 mm height had a flange thickness of 5 mm and a web thickness of 7.5 mm.

In this study, the concrete compression strength levels were also variable factors. Reinforced high strength and normal strength concrete were used for the purpose of this research. In both HSC mixes, air-dry condition aggregates were used. Graded silica sands with maximum nominal size of 4.75 mm was used as fine aggregate, and crushed granite with maximum nominal size of 10 mm was used as coarse aggregate. Table 1 shows the particle size analysis of the fine aggregates. Ordinary Portland Cement (OPC) which corresponds to the ASTM C150 with chemical properties shown in Table 2 was used in all mixes. The Rheobuild 1100 was used as a Super plasticizer (SP) in both mixes to attain acceptable workability. The SP is dark brown in color with specific gravity of approximately 1.195 and a pH within the range of 6.0-9.0 (Sajedi and Razak 2011). Table 3 shows the mix properties of the concrete materials. Short length channels are used due to the limitation in the size of concrete slab. In accordance with the site situations, all push-out

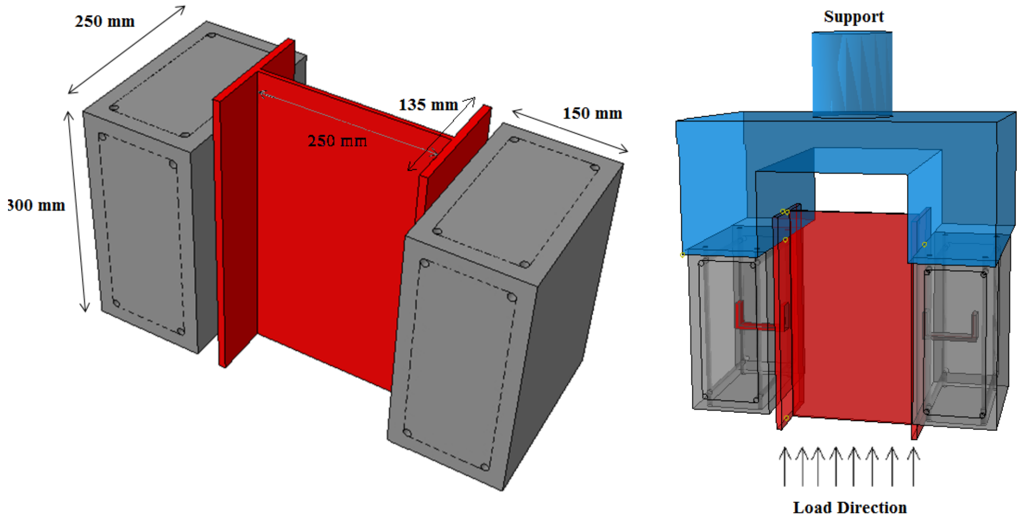


Fig. 1 Details of typical specimen used in experimental push-out test

Table 1 Particle size analysis of silica sand (SS) based on BS 822: Clause 11

Sieve size (μm)	Sieve No.	$W_{SS} + W_S$ (g)	W_S (g)	W_{SS} (g)	Ret. %	Cum. Ret. %	Pass %
4750	3/16 in	409.9	408.3	1.6	0.32	0.032	99.68
2360	NO.7	462.3	375.7	86.6	17.33	17.65	82.35
1180	NO.14	437.2	343.0	94.2	18.85	36.5	63.50
600	NO.25	450.7	316.2	134.5	26.93	63.42	36.58
300	NO.52	379.1	288.7	90.4	18.09	81.51	18.49
150	NO.100	322.1	274.8	47.3	9.47	90.99	9.02
75	NO.200	309.9	275.2	34.7	6.94	97.92	2.08
Pan	-	250.8	240.4	10.4	2.08	-	0.00
Total				499.7		388.31	

*Fineness modulus = 388.31/100 = 3.88 (Neville 2008, Neville and Brooks 2008); Water absorption for silica sand is 0.93%; W_{SS} = Silica sand weight; W_S = Sieve weight; Cum. Ret = Cumulative retained

Table 2 Composition of cementitious materials for OPC and slag used (% by mass)

P_2O_5	SiO_2	Al_2O_3	MgO	Fe_2O_3	CaO	MnO	K_2O	TiO_2	SO_3	CO_2	LOI
0.068	18.47	4.27	2.08	2.064	64.09	0.045	0.281	0.103	4.25	4.20	1.53

Table 3 Mix proportions of high strength concrete materials by weight

Mix no	Cement (kg/m^3)	Coarse aggregate (kg/m^3)	Fine aggregate (kg/m^3)	Water (kg/m^3)	Silica fume (kg/m^3)	SP (%)	W/C	Modulus of elasticity (GPa)	Compressive strength (MPa)
H Series	460	910	825	168	40	0.5	0.37	39	82
N series	360	940	870	180	-	1	0.50	32	63

specimens were cast in a horizontal position. For both sides of specimen slabs, a reliable quality of the concrete was assumed as well. Prior to testing, all specimens were cured in water for 28 days.

Standard cylinders with 150 mm diameter and 300 mm length and standard cubes with 100 mm length were cast simultaneously with the push-out specimens in order to obtain the compressive strength. Prior to the day of testing, all cylinders and cubes were cured in water. With the cylinder and the cube compression tests combined, the concrete strength was achieved. For the purpose of the compressive strength test procedure, the requirements of the ASTM C39 (ASTM 2005) were applied and the mean values of the concrete compression strength were used in the calculations

2.2 Loading and test procedure

In order to develop composite action in a beam, shear connectors are utilized. The connectors should have the ability of transferring shear forces even under severe load reversals. For the purpose of developing additional data and understanding the behaviour of channel shear connectors embedded in the solid concrete slab, the current study was carried out.

As shown in (Fig. 2(a)-(b)), a 600 kN capacity universal testing machine was used to apply the load. While loading the slabs, specific support was applied and a load control of 0.04 mm/s was used as the loading rate for all specimens. Prior to every loading procedure, specimens were rearranged to suit the unidirectional nature of the load test frame. In monotonic loading, the load is increased until failure. The steel I beams are positioned on the deck of the universal test machine. Varying the orientation of the channel connector creates a variation in the connector's ultimate strength and relative stiffness (Maleki and Bagheri 2008b). This fact was considered in the push-out test and at the beginning of every test for all specimens (Fig. 1), where the same orientation for

(a) Specimen sets up

(b) Specimen after fracture

Fig. 2 Push-out test setup

Table 4 Different parameters of testing channel shear connectors

Input Parameters					Output parameter
Slip	t_f	t_w	f_{cu}	L_c	P

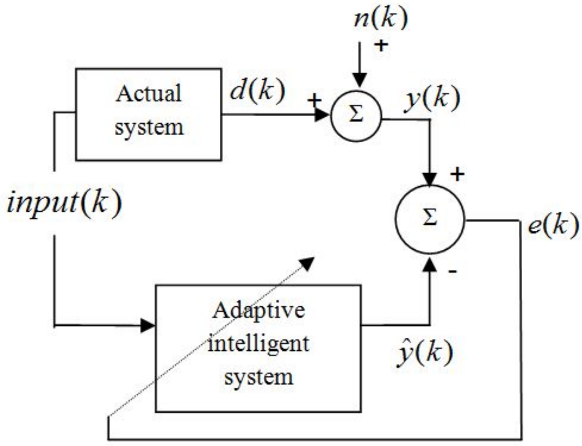


Fig. 3 System modelling using an adaptive intelligent system (Mohammadhassani *et al*. 2013)

channels was considered. The universal test machine automatically records the practical load and relative slip between the I-beam and the concrete block at each time step.

3. Numerical method

3.1 Data availability

In this research, the data are based on the parameters presented in Table 4 and the compression test of concrete used in the slab. The data set involves 1197 data points (instances) that are collected from the push-out tests with each instance being represented by a 5-dimensional real-valued vector. The vector also acts as the input parameters shown in Table 4 with the output being its corresponding prediction of shear capacity of the channel shear connectors.

The applied slip between concrete block and steel I-beam, concrete cylinder strength f_c, thickness of channel flange t_f, thickness of channel web t_w, and the length of channel shear connector (l_c,) formed the input parameters, while the output is the shear capacity of the channel shear connector, P.

3.2 System modelling

In order to suit unknown actual/engineering system transfer function, system modeling alters the parameters of an adaptive intelligent system (like ANN, ANFIS). Fig. 3 illustrates a schematic of the system modeling problem utilizing the adaptive intelligent system. As can be seen from this figure, to ensure accurate estimation of the actual system, the parameters of the estimated intelligent system are tuned using proper learning methods. In brief, performance function, normally the mean squared error (MSE) between the output of the intelligent system and the actual response is minimized.

The objective function in system modelling problems is expressed as follows

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

where $y(k)$ is the 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 the desired output or the semi desired output.

3.3 Fuzzy expert system

Uncertainties and vague concepts can be processed appropriately by human reasoning. Fuzzy logic enables the modelling of uncertainties and the thinking, reasoning and perception of the human brain (Abraham 2005). According to the Boolean logic, only two concepts were normally applied; ‘True’ or ‘False’, by 1 and 0 respectively. Hence, a proposition can only be true or false. However, in Fuzzy logic, the classical theory of binary membership in a set is extended to incorporate memberships between 0 and 1 and hence allows intermediate values between these two values. Therefore, each proposition can be either True or False to a certain degree between them. A classical set A, $A \subseteq X$ with X as the space of objects and x as an element of X, is defined as a collection of elements $x \in X$, such that x can either belong or not belong to the set A. Eq. (2) below describes the set A

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

Whereas, 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. 4 illustrates two sets, which are based on the Boolean logic and the fuzzy logic respectively.

3.4 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. A fuzzy rule, like a conventional rule in artificial intelligence, has two components: an ‘IF’ part and a ‘THEN’ part, also referred to as antecedent and consequent, respectively. Eq. (4) shows the main structure of the fuzzy rule

$$IF < \text{antecedent} > THEN < \text{consequent} > \tag{4}$$

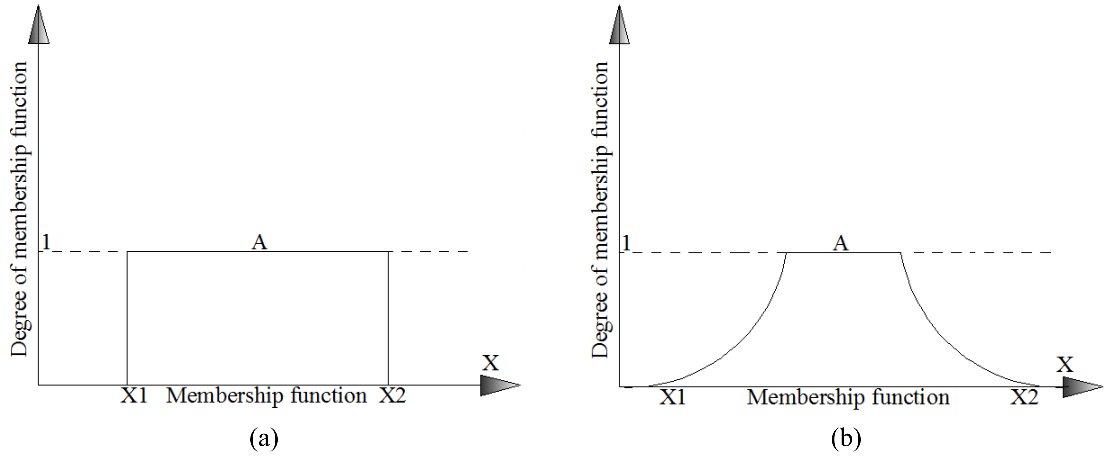


Fig. 4 An example of: (a) classical boolean set; and (b) fuzzy logic set (Mohammadhassani *et al*. 2013)

The antecedent of a fuzzy rule can conditionally be satisfied to a degree. Using AND, OR and NOT logic operators, the antecedent of a fuzzy rule may combine multiple simple conditions into a complex string, similarly to that of conventional rules. The outcome 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

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

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

Essentially, fuzzy inference systems are composed of 4 blocks (Fig. 5) and incorporate an expert's experience into the system design. A FIS comprises of a 'fuzzifier' which, through membership functions that represent fuzzy sets of input vectors, transforms the 'crisp' inputs into fuzzy inputs. Besides, it contains knowledge-base which includes the information given by the expert in the form of linguistic fuzzy rules. An inference-system (Engine) uses them together through a reasoning method and a 'defuzzifier' through which the fuzzy results of the inference were transformed into a crisp output using a 'defuzzification' method (Mohammadhassani *et al*. 2013).

The knowledge-based comprises of two components: the membership functions of the fuzzy sets used in the fuzzy rules which are known as database, and a collection of linguistic rules that are combined by a specific operator which is known as a rule - base. Fig. 5 illustrates the generic structure of a FIS. The two common types of FIS differ in accordance with the differences between the specifications of the consequent part of fuzzy rules (Eqs. (5) and (6)). In the first fuzzy system, the inference method proposed by Mamdani and Assilian (1975) was used in which fuzzy sets defined the rule consequent and has the structure of Eq. (5).

Takagi and Sugeno (1985) proposed TSK, the second fuzzy system which contains an inference engine, where instead of a fuzzy set, a weighted linear combination of the crisp inputs was used for

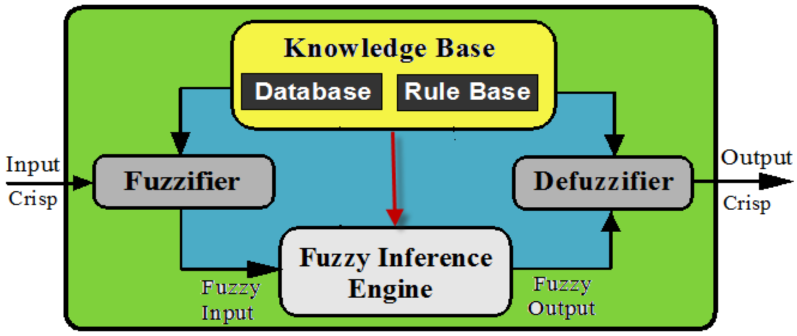


Fig. 5 A flow diagram of a fuzzy inference system (FIS) (Mohammadhassani *et al*. 2013)

the conclusion of a fuzzy rule Eq. (6) presents the structure of the TSK system. For the purpose of approximating large nonlinear systems, the use of the TSK models is suitable.

Based on an expert's knowledge, the knowledge-base containing the database and rule-base of a FIS can be constructed. For this purpose, the membership functions and rules were to be selected by the expert. This enables fuzzy models to help in extracting expert knowledge at an appropriate level. Since the fuzzy systems can also be constructed from data, the problem of knowledge acquisition can be alleviated. In order to analyse the data with the best possible accuracy, a variety of techniques have been used. With the use of available data, there are two common approaches for constructing a FIS. In the first approach, the rules of the fuzzy system are often designated a priori and during the learning process, the parameters of the membership functions are adapted from input to output data using an evolutionary algorithm (e.g., genetic algorithm). Meanwhile, the second approach is where the fuzzy system can be generated using hybrid neural nets that define the shape of the membership functions of the premises. This learning procedure and architecture is being referred as an adaptive network-based fuzzy inference system (Jang 1993).

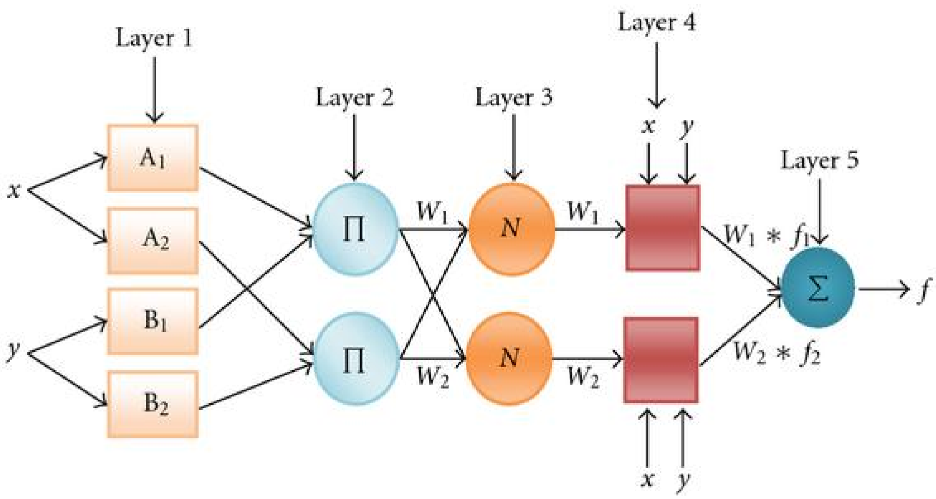


Fig. 6 ANFIS architecture (Mohammadhassani *et al*. 2013)

3.5 Adaptive network-based fuzzy inference system (*ANFIS*)

A multilayer feed-forward network in which each node performs a particular function on incoming signals and a set of parameters pertaining to this node is called the ANFIS (Jang 1993). ANFIS has the ability to map unseen inputs to their outputs by learning the rules from previously seen data, just like the ANN. Fig. 6 illustrates a simple structure of this type of network having just two inputs of *x* and *y* and one output of *f* is.

ANFIS contains five layers in its architecture which include the fuzzify layer, product layer, normalized layer, defuzzifier layer, and total output layer, as shown in Fig. 6. It is emphasized here that the general form of a first-order TSK type of fuzzy if–then rule has been given by Eq. (7) by assuming just two membership functions for each of the input data x and y. Here the rule i of the ANFIS is re-written as

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

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

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

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

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

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

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

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

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

$$O_i^5 = \sum_{i=1}^{n} \overline{w_1}, \quad f_i i = 1, 2, \ldots, n \tag{13}$$

4. Results and discussion

4.1 Experimental results

Normally, the behaviour of shorter channels differs than that of the longer channels. Slabs with longer channels experience concrete cracking on the sides of the slabs when channel fracture occurs, but such is not the case with slabs with shorter channels. Hence, it can be assumed that in a similar condition, concrete cracks more in specimens with longer channel embedded into it. In recent studies conducted by Maleki and Bagheri (2008a), Maleki and Mahoutian (2009) and Shariati *et al*. (2010), this matter was also observed in other types of concrete.

The effect of channel height can be assessed not only by taking into consideration the height of the channel but by considering pairs of similar specimens as well. In this case, there are two different types of HSCs, each with two similar pairs of channel embedded into it. For each series, the height of the connector changed from 75 mm to 100 mm. The specimen with the 100 mm high channel connectors carried a slightly higher load compared to the specimens with 75 mm high channel connectors as can be seen from the load-slip curves of monotonic loading (Fig. 7).

This might be due to the fact that the shorter channel connectors have a tendency of concentrating the applied load on a smaller area. It can also be seen from the curves that the specimen with 100 mm high channels is more flexible than the one with 75 mm high channels. For the 100 mm high channels, the amount of slip at the ultimate load level was 6.5-9 mm as compared to 4-8 mm for that of the 75 mm high channels.

For the design of shear connector, static strength is necessary and ductility is an essential assumption which is then confirmed throughout the ultimate slip (displacement) (Shim 2004). The load-slip for the monotonic load of all specimens is shown in Fig. 3. For the purpose of extracting

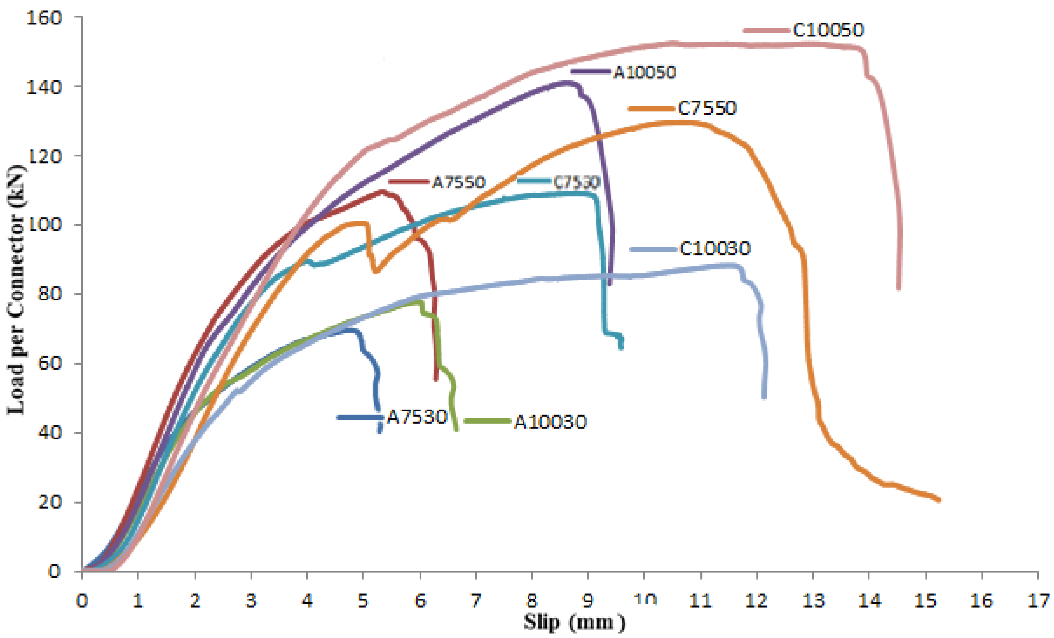


Fig. 7 Load-slip curves of the specimens under monotonic loading

the mechanical properties of the channel connector, the load-slip curve for one channel is used. The slip occurs between the I-beam and the concrete block under monotonic and cyclic loading. Since the slip is larger than 4 mm in all cases, it can be concluded based from the static curve that there is sufficient ductility for all channel connectors in HSC. For all specimens, the relative slip is between 4-9 mm at the peak load for the monotonic loading. Consequently, the different levels of HSC are not significant for the connector ductility in the HSC push-out test. In all specimens, as illustrated by the load-slip curve, the load capacity reduces quickly beyond the peak load and the load-slip curve comes to a sudden termination. This shows that all specimens have a yield plateau which means that when the load reaches its peak, there is an increase in slip.

4.2 Numerical results (*Developing the ANFIS model for the prediction of shear capacity of channel shear connectors*)

First of all, the data are normalized through the use of a Gaussian normalization technique. Subsequently, a random selection was conducted where 80% of the normalized data were chosen as training data and the remainder of 20% as testing data. With reference to Fig. 8, the ANFIS models with different parameters (total five) as inputs are implemented with the use of the MATLAB programming language version R2010a.

For the purpose of generating the FIS structures, Genfis2 function based on subtractive clustering method is used. In order to determine the best structure with the appropriate membership function parameters, two processes are involved namely ‘Learning’ and ‘Testing’. Throughout the learning process, the membership functions of the inputs are primarily generated using subtractive clustering. Then, a back propagation algorithm in combination with a recursive least squares method are used for the tuning of the membership function parameters. This is followed by the testing step where the generalization capability of the generated model is inspected. The number of membership functions was gradually increased to reduce the Mean Square Error (MSE) obtained by this method. This is done by lowering the range of influence of cluster centres in a trial and error and step by step manner.

The structure of implemented ANFIS is illustrated in Fig. 8.

4.3 Results of numerical analysis

Linear Regression (LR) is a scheme that is excellent, simple and yet effective and is used to predict domains with numeric attributes. The linear models operate as building blocks for learning tasks that are more complex. In order to establish a relationship between the input and output data for the proposed ANFIS modelling, LR analysis is carried out.

The MSE and Correlation Coefficient (R) values are used to evaluate the comparative methods in this study. MSE is a risk function which corresponds to the expected value of the squared error

Table 4 Comparison of MSE and R values from ANFIS and *LR*

	Training Set			Testing set		
Methods	Instances	MSE	R^2	Instances	MSE	R^2
LR	947	0.3949	0.7779	141	0.3357	0.8167
ANFIS	947	0.0687	0.9650	141	0.1271	0.9346

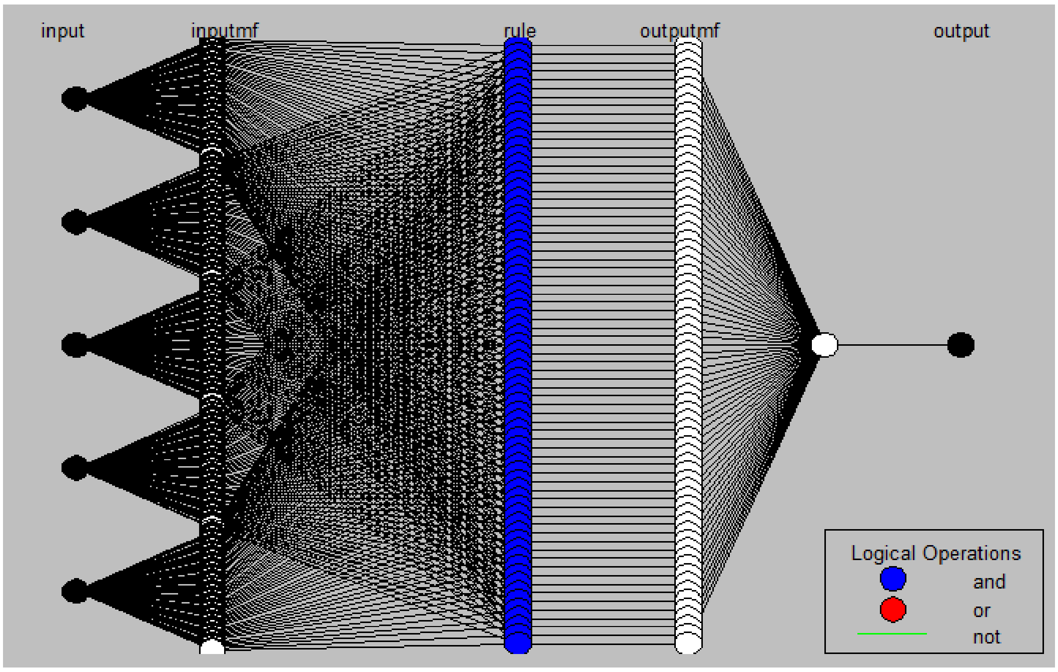


Fig. 8 Structure of implemented ANFIS

loss or quadratic loss while R is the degree of success in reducing standard deviation (SD). It is used extensively in the sciences as a measure of the strength of linear dependence between two variables. The MSE and R^2 are calculated in Eq. (1) as follows

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

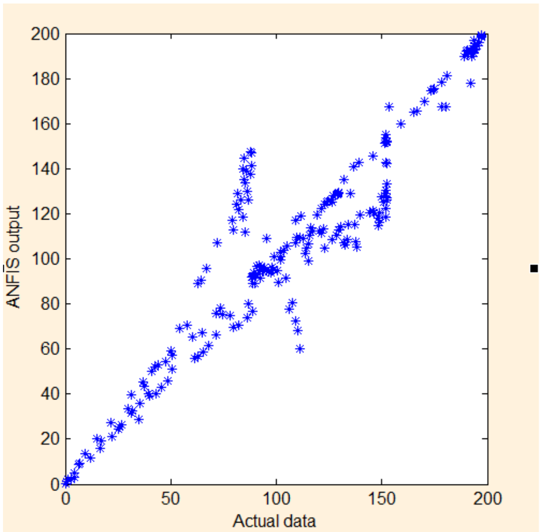
where $\hat{y}(k)$, $y(k)$ and y_{ave} is the output predicted by ANFIS, actual (observed) output and averaged actual output, respectively, and L is the total number of training/testing instances. The results of MSE and R^2 obtained using the ANFIS and the LR separately for training and testing data are summarized in Table 5.

The MSE values derived from ANFIS are more than 2 times smaller compared to the values from the classical linear regression as shown in Table 5. Moreover, the R^2 value derived from ANFIS from train data is 0.9650 which is an exciting value nearest to 1 for a scientist. The outcome of the experiments demonstrates that the difference between the two comparative methods is more evident in the test set. The prediction of shear capacity of channel shear connectors provided by LR and ANFIS for the test data is shown in Fig. 9. The actual and predicted data are represented by the horizontal and vertical axes respectively. A direct linear relation between the actual and predicted data should be the outcome of a precise modelling. For the prediction of shear capacity of channel shear connectors, the proposed ANFIS method is highly accurate and precise compared to the classical LR as revealed in Fig. 9.

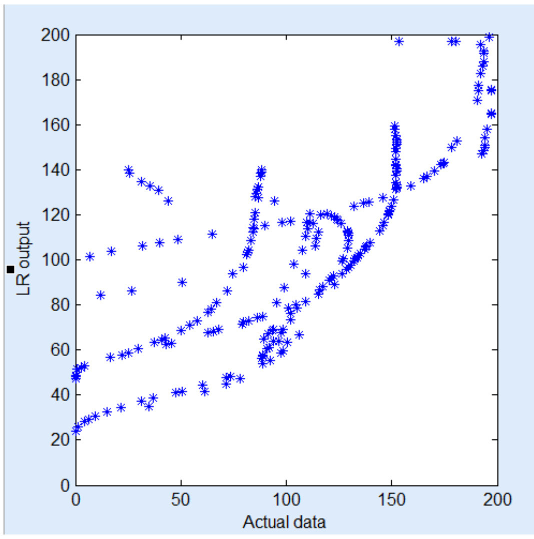
The modelled fuzzy surfaces shown in Figs. 10 and 11 can be used to visualize the relation between input variables and output. The output surface of a FIS model can be examined through the use of a Graphical User Interface (GUI) tool. The GUI offers a visual impression of the possible combinations of the two input variables and the output in 3-D which is a fast visual method of analysing and predicting the shear capacity of channel shear connectors.

Based on the data shown in Table 4, the FIS provides a mathematical solution to determine the shear capacity of channel shear connectors.

Figs. 10 and 11 illustrate the input-output surfaces, namely the nonlinear and monotonic surfaces, which demonstrate the response of the ANFIS model to varying values on 'strain in tie section' prediction.



(a)



(b)

Fig. 9 The prediction of shear capacity of channel shear connectors from: (a) linear regression; (b) ANFIS

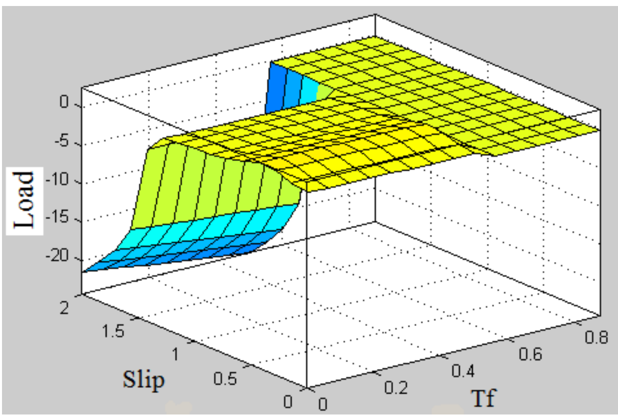


Fig. 10 Fuzzy surface: slip and t_f versus load prediction

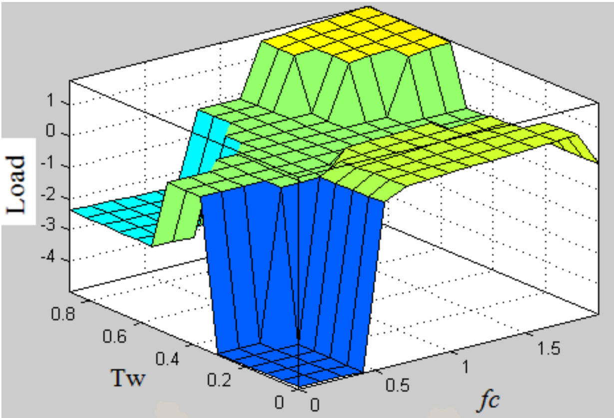


Fig. 11 Fuzzy surface: *Tw* and compressive strength of concrete versus load prediction

5. Conclusions

Due to its complex behaviour and lack of valid approaches, the prediction of shear capacity of channel shear connectors is very difficult. In this study, the researchers examined and compared the use of ANFIS as a non-linear tool with LR as a linear tool in predicting the shear capacity of channel shear connectors. The outcome showed that the proposed model offers an adequate prediction of the shear capacity of channel shear connectors at varying slip, flange of web and thickness, length and concrete compression strength. For both training and testing sets, the value of MSE derived from ANFIS is more than two times times lesser than that of LR and thus more accurate than the classical LR. In conclusion, for the purpose of predicting the shear capacity of channel shear connectors, the performance comparison of both ANFIS and LR for the test data shows that the proposed ANFIS method is more accurate than the classical LR.

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