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ORIGINAL ARTICLE

ANFIS-based prediction of moment capacity of reinforced concrete slabs exposed to fire

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Abstract Reinforced concrete slabs, just as the other structural elements, are highly affected by the high temperatures. Due to the decrease in strength of reinforced concrete members under high temperature, bearing moment capacity of reinforced concrete slabs also decreases. In this study, a prediction model is investigated in order to determine the bearing moment capacities of reinforced concrete slabs under high temperature. Pre-calculated moment capacities of slabs exposed to fire are predicted by the implementation of adaptive neuro-fuzzy inference system (ANFIS) and the prediction performance of ANFIS model is investigated. The bending capacities of slabs with different concrete characteristics and different times of exposure are calculated. High temperature resulting from the duration of fire exposure is calculated as a function of time in accordance with ISO 834. The temperature distribution inside the slab is determined by the adoption of a steady-state one-dimensional heat transfer. The slab was separated into slim slices and the heat in each slice is determined depending on the time of exposure. Forces and resistance of materials under fire exposure are calculated by applying the reduction coefficients in Eurocode 2. Results confirm the high prediction capability of ANFIS model.

Keywords High temperature · Fire · Reinforced concrete slabs · Bearing capacity · Adaptive neuro-fuzzy inference system

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List of symbols

T	Temperature based on time of fire exposure (°C)
t	Time of fire exposure (min)
T_a	Ambient temperature (°C)
k_c	Concrete compressive strength reduction coefficient
f_{CT}	Local compressive strength of concrete (at increasing temperature)
$f_{C20\,°C}$	Concrete compressive strength at 20 °C (N/mm^2)
k_s	Steel tensile strength reduction coefficient
f_{suT}	Local tensile strength of steel (at increasing temperature) (N/mm^2)
$f_{su20\,°C}$	Steel tensile strength at 20 °C (N/mm^2)
Q	Heat transfer rate
A	Surface area of slab (mm^2)
$T_{\infty 1}$, $T_{\infty 2}$	Temperatures on both faces of slab with no internal heat transfer (°C)
T_1	Temperature on the slab face that is exposed to fire (°C)
T_2	Temperature on the slab face that is not exposed to fire (°C)
h	Height of slab (mm)
h_1, h_2	Heat transfer coefficients (W/m^2 K)
k	Heat transfer coefficient of concrete (W/mK)
R_t	Total heat resistance
y	A point inside the slab
$T(y)$	Temperature at a point inside the slab (°C)
D	Slice number of slab
F_s	Tensile force of reinforcement (N)
k_{si}	Steel tensile strength reduction coefficient in ith slice
f_{yd}	Yield strength of reinforcement at 20 °C (N/mm^2)

A_{si}	Reinforcement area in ith slice (mm^2)
F_c	Concrete compressive strength (N)
f_{cd}	Concrete compressive strength at 20 °C (N/mm^2)
k_{ci}	Concrete compressive strength reduction coefficient in ith slice
Δy	Height of each slice of slab (depth)
a	Compressive stress block depth (mm)
M_u	Ultimate moment capacity of slab (N mm)
d	Effective depth of slab (mm)
d'	Concrete cover of slab (mm)
i	Sequence of slice
$O_{n,i}$	Output of ith node at nth layer
$\mu_{Ai}(x)$	Membership grade of A at ith node
$\mu_{Bi}(y)$	Membership grade of B at ith node
w_{i}	Multiplication of signals at ith node
$\bar{w}_i$	Firing rate of ith node
$\bar{w}_i f_i$	Output value of ith node
O_i	Calculated moment capacity value of ith data
P_i	Moment capacity value of ith data predicted by NN model
N	Number of data used for training and testing of NN
R^2	Coefficient of determination
RMSE	Root-mean-squared error (N mm)
MBE	Mean bias error (N mm)

1 Introduction

The resistance of load-carrying members determines the fire resistance of a structure. Reinforced concrete slabs, just as the other structural elements, are highly affected by the high temperatures. Due to the decrease in strength of reinforced concrete members under high temperature, bearing moment capacity of reinforced concrete slabs also decreases. In order to calculate the moment capacity of fire-exposed reinforced concrete slabs, the parameters such as the increasing temperature, the distribution of temperature in slab, cross section and material properties, tensile and compressive forces generated in slices, the depth of equivalent rectangular stress block, the balance of internal forces must be determined. It is required to make many complex calculations to obtain these parameters. Using the fuzzy neural networks model to effectively estimate these parameters is a successful way to eliminate this complexity. A wide range of literature survey has indicated that there is no study related to modeling of moment capacity by means of fuzzy neural networks.

In this study, an estimation model to predict the bearing moment capacity of reinforced concrete slabs exposed to fire is developed by using fuzzy neural networks. Pre-calculated moment capacities of reinforced concrete slabs exposed to fire are predicted with ANFIS model.

Recently, artificial intelligence techniques can provide solutions for wide range of civil engineering problems. Lee, in his study on the determination of compressive strength of concrete, developed an artificial intelligence system to predict the compressive strength [1]. Akbulut et al. [2] developed a neuro-fuzzy system and used it to predict the degree of humidity and shear modulus of sand used in the construction. The results of neuro-fuzzy and multiple regression analysis are compared, and neuro-fuzzy results are found to be more appropriate.

Özsoy and Fırat [3] used ANN to predict the horizontal displacement values that occur in structure due to various reasons. Hola and Schabowicz [4] conducted a study on ANN-based determination of concrete compressive strength obtained by nondestructive testing methods and showed that the ANN is very convenient.

Topçu and Sarıdemir [5] used the aggregate waste shredded from aerated concrete as crushed stone in concrete production. The authors developed an ANN model and compared the results with experimental findings. Topçu et al. [6] investigated the use of optimum pozzolan cement as an additional binding material. The resistance values of cements with different amounts of pozzolan are estimated with the use of neuro-fuzzy system and ANN models. Karahan et al. [7] conducted a study on ANN approach to estimate long-term strength properties of steel fiber-reinforced concrete (SFRC) containing fly ash and developed a neural network model to investigate the mechanical properties of SFRC containing fly ash. Bilgehan and Turgut [8] tested the compressive strength of concrete core samples of reinforced concrete buildings with different ages and used ultrasound device to obtain required data. The obtained data were used as input data, whereas the output data were set to be the compressive strength of concrete. The results indicated the ANN's estimation capability of compressive strength. Bilgehan and Turgut [9] developed an ANN architecture that accounts for concrete intensity in addition to input values obtained by ultrasound technique. The results of this ANN model are found to be very reasonable. Bilgehan et al. [10] performed a study on the buckling analysis of cracked prismatic columns subjected to axial loads using ANN and the transfer matrix method. Yenigün et al. [11] used ANN and classical formulations in their study for estimating the sediment of Euphrates basin. Bilgehan [12] performed a comparative study that takes into account the fuzzy neural network and a new ANN architecture which implements the speed and intensity of ultrasound as input and compressive strength of concrete as output. The author observed that the fuzzy neural network model gives more consistent results in comparison with ANN. In Nazari's [13] work, compressive strength of lightweight inorganic polymers (geopolymers) produced by fine fly ash and rice husk–bark ash together with palm oil clinker (POC) aggregates has been investigated experimentally and modeled based on fuzzy logic. An adaptive neuro-fuzzy inference system (ANFIS) is used to detect the possible damage location in a concrete bridge deck modeled by finite element method in Tarighat's paper [14]. Yuan et al. [15] researched on the structured and unstructured factors which affect the concrete quality. Two hybrid models were proposed in their paper, one was the genetic-based algorithm and the other was the adaptive network-based fuzzy inference system (ANFIS). Dilmac and Demir [16] studied the ANFIS-based modeling of high-strength concrete under uniaxial loading. The results are compared to those of analytical models and found to be in a good agreement.

Additionally, some studies that examined the effect of high temperature on concrete or reinforced concrete elements are also available in the literature. Chen et al. [17] achieved the values of compression and splitting tensile strength of concrete that have been cured at different periods and exposed to high temperature. Erdem [18] investigated the performance of fire-exposed reinforced concrete beams. The results demonstrated the importance of concrete cover in strength of the beam against fire. Using the ISO 834 standards, Xu and Wu [19] have experimentally investigated the heat resistance of four full-scale L-section, four of T-section, a square cross section, and four + section reinforced concrete columns. Ellobody and Bailey [20] conducted a study on modeling of unconnected pre-stressed concrete slabs exposed to fire. Bailey and Ellobody [21] made a series of tests to investigate the fire resistance of single-span concrete slabs with different characteristics of materials. Bailey and Ellobody [22], in another study, have investigated the behavior of the entire structure with fire-exposed pre-stressed concrete slabs. Tanyildizi [23], in his study, developed of a fuzzy logic model for the prediction of mechanical properties of lightweight concrete exposed to high temperature. Erdem [24] developed a neural network model to predict the moment capacity of reinforced concrete slabs exposed to fire.

2 Moment capacity of reinforced concrete slab exposed to high temperature

In order to calculate the moment capacity of fire-exposed reinforced concrete slabs, the high temperature resulting from the time of fire exposure, heat distribution in the slab and reduction in material strength should be determined. After the determination of these parameters, the tensile and compression forces that occur in the slab should be examined. The moment capacity is determined when the forces are in equilibrium [24]. In order to examine the effects of high temperature on material properties and moment capacity of slab, temperature changes must be known. The increase in temperature slab results in deterioration of material and reduction in the moment capacity. It is required to know the heat distribution in the slab in order to obtain the change in material properties. To achieve this, cross section of the concrete slab is divided into slices and the material properties, reduction coefficients and mechanical properties of each slice are determined.

2.1 Temperature–time relationship

In this study, ISO 834 is utilized to define the temperature–time relationship [25]. In ISO 834 temperature–time curve equation is expressed by Eq. 1.

$$T = 345\log(8t+1) + T_a \tag{1}$$

2.2 Concrete compressive strength and steel tensile strength under high temperature

Exposure to high temperatures causes a decrease in compressive strength of concrete. This reduction should be taken into account in calculations. Using a temperature in each location, local compressive strength of the concrete can be calculated by Eq. 2 given in Eurocode 2 [26].

$$\frac{f_{CT}}{f_{C20^\circ C}} = k_c \tag{2}$$

$$\begin{array}{ll} k_c = 1 & T \le 100 \\ k_c = 1.067 - 0.00067T; & 100 \le T \le 400 \\ k_c = 1.44 - 0.0016T; & 400 \le T \le 900 \\ k_c = 0; & T \ge 900 \end{array}$$

Equation 3 is used to determine the values of decreasing tensile strength due to temperature.

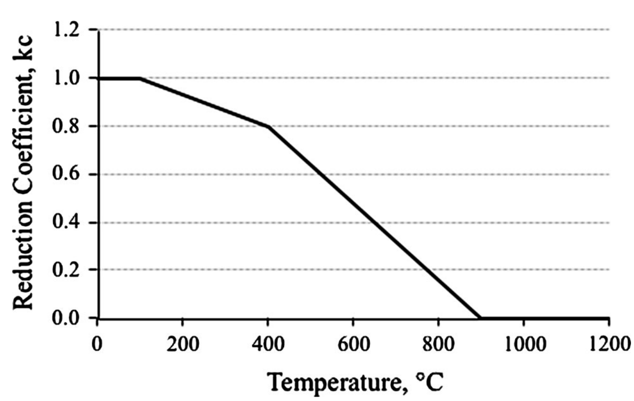


Fig. 1 Temperature-reduction coefficient relationship for concrete

$$\frac{f_{suT}}{f_{su20^\circ C}} = k_s \tag{3}$$

$$\begin{array}{ll} k_s = 1; & 0 \le T \le 350 \\ k_s = 1.899 - 0.00257T; & 350 \le T \le 700 \\ k_s = 0.24 - 0.0002T; & 700 \le T \le 1200 \\ k_s = 0; & T \ge 1200 \end{array}$$

The temperature–reduction coefficients relationship of concrete and steel is illustrated graphically in Figs. 1 and 2, respectively [26].

As can be observed from Fig. 1, the concrete does not lose its compressive strength up to 100 °C and looses 20 % of its normal temperature resistance at 400 °C, about 70 % at 700 °C, and 100 % at 900 °C.

Figure 2 illustrates that the tensile strength of steel starts to decrease at 350 °C, and it looses 20 % of strength at 400 °C, 90 % at 700 °C, and 100 % at 1200 °C.

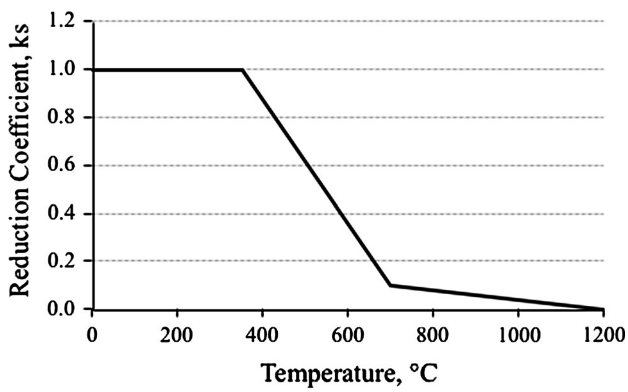


Fig. 2 Temperature–reduction coefficient relationship for steel

2.3 Steady heat transfer in plane slab

It is possible to model the heat transfer as continuous and one dimensional. The concept of heat resistance can be used to determine the rate of steady-state heat transfer in slab. As shown in Fig. 3, the rate of continuous heat transfer can be expressed by Eqs. 4–6 using the total heat resistance on two surfaces [27, 28].

$$\frac{q}{A} = \frac{T_{\infty 1} - T_1}{\frac{1}{h_1}} = \frac{T_1 - T_2}{\frac{h}{k}} = \frac{T_2 - T_{\infty 2}}{\frac{1}{h_2}} \tag{4}$$

$$\begin{aligned} T_{\infty 1} - T_1 &= \frac{q}{A}\frac{1}{h_1} \\ T_1 - T_2 &= \frac{q}{A}\frac{h}{k} \\ T_2 - T_{\infty 2} &= \frac{q}{A}\frac{1}{h_2} \end{aligned} \tag{5}$$

$$Q = \frac{T_{\infty 1} - T_{\infty 2}}{R_t} \tag{6}$$

where, R_t, total heat resistance, can be expressed by Eqs. 7 and 8.

Fig. 3 Heat transfer in reinforced concrete slab

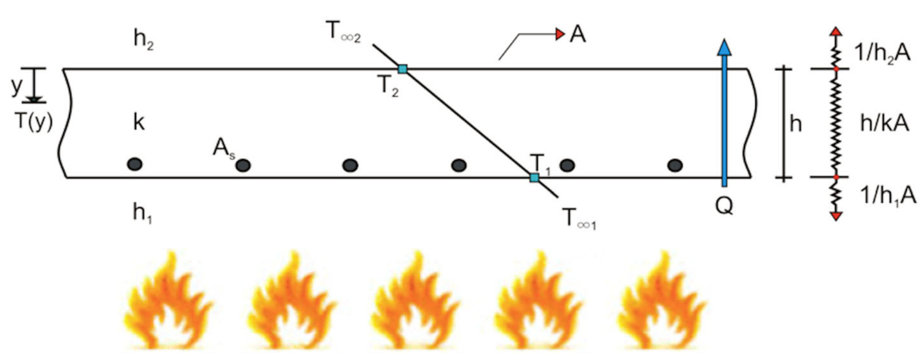
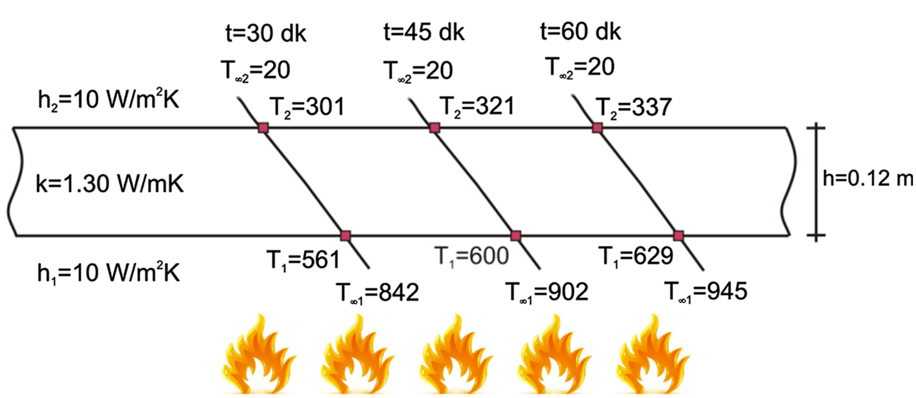


Fig. 4 Heat distribution based on duration of fire exposure



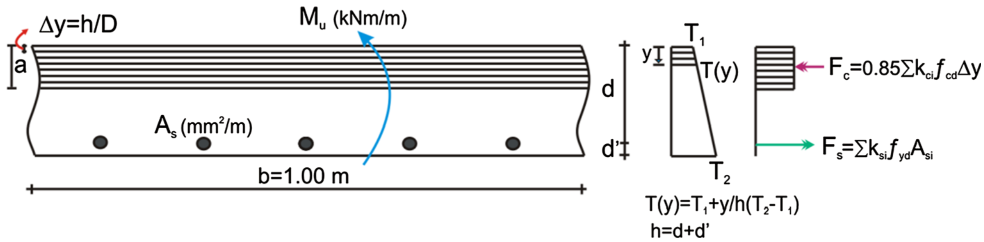


Fig. 5 Temperature change in slab and forces

$$R_t = R_1 + R_s + R_2 \tag{7}$$

$$R_t = \frac{1}{h_1 A} + \frac{h}{kA} + \frac{1}{h_2 A} \tag{8}$$

T(y), the temperature at point y in any slice in slab, can be expressed by Eq. 9.

$$T(y) = T_2 + (T_1 - T_2)\frac{y}{h} \tag{9}$$

The temperature values that occur on two faces of reinforced concrete slab have been calculated for the cases $t = 30, 45$, and 60 min of fire exposure as can be observed from Fig. 4.

As can be seen from Fig. 5, Eq. 10 can be used to calculate the tensile force in the steel reinforcement.

$$F_s = \sum_{\mathrm{i}=1}^{D} k_{si} f_{\mathrm{yd}} \mathrm{A}_{\mathrm{si}} \tag{10}$$

The compression forces for unit width of the concrete can be obtained from the summation of compression forces expressed by Eq. 11.

$$F_c = 0.85 \sum_{i=1}^{\frac{a}{\Delta y}} k_{ci} f_{ci} \Delta \mathrm{y} \tag{11}$$

Eqs. 10 and 11 must be equal for the case that the forces are in equilibrium in the cross section. If they are not equal, a value is reduced gradually and the calculation is repeated until Eqs. 10 and 11 are equal. When the forces are in equilibrium in the slab, moment capacity of slab (M_u) can be calculated by Eq. 12 [24–29].

$$M_u = 0.85 \sum_{i=1}^{\frac{a}{\Delta y}} k_{ci} f_{cd} \Delta \mathrm{y} \left(d - \frac{\Delta y}{2} - i \Delta y \right) \tag{12}$$

In this study, moment capacity prediction of fire-exposed RC slabs is carried out by means of ANFIS whose details are explained in following section.

3 Fuzzy neural networks, ANFIS

3.1 Artificial neural network (ANN)

The artificial neural network (ANN) is a powerful tool to identify the relevance of parameters as well as interaction between them. This approach is considered to be extremely useful if the relationships of parameters are quite complex and the nonlinearity is high [30–32]. For the solution of several engineering problems, the back-propagation (BP) learning algorithm is prominent among many kinds of ANNs [33–35]. The network can learn and adjust the weights of relations between layers after the set of training data is described. This process is repeated until the performance of network is sufficient for the training data and can be consequently implemented for classification or prediction of different set of data output. It is possible to reduce the required number of training data via optimizing the architecture of NN and selecting appropriate input parameters. The more training data are necessary, however, for the case in which the relation between the input and output parameters is more complex and nonlinear [36].

Figure 6 illustrates how a neuron performs a process by taking a set of inputs "*p*," weighting them "*w*," summing them up, adding a bias "*b*," and utilizing the results as an argument for a function with a single value. This function is called the transfer function "*f*," and it results in the neuron output "*a*" [37].

3.2 Fuzzy sets and logic

Zadeh introduced the fuzzy sets and logic concepts as a replacement of Aristotelian logic (1 or 0, exist or not exist) [38]. In fuzzy approach, the focus is generally on the occasions where linguistic uncertainties are of concern in control mechanism of the phenomena. The uncertainties here do not refer to random, probabilistic and stochastic variants; rather it means variations all of which are based on the numerical data. Observing the fact that the important factors in human thinking are not related to numbers but levels of fuzzy sets, Zadeh has focused more on fuzzy approach. According to his opinion, furthermore, each word in a natural language was a brief definition of a fuzzy subset at a space of conversation through which the meaning is conveyed. Accordingly, Zadeh presented linguistic variables as variables whose values are sentences of a natural or artificial language. Statements such as "if–then" are used as fuzzy propositions to define the state of a system and the truth value of proposition defines the matching accuracy of description. The allowance of partial

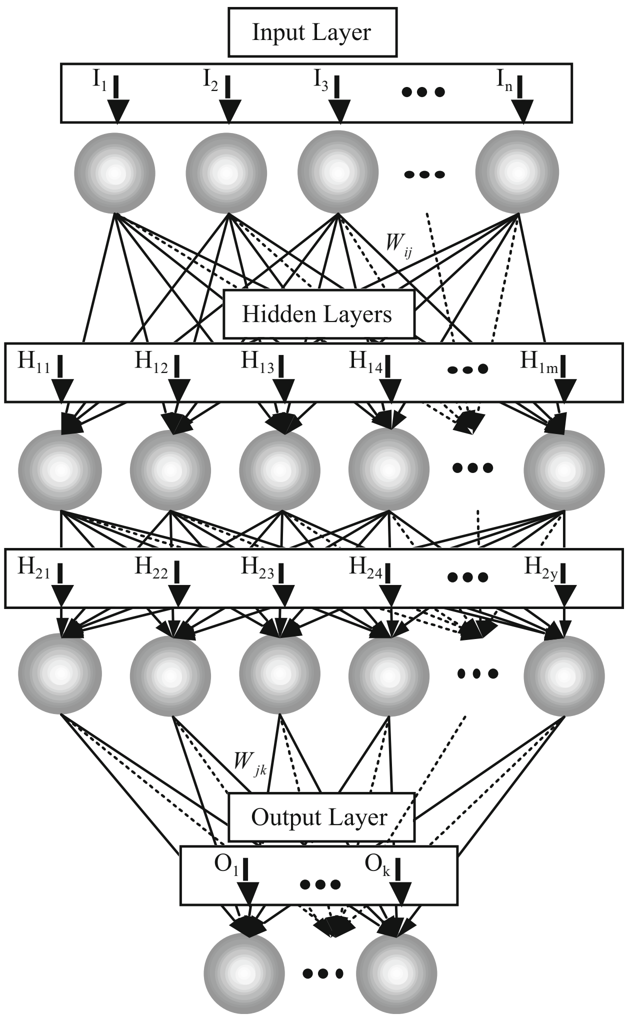


Fig. 6 Typical artificial neural network architecture

belonging of any object to different subsets of the universal set rather than belonging to a single set only is the main idea in the fuzzy logic. By assigning values between 0 and 1 by means of a membership function, partial belonging can be defined numerically. The measurements can be fuzzified even though they are implemented as crisp quantities. In case a form of uncertainty occurs because of imprecision, ambiguity or vagueness, the variable is fuzzy and can be defined by a membership function. In practical applications, the membership function is implemented as linear for the purpose of simplifying the computations [39].

3.3 Adaptive neuro-fuzzy inference system

Jang [40] has introduced the adaptive neuro-fuzzy inference system (ANFIS) as a universal approximator. ANFIS is able to approximate a continuous function on a set of data to a degree of precision and is a new improved modeling approach for the determination of behavior of inaccurately described complex dynamical systems [41, 42]. The main purpose of an ANFIS is to create indefinite fuzzy rules by means of a given input–output data. Thus, in parameter estimation, where the given data are such that the system associates measurable system variables with an internal system parameter, a functional mapping may be constructed by ANFIS that approximates the process of estimation of the internal system parameter [43]. The fuzzy inference system has some deficiencies on the adaptation to cope with changing external environment even though it is composed of systematized data demonstration in the form of fuzzy ''if–then'' rules. As a result, adaptive neuro-fuzzy modeling has been introduced by the incorporation of neural network concepts. The adaptive inference system consists of a network that has a number of interconnected nodes. Those nodes are defined by a node function that consists of fixed or changing variables. Via adjusting the variables of node functions, the network is "learning" the behavior of given dataset throughout the training phase. The main purpose of the basic learning algorithm, the BP, is to keep the measured or defined error at minimum level. The error is usually described by summing of squared differences between desired and the actual model outputs [44]. Takagi and Sugeno [45] investigated the fuzzy-based modeling for the first time. In this current study, the ANFIS modeling architecture is based on the first-order Takagi–Sugeno model that is schematically illustrated in Fig. 7.

$$\textit{Rule. If } \xi \textit{ is } A_j \textit{ and } \beta \textit{ is } B_k \textit{ then } f_i = p_i \times \xi + q_i \times \beta + r_i \tag{13}$$

where $j = 1, 2,\ldots, m$; $k = 1, 2,\ldots, n$.; and $i = 1, 2,\ldots, m \times n$.

A and B are the fuzzy sets defined for ξ and β, respectively. The parameters m and n indicate the number of membership functions defined by the indicated fuzzy input variables, f is a linear consequent function defined in terms of the input variables, and p, q, and, r are the consequent parameters of the Takagi–Sugeno fuzzy model [45].

Two fuzzy if–then rules for first order Takagi–Sugeno fuzzy model are given in Eqs. 14 and 15:

$$\textit{Rule 1. If } \xi \textit{ is } A_1 \textit{ and } \beta \textit{ is } B_1 \textit{ then } f_1 = p_1 \times \xi + q_1 \times \beta + r_1 \tag{14}$$

$$\textit{Rule 2. If } \xi \textit{ is } A_2 \textit{ and } \beta \textit{ is } B_2 \textit{ then } f_2 = p_2 \times \xi + q_2 \times \beta + r_2 \tag{15}$$

The resulting Takagi–Sugeno fuzzy reasoning system is shown in Fig. 8. Here, the output is the weighted average of the individual rules outputs and is itself a crisp value. In this model, nodes of the same layer have similar functions,

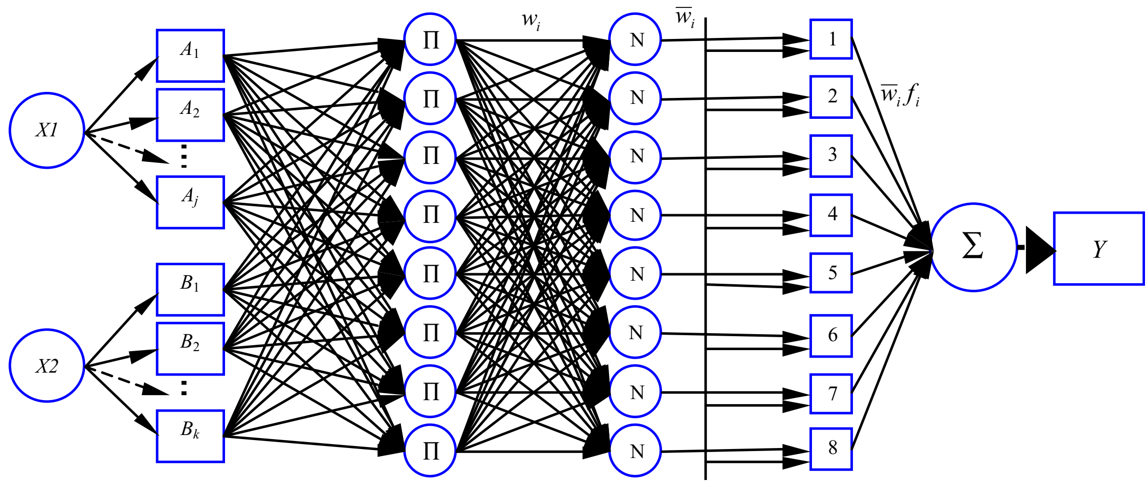
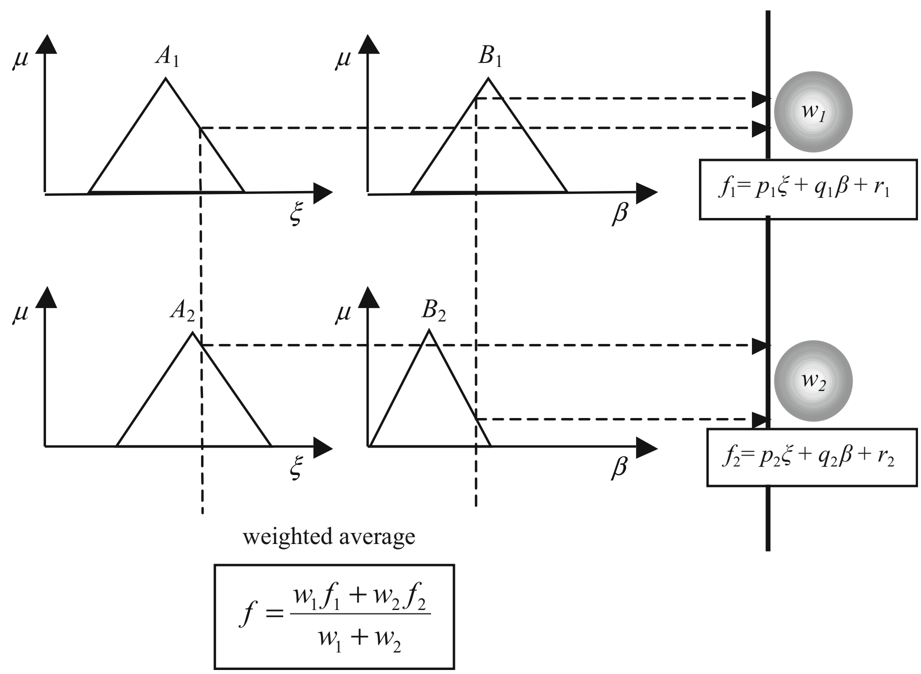


Fig. 7 ANFIS topology based on the first-order Takagi–Sugeno model for the prediction

Fig. 8 First-order Takagi–Sugeno fuzzy model with two rules and two input parameters



as described below. The output of the ith node in layer l is denoted as $O_{l,i}$. The fuzzy inference system shown in Fig. 7 is composed of five layers explained as follows. Each layer involves several nodes. The output signals from the nodes of the previous layer will be accepted as the input signals in the current layer. After manipulation by node function in the current layer, the output will be served as input signals for the subsequent layer.

3.3.1 Layer 1

The first layer of this architecture is the fuzzy layer. Each node of this layer makes the membership grade of a fuzzy set. Every node in this layer is an adaptive node with a node function that may be a generalized bell membership function (Eq. 16), a Gaussian membership function (Eq. 17), or any membership functions.

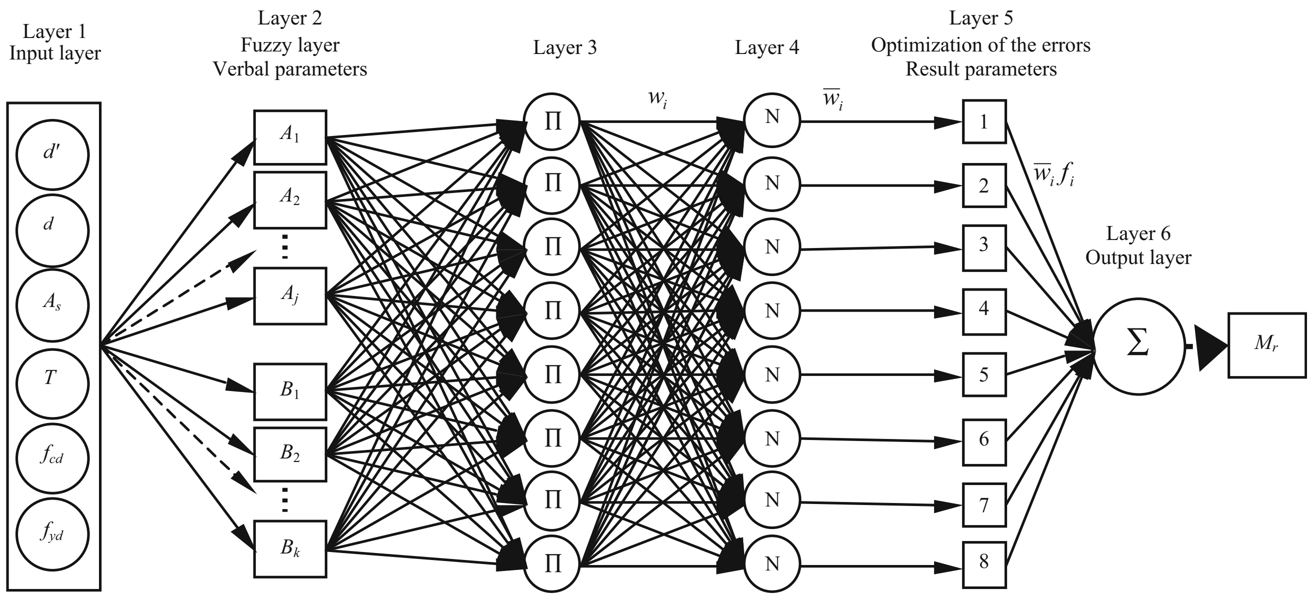


Fig. 9 ANFIS architecture based on Takagi–Sugeno model used in the study

Table 1 Values of parameters taken into account in the analysis

Parameter	Value	Unit
k	1.30	W/mK
h_1	10	W/m^{2}K
h_2	10	W/m^{2}K
d'	10, 20, 30, 40	mm
d	100, 110, 120, 130	mm
A_s	679, 924, 1206	mm^2
t	0, 3, 5, 7, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, 95, 100, 105, 110, 115, 120, 125, 130, 135, 140, 145, 150, 155, 160, 165, 170, 175, 180, 185	min.
f_c	20, 25, 30, 35	N/mm^2
f_y	220, 420	N/mm^2

$$O_{1,j} = \mu_{Aj}(\xi) = \frac{1}{1 + \left|\xi - \frac{c_j}{a_j}\right|^{2b_j}} \quad j = 1, 2, \ldots, m \tag{16}$$

$$O_{1,k} = \mu_{B_k}(\beta) = \exp\left[-\left(\frac{\beta - c_k}{a_k}\right)^2\right] \quad k = 1, 2, \ldots, n \tag{17}$$

where a_i, b_i, and c_i are premise parameters. Also ξ is the input to node i, and A_i is the linguistic label associated with this node function. Premise parameters change the shape of membership function [46].

3.3.2 Layer 2

Every node in this layer is a fixed node, marked by a circle, labeled Π, representing the firing strength of each rule, and is calculated by the fuzzy 'and' connective of 'product' of the incoming signals, i.e., Π-norm operation (Eq. 18):

$$O_{2,i} = w_i = \mu_{A_j}(\xi) \times \mu_{B_k}(\beta) \tag{18}$$

The output signal w_i denotes the firing strength of the associated rule.

3.3.3 Layer 3

In this layer, every node is a fixed node labeled N, representing the normalized firing strength of each rule. The ith node calculates the ratio of the ith rule's firing strength to the sum of the rules' firing strengths by using Eq. 19.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{\sum_{t=1}^{m\times n} w_t} \tag{19}$$

The outputs of this layer are called normalized firing strengths.

3.3.4 Layer 4

Every node in this layer is an adaptive node with a node function represented by Eq. 20, indicating the contribution of the ith rule toward the overall output.

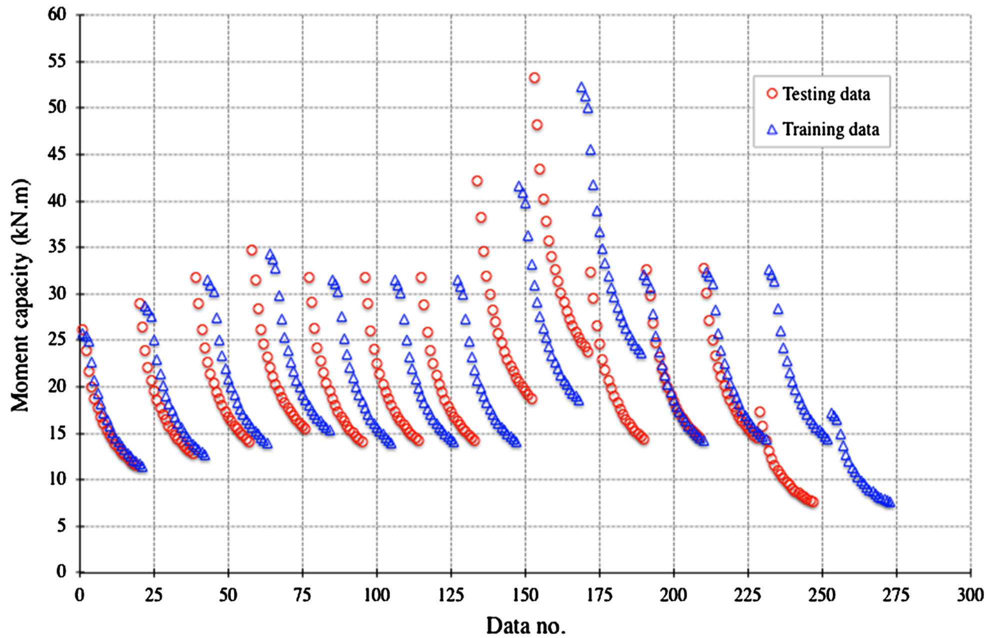


Fig. 10 Moment capacity values in training and testing sets

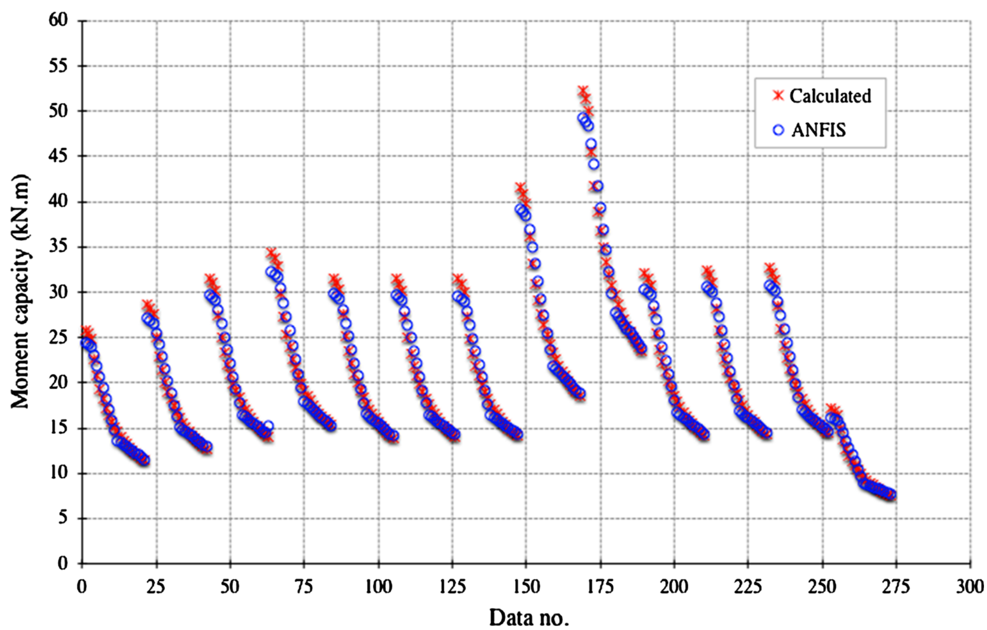


Fig. 11 Moment capacity values calculated versus ANFIS for training data

$$O_{4,i} = \bar{w} \times f_i = \bar{w} \times (p_i \times \xi + q_i \times \beta + r_i) \tag{20}$$

where $\bar{w}_i$ is the output of layer 3, and p_i, q_i, and r_i are the parameter set. Parameters of this layer are referred to as consequent parameters. The consequent parameters of f_i in this layer are to be adapted in order to minimize the error between the neuro-fuzzy inference system outputs and desired results.

3.3.5 Layer 5

This layer's single node is a fixed node labeled Σ and marked by a circle, indicating the overall output as the summation of all incoming signals calculated by Eq. 21

$$O_{5,i} = \sum_{i=1} (\bar{w} \times f_i) = \frac{\sum_i (w_i \times f_i)}{\sum_i w_i} = P_{cr} \tag{21}$$

ANFIS model developed for this study consists of six neurons in the input layer and one neuron in the output layer. Input parameters are concrete cover of slab (d'), effective height (d), area of reinforcement placed in tensile zone (A_s), fire exposure time (t), compressive strength of concrete (f_c) and yield strength of reinforcement (f_y). The ANFIS structure implemented in this study is illustrated with input and output parameters in Fig. 9. When obtaining the moment capacities of reinforced concrete slabs with fuzzy neural network, the

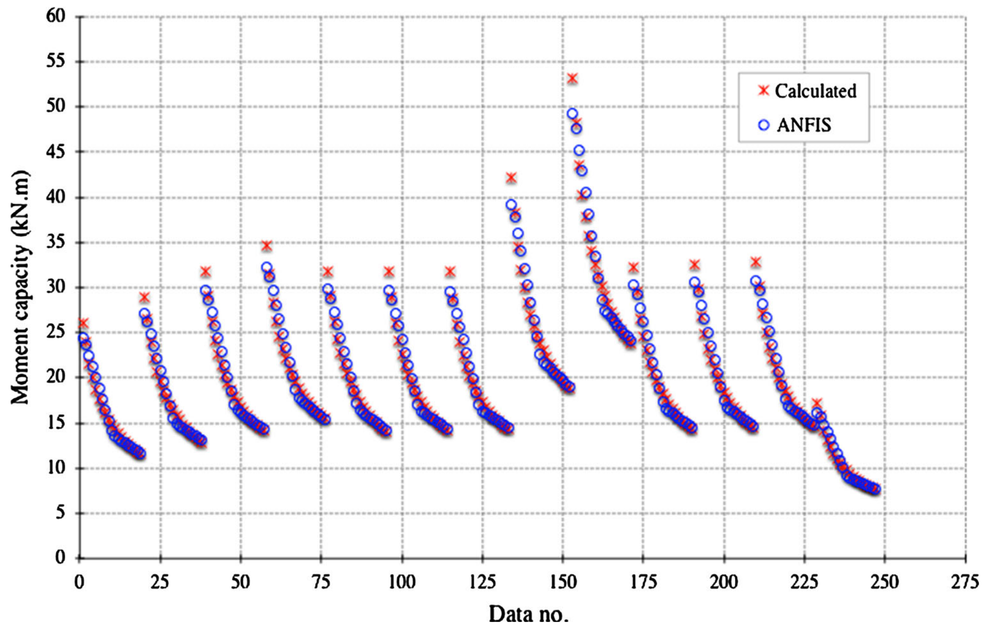


Fig. 12 Moment capacity values calculated versus ANFIS for testing data

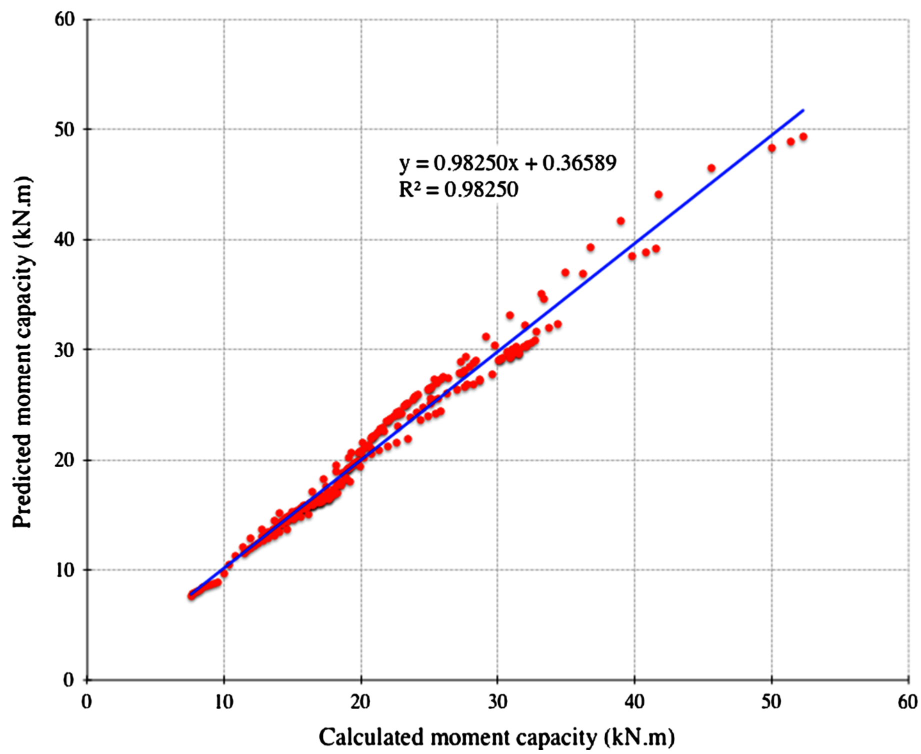


Fig. 13 Predicted and calculated moment capacity values for training

values k, h_1, and h_2 are kept constant. The values of input layer variables and some parameters in developed model are given in Table 1. In this analysis, 55 % of 520 data are used as training set and 45 % are used as testing set. The sets are normalized by using the maximum values of parameters. The parameters that are utilized for performing the ANFIS analysis are selected based on trial-and-error method. The training model is randomly selected.

4 Results and discussion

In this study, an ANFIS model is developed using 520 data in order to predict the moment capacities of fire-exposed reinforced concrete slabs, and the obtained results are compared. The training and testing sets used in ANFIS model are given in Fig. 10.

The relationship between the results of ANFIS and calculated values for training and testing sets are given in

Fig. 14 Predicted and calculated moment capacity values for testing

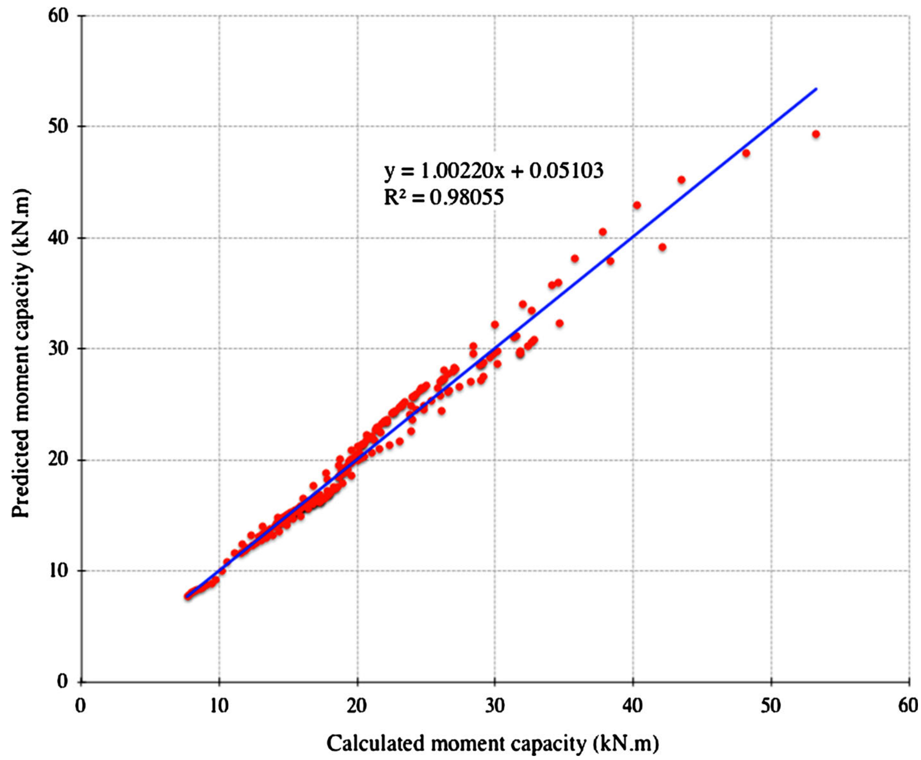


Table 2 Global statistical values obtained for ANFIS

Global statistics	Training set	Testing set
R^2	0.98250	0.98407
RMSE (N mm)	1.02908	1.01951
MBE (N mm)	−0.00001	0.09552

Figs. 11 and 12, respectively. The results indicate that the ANFIS model can successively predict the change in moment capacities of reinforced concrete slabs exposed to high temperature.

Correlation coefficient of ANFIS model is 0.98250 for testing and 0.98407 for training. These values indicate the performance of ANFIS model for predicting the moment capacity. The moment capacity values for training and testing sets obtained by ANFIS model and calculated values are illustrated graphically in Figs. 13 and 14, respectively.

The findings of this study are illustrated graphically and the results are expressed with the global statistical parameters such as coefficient of determination (R^2), root-mean-square error (RMSE), and mean bias error (MBE).

R^2, whose ideal value is 1, is used to observe the linear relationship between the calculated and predicted values. RMSE, whose ideal value is 0, gives idea about the short-term performance. It is always positive and has unit of N mm. MBE, whose ideal value is 0, accounts for long-term performance of correlations by comparing the deviations of calculated and predicted values and has unit of N mm. These parameters are expressed by Eqs. 22–24, respectively.

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N} (O_i - P_i)^2}{\sum_{i=1}^{N} (O_i - O_{ort.})^2} \right) \tag{22}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (P_i - O_i)^2}{N}} \tag{23}$$

$$MBE = \frac{\sum_{i=1}^{N} (P_i - O_i)}{N} \tag{24}$$

The statistical results for training and testing sets are given in Table 2. This study represents that the ANFIS approach for determination of moment capacities of fire-exposed reinforced concrete slabs gives appropriate results.

5 Conclusions

In this study, the effective parameters on moment capacity of fire-exposed reinforced concrete slabs such as effective depth (d), concrete cover (d'), reinforcement area (A_s), compressive strength of concrete (f_{cd}), steel yield strength (f_{yd}) and time of fire exposure (t) are used as input parameters, whereas the ultimate moment capacity (M_u) is used as output parameter.

The effects of d, d', A_s, f_{cd}, f_{yd} and t on moment capacity are investigated and predicted by means of adaptive neuro-fuzzy inference system. A dataset is generated by calculating the moment capacities of fire-exposed reinforced concrete slabs with various properties. In fuzzy neural network analysis, coefficient of determination values is obtained as 0.98250 for training set and 0.98407 for testing set. These values indicate that the fuzzy neural network model works quite successively. It is possible to observe that moment capacities can be predicted with the use of fuzzy neural network model without having to deal with complex calculations.

The future studies on this subject should consider reinforced concrete slab insulation in addition to all of the aforementioned parameters. Furthermore, the bond effect of fiber-reinforced polymers on moment capacity of fire-exposed reinforced concrete slabs should be studied in further researches.

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