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Computational estimation of the earthquake response for fibre reinforced concrete rectangular columns

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Abstract. Due to the impressive flexural performance, enhanced compressive strength and more constrained crack propagation, Fibre-reinforced concrete (FRC) have been widely employed in the construction application. Majority of experimental studies have focused on the seismic behavior of FRC columns. Based on the valid experimental data obtained from the previous studies, the current study has evaluated the seismic response and compressive strength of FRC rectangular columns while following hybrid metaheuristic techniques. Due to the non-linearity of seismic data, Adaptive neuro-fuzzy inference system (ANFIS) has been incorporated with metaheuristic algorithms. 317 different datasets from FRC column tests has been applied as one database in order to determine the most influential factor on the ultimate strengths of FRC rectangular columns subjected to the simulated seismic loading. ANFIS has been used with the incorporation of Particle Swarm Optimization (PSO) and Genetic algorithm (GA). For the analysis of the attained results, Extreme learning machine (ELM) as an authentic prediction method has been concurrently used. The variable selection procedure is to choose the most dominant parameters affecting the ultimate strengths of FRC rectangular columns subjected to simulated seismic loading. Accordingly, the results have shown that ANFIS-PSO has successfully predicted the seismic lateral load with $R^2 = 0.857$ and 0.902 for the test and train phase, respectively, nominated as the lateral load prediction estimator. On the other hand, in case of compressive strength prediction, ELM is to predict the compressive strength with $R^2 = 0.657$ and 0.862 for test and train phase, respectively. The results have shown that the seismic lateral force trend is more predictable than the compressive strength of FRC rectangular columns, in which the best results belong to the lateral force prediction. Compressive strength prediction has illustrated a significant deviation above 40 Mpa which could be related to the considerable non-linearity and possible empirical shortcomings. Finally, employing ANFIS-GA and ANFIS-PSO techniques to evaluate the seismic response of FRC are a promising reliable approach to be replaced for high cost and time-consuming experimental tests.

Keywords: ANFIS; PSO; GA; ELM; fibre-reinforced concrete; Seismic response; compressive strength

1. Introduction

In the presence of reinforcement fibres inside the concrete mix, fibrous concrete is a composite while its tensile and compressive strength has been tremendously increased. It is also highly energy-absorbing and can't be easily annihilated under the impact loads, also has functional properties such as high strength, high ductility, energy absorption and cracking resistance with many applications. For example, instead of conventional reinforced concrete, fibrous concrete can be used in the construction of industrial flooring or used in the construction of impact-resistant masonries such as burial masonry structures and explosive masonry warehouses. Indeed, a concrete-formed masonry has a great capability to absorb impact energy, thus appropriate in making airport runways. Other FRC applications include the construction of prefabricated building components such as canopy panels or concrete spraying on curved surfaces such as tunnels. The concrete application in a structure has the merits of being insulated against sound and high-speed performance, however, the presence of fibres within the concrete is completely random with rare usage. Using this concrete in the construction of beams and columns or similar structures is favorable; however, the use of traditional method of steel grating is more economical and convenient. Respectively, a variety of fibres can increase the strain capacity, impact

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Table 1 Typical Fibre features

Fibre type	Specific gravity (kg/m^3)	Modulus of elasticity (Gpa)	Tensile strength (Mpa)	Elongation at break (%)	Acid/Alkali resistance
Polypropylene (PP) (Deng *et al.* 2006, Behfarnia *et al.* 2014, Snoeck *et al.* 2015)	910	1.5-12	240-900	15-80	High
Polyethylene (PE) (Zollo 1997, Arnon Bentur 2007)	920-960	5-100	80-600	4-100	High
Steel (ST) for comparison (Xu *et al.* 2000)	7840	200	500-2000	0.5-3.5	Low to High

resistance, energy absorption, wear resistance and tensile strength of concrete. Generally, the use steel fibre structures can be a complementary role for rebar. Steel fibres could resist on the crack propagation and could increase the concrete resistance to fatigue, impact, shrinkage and thermal stress. Polymeric fibres used in concrete are organic polymer derivatives including various formulations as nylon, acrylic, polyester, aramid, polyethylene (PE), polypropylene (PP) and carbon. The mechanical and physical properties of polymeric fibres and approximate costs are shown in Table 1.

Fibre application can decline the requirement(s) of transverse reinforcement in FRC members, particularly for their seismic design (McMullin *et al.* 1993, Jalali *et al.* 2012, Shahi *et al.* 2013, Ghassemieh *et al.* 2015, Park *et al.* 2016, Bossio *et al.* 2017, Zandi *et al.* 2018) as important criteria to some critical members while needing many reinforcements as beam to column joint(s) (Daie *et al.* 2011, Jalali *et al.* 2012, Shao *et al.* 2015, Shah *et al.* 2016c, Shah *et al.* 2016d, Khorami *et al.* 2017a, Shao *et al.* 2018, Shariati *et al.* 2018b, Chen *et al.* 2019a, Shariati *et al.* 2019g). Accordingly, using fibre is able to efficiently resolve the rebar's congestion in the joints to properly surpass the construction quality. In this case, the positive influence of fibre should be taken in the evaluating of ultimate strength and other properties of FRC members adjusted to the seismic loads as ductility and failure and energy dissipation capacity. Despite few designing codes like Eurocode 8 and ACI 318 (Committee *et al.* 2008), these codes is not the case in the favorable impact of fibre. Typically, the current design previsions of FRC members are experimental and globally differ (Hamidian *et al.* 2011, Shariati *et al.* 2011b, Sinaei *et al.* 2012, Mohammadhassani *et al.* 2014a, Ziaei-Nia *et al.* 2018, Shariati *et al.* 2019a). Although the mathematical modelling of the ultimate strengths of FRC rectangular columns subjected to simulated seismic loading is suggested in few studies (McCulloch *et al.* 1943, Thai *et al.* 2012, Aghakhani *et al.* 2015), the major objective of this research is to avoid from the high nonlinearity of mathematical methods by applying soft computing methodology. Indeed, soft computing methods have not required the knowledge of internal system while providing a compact solution for multi-variable problems. AI[1] techniques have recently played a significant role in engineering goals' progression (Shariati *et al.* 2020). ANNs[2] as a sub-branch of AI could solve the three various shortcomings as 1) function-approximation, 2) classification, and 3) time series prediction (Singh *et al.* 2005, Shariati 2008, Prasad *et al.* 2009, Mohammed *et al.* 2011, Mohammadhassani *et al.* 2013, Mohammadhassani *et al.* 2014b, Mohammadhassani *et al.* 2014c, Mohammadhassani *et al.* 2015b, Shariati *et al.* 2019c). Considering all the cases, a raw model of ANN is generally developed and trained by the optimization techniques like classic algorithms as backpropagation algorithms (LeCun *et al.* 2015, Paknahad *et al.* 2018, Toghroli *et al.* 2018a). However, some disadvantages such as being stuck in local extremums and having trouble in crossing plateaus of the error function landscape are the deficiencies of classic algorithms (Jadav *et al.* 2012, Xu *et al.* 2019). Addressing these drawbacks, metaheuristic optimization algorithms such as GA (Whitley 1994, Shariati *et al.* 2019c), PSO[3] (Kennedy *et al.* 1997), and ICA[4] (Atashpaz-Gargari *et al.* 2007) can be used. The global search feature of these algorithms can improve the performance of ANN in some cases (Shariati *et al.* 2010, Shariati *et al.* 2011c, Shariati *et al.* 2011d, Shariati *et al.* 2013, Shariati *et al.* 2015b, Li *et al.* 2019, Shao *et al.* 2019a). Few studies have been performed in ANNs and the optimization techniques to solve the nonlinear and sophisticated engineering problems.

According to the different applications of structural components, the compressive strength is the critical feature of the concrete (Sahab 2008, Aghakhani *et al.* 2015, Arabnejad Khanouki *et al.* 2016, Shah *et al.* 2016b, Toghroli *et al.* 2017, Heydari *et al.* 2018, Shariati *et al.* 2018a, Toghroli *et al.* 2018b, Katebi *et al.* 2019, Milcic *et al.* 2019, Shao *et al.* 2019b, Shi *et al.* 2019b, Trung *et al.* 2019b, Xu *et al.* 2019, Zhao *et al.* 2019, Safa *et al.* 2020). Therefore, the composite beams and floor systems that faced the axial and compressive forces should be investigated under several loading patterns (Shariati 2013, Shariati *et al.* 2016b, Mansouri *et al.* 2017, Hosseinpour *et al.* 2018, Davoodnabi *et al.* 2019, Luo *et al.* 2019, Sajedi *et al.* 2019, Xie *et al.* 2019). Besides, the compressive, tensile, and flexural strength of concrete can be evaluated while subjected to different experimental analyzes, and hence, different design parameters and loading scenarios can be estimated with respect to the highest risk (Sinaei *et al.* 2011, Shariati *et al.* 2012a, Safa *et al.* 2016, Shahabi *et al.* 2016d, Toghroli *et al.* 2016, Paknahad *et al.* 2018). Also, the effectiveness of cementitious additives has been proved by precursor studies where the slag and fly ash represented the

[1] Artificial intelligence
[2] Artificial neural networks
[3] particle swarm optimization
[4] imperialist competitive algorithm

most significant role (Shariati *et al.* 2010, Sinaei *et al.* 2011, Shariati *et al.* 2012b, Shariati *et al.* 2012a, Shariati *et al.* 2012e, Shariati *et al.* 2012d, Shariati 2013, Shariati *et al.* 2013, Shariati *et al.* 2014a, Shahabi *et al.* 2016a, Shahabi *et al.* 2016b, Shariati *et al.* 2016a, Tahmasbi *et al.* 2016, Khorramian *et al.* 2017, Hosseinpour *et al.* 2018, Nasrollahi *et al.* 2018, Wei *et al.* 2018b, Davoodnabi *et al.* 2019).

The compressive strength has been widely discussed and investigated in previous papers, and different concrete mixtures represented various structural behaviors along with the experimental tests (Shariati *et al.* 2011a, Shariati *et al.* 2012c, Mohammadhassani *et al.* 2013, Shariati *et al.* 2015a, Shahabi *et al.* 2016c, Shi *et al.* 2019c). Therefore, new mix proportions should be assessed under the compressive tests. Besides, using artificial intelligence, which has been proved to be a convenient approach for engineering applications, could be a wise solution to address the future necessities of experimental analyzes. Consequently, analytical algorithms could be performed on prior experimental studies to predict and evaluate the obtained results (Hamdia *et al.* 2015, Mohammadhassani *et al.* 2015a, Shao and Vesel 2015, Toghroli 2015, Mansouri *et al.* 2016, Thang *et al.* 2016, Khorami *et al.* 2017b, Sari *et al.* 2018, Shao *et al.* 2018, Shariat *et al.* 2018, Armaghani *et al.* 2019, Shariati *et al.* 2019h, Shi *et al.* 2019a, Trung *et al.* 2019a).

The steel-concrete composite components have been proposed to mitigate the lack of mechanical properties, such as compressive strength. On the other hand, the composite systems have several types that should be investigated by the experimental and analytical tests (Shariati *et al.* 2012b, Shariati 2014, Shariati *et al.* 2014a, Shariati *et al.* 2014b, Khorramian *et al.* 2015, Shariati *et al.* 2015c, Khorramian *et al.* 2016, Tahmasbi *et al.* 2016, Shariati *et al.* 2017, Sadeghipour Chahnasir *et al.* 2018, Wei *et al.* 2018a). Generally, the compressive strength of concrete could affect the composite systems performance; hence each new concrete mixture should be investigated experimentally and analytically and then used in the composite constructions (Arabnejad Khanouki *et al.* 2011, Sinaei *et al.* 2011, Mohammadhassani *et al.* 2014a, Mohammadhassani *et al.* 2014c, Arabnejad Khanouki *et al.* 2016, Shah *et al.* 2016a, Heydari and Shariati 2018, Luo *et al.* 2019, Shao *et al.* 2019a, Shao *et al.* 2019b, Shi *et al.* 2019c, Xie *et al.* 2019)

Since the pavement would tolerate the direct punch forces and static compressions, the compressive strength of pavement materials such as pervious concrete is one of the most fundamental features in pavement designs which should be enhanced by additive powders like slag and fly ash (Toghroli *et al.* 2017, Bazzaz 2018, Bazzaz *et al.* 2018, Toghroli *et al.* 2018b).

Concrete additives are applied to improve the mechanical and chemical properties of the concrete. However, the use of cementitious materials and pozzolans such as FA, slag, silica fume, metakaolin, perlite, and other additives have been carried out to develop the performance of concrete (Shah *et al.* , Ismail *et al.* 2018, Zhao *et al.* 2018, Safa *et al.* 2019, Shariati *et al.* 2019f). Besides, FA and slag had a significant effect on the quality of concrete, especially the compressive strength (Arabnejad Khanouki *et al.* 2010, Abedini *et al.* 2017, Nosrati *et al.* 2018, Abedini *et al.* 2019, Sajedi and Shariati 2019). In addition, various methods are currently used to evaluate the structural health monitoring; hence, constructions produced from concrete should be appropriately inspected during serviceability (Hamidian *et al.* 2012).

A research by (Ahmadi *et al.* 2017) has predicted the compressive strength of CCFT[5] by using ANN while compared the results with the experimental results. ANN has been nominated as a reliable predictor and an efficient tool in the prediction of compressive strength of CCFT. A research has estimated the ductility of reinforced concrete (RC) beams (Bengar *et al.* 2016), concluding that ANN could be taken in the predictions with less scatter than the statistical methods. Researches by (Amirian *et al.* 2018a, Amirian *et al.* 2018b) have studied the application of ANN in the modelling of compaction-dilation data and evaluating the performance of unconventional oil reservoirs while focusing on ANNs in the performance evaluation of oil reservoirs. Recent researches have studied the strain of tie section of high-strength-self-compacting (HSSCC) deep beams by developing an ANN model and LR[6] model. In this study, ANN model could gain a performance index 90 times better than LR model. A research by (Liu *et al.* 2019) have employed an ANN model for the rapid numerical simulation and seismic performance prediction of RC columns. Therefore, high agreement between the model and test results has validated the application of ANN in this area. To assess the applicability of ANN in compressive strength prediction by P-, S-, and R-wave velocities, a research by (Park *et al.* 2019) has resulted that considering all P-, S-, and R-wave velocities have led to more accurate results than only P-wave velocity. A research by (Chen *et al.* 2018) has utilized a hybrid ANN-PSO model in the shear strength's prediction of squat RC walls. Comparing ANN-PSO with other predictive models has revealed the superiority of ANN-PSO. A research by (Chen *et al.* 2019b) has employed hybrid ANN-GA and ANN-ICA models to control and secure the retaining walls in dynamic conditions, therefore, ANN-ICA has shown better performance indices than ANN-GA. A research by (Shariati *et al.* 2019b) has studied the utilization of various hybrid models including ANN-ICA, ANN-PSO, ANN-GA, and ANN-ABC[7] in the prediction of slope stability under dynamic and static conditions, resulting the higher capability of ANN-PSO. The partial inclusion of fibre in FRC has led to the property changes such as mechanical properties. Despite the occurring of these changes in test, realizing the most effective parameter might not be possible. Addressing this problem, ANFIS (Ali 2015, Sedghi *et al.* 2018) has been used with the incorporation of two main population-based metaheuristic algorithm as PSO and GA to determine the most dominant factors for FRC seismic response and compressive strength prediction. Furthermore, an ELM algorithm has employed to challenge of hybrid algorithms results. ANFIS as a neural network

[5] concrete-filled steel tubes

[6] Linear regression

[7] Artificial bee colony

intelligence system can learn and adapt automatically (Toghroli *et al.* 2014, Sedghi *et al.* 2018) and against many analytical processes has not required the system parameters to be known, thus its more straightforward solutions can be adopted for multivariable problems. ANFIS has been applied to choose the most dominant parameters for the flexural strength prediction and could remove the vagueness of the process by eliminating some input factors to generate the best prediction conditions. In other words, ANFIS has been applied to convert the multiple performance characteristics into a single performance index. Subsequently, fuzzy systems are used to interpret and assess the data; however, some problems have already been observed by using these algorithms as accuracy and versatility. In this respect, ANFIS algorithm has been adopted to works along with two different pioneer hybrid metaheuristic algorithms as PSO and GA to detect the most determining seismic response characteristics of FRC and to predict the compressive strength of FRC. PSO is an evolutionary intelligence algorithm inspired by the social behavior of fish schooling or bird flocking (Chen *et al.* 2018). Due to the relatively conventional approach of laboratory data in concrete sector, as well as investigations on the application of different fibres to improve the structural strength of concrete and to increase its microstructure homogeneity, AI can be well suited to optimize, estimate and predict the structural characteristics of fibrous concrete. GA is a particular type of evolutionary algorithm that utilizes evolutionary biology techniques like inheritance, biological mutation and Darwin's selection principles to find the optimum formula for prediction or pattern matching. GA is a good option for the regression-based prediction techniques, also as a programming technique to solve the problems by using genetic evolution. This study as hybrid metaheuristic methods based on fuzzy-inference techniques has performed ANFIS-PSO and ANFIS-GA algorithms to predict both lateral seismic load as dynamic response and compressive strength of FRC. In this regard, a verified experimental database from investigated the seismic response of FRC rectangular columns has been carried out. An ELM algorithm has been also employed as a generally proved AI to evaluate the presented results which are ultimately discussed and compared.

2. Methodology

2.1 Flexural strength models

Considering the calculation of flexure strength of RC columns, the model by applying ACI rectangular concrete stress block in the compressive zone of calculation section is well known. By using the mean compressive stress of 0:85f 0c in this block and the final compressive strain of concrete of 0.003, the theoretical flexural strength of RC columns could be computed. Few developed compressive stress blocks are suggested like New-RC model in Japan and CEB-FIP MC90 in Europe. In contrast, all of the models have typically required a complicated calculation. Moreover, as a comparative flexural strength model, the current research has presented a simplified block calculation model suggested by CEB-FIP MC90. On the other hand, regarding the discrepancy between the resistance of RC beams and columns adjusted to seismic loads, this study has used the strength models developed based on the study of RC/FRC columns. Ignoring the low amount of compressive reinforcement and proposing the height of concrete compression zone (x) with uniform stress block can be provided by below equations

$$\chi = \frac{\omega_1}{k_c} d = \frac{\rho_1 f_{yl}/f_{1c}}{(1-f_{1c}\ /\ 250)} d' \tag{1}$$

$$f_{1c} = 0.95 f_c' \tag{2}$$

Based on the moment equilibrium in the cross-section of column, the flexural capacity (moment) of RC column is computed as

$$M_u = A_{sl} f_{yl} z = A_{sl} f_{yl} (1 - 0.5\chi/\ d') d' \tag{3}$$

Z = the inner lever arm

Since the applied inner lever arm is less than the one achieved in a more realistic stress distribution (in theory), even for RC columns, the model should be conservative when used for the prediction of flexural strength of column. The shear resistance mechanism of RC column has been initially introduced by a model. According to Fig. 1(a), the shear strength of RC column has included 3 main parts 1) concrete contribution V_c, 2) truss-mechanism component V_s, and 3) the contribution from axial load V_p (Eq. (4)).

$$V_n = 0.29\sqrt{f_c'} bd + \frac{d-c}{2a} p + \frac{A_v f_{yt} d' cot 30^0}{S} \tag{4}$$

At the same time, the lateral component force attained from the non-directive tensile actions of fibre at main diagonal cracked section could maintain the fourth shear contribution to the total shear resisting of FRC columns, say the one provided by fibre V_f (Fig. 1(b)). Subsequently, to represent the positive impacts of fibre, the compressive depth C_R of FRC column under seismic action could be regarded as 50% of the overall column depth. Thus, the original model is initially modified as $V_{Priestley}$. Considering the discrepancy between the experimental and calculated shear strengths of the modified model $V_{\text{Priestley}}$, simplification, uniformity of calculation and the enhancing effect of fibre are expressed according to the basic concrete compressive, thus the relative nominalized difference rates of all the shear failure specimens have been attained. The relationship between the volume fraction of fibre and the relative nominalized difference ratios are presented in Fig. 2.

Accordingly, divers rates are linearly increased by the raise of fibre in concrete, meaning that the contribution of shear strength from fibre has been linearly increased by applying the volume fraction of fibre in concrete. Thus, V_f is

$$V_f = (11_{\rho F} + 0.044)\sqrt{f_c'} A_e \tag{5}$$

Applying the Eq. (5) and the re-considerations in modified model, all shear strength of FRC columns under seismic loads could be computed as

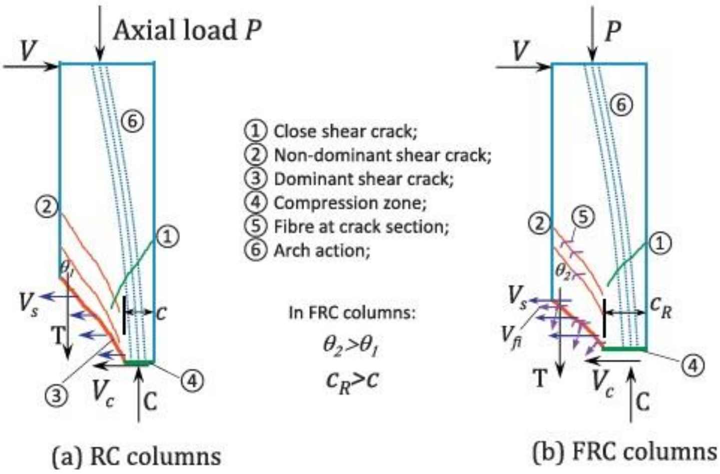

Fig. 1 The shear transfer mechanisms consideration in RC/FRC columns (Cai *et al.* 2017)

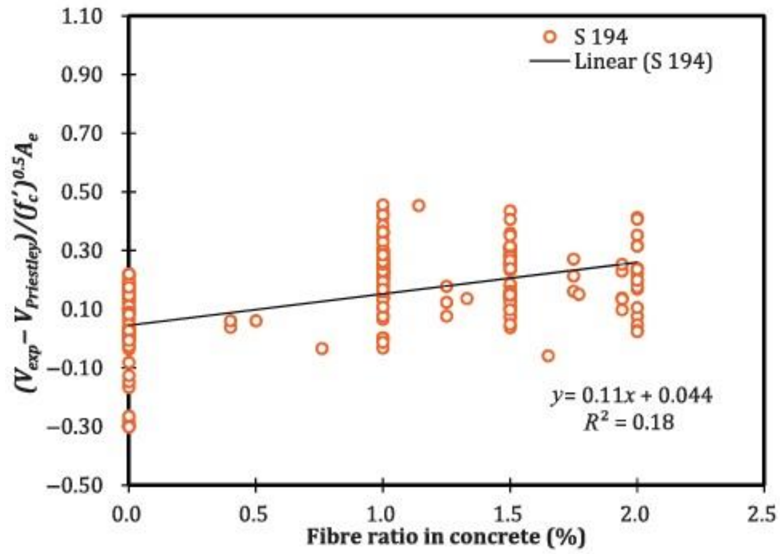

Fig. 2 Fiber volume ratio vs relative difference ratio$(V_{\text{exp}} - V_{\text{Priestley}})/(f'_{\text{c}})^{0.5} A_e$ (Cai and Degée 2017)

$$V_{FRC} = 0.29\sqrt{f_c'}A_e + \frac{d'}{4a}p + \frac{A_v f_{yt} d'}{S} + (11_{\rho F} + 0.044)\sqrt{f_c'}A_e \tag{6}$$

2.2 Ultimate flexure capacity

Modifying the moment calculation of FRC column(s) is calculated as Eqs. (7) and (8)

$$M_{FRC} = k_n k_{sp} A_{sl} f_{yl}(1 - 0.5\chi_f/d')d' \tag{7}$$

$$k_{sp} = 1.3 - 0.05(a/d) \geq 0.95 \tag{8}$$

Therefore, based on the current database, k_{sp} is taken as more significant than 0.95. The proposed moment model is able to evaluate the experimental outcomes with a better agreement compared to the existed models.

3. Analytical assessment

3.1.1 ANFIS algorithm and architecture

An adaptive network is a multilayer feed-forward the network including of nodes and connected by directed links, whose node(s) performs an especial performance on its incoming signals to produce a single node output. Each link in an adaptive network specifies the direction of signal flow from one node to another, besides no weights is related to the link. Particularly, the configuration of an adaptive network conducts a static node performance on its incoming signals to produce a single node output, and each node performance is a parameterized performance with modifiable parameters. By changing these parameters, the node functions and the overall behavior of adaptive network are also altered. Fig. 7 represents the whole system architecture consisting of five layers as product layer, de-

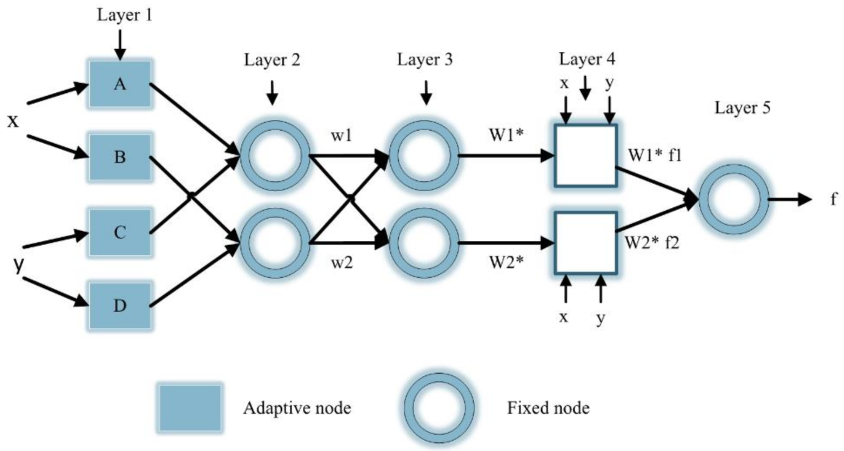

Fig. 3 The basic architecture of ANFIS

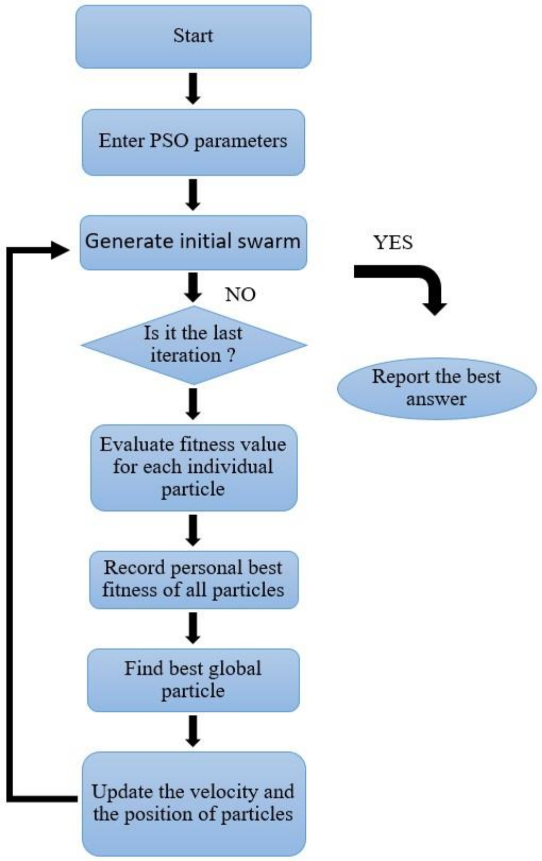

Fig. 4 The flowchart of sequential steps of PSO algorithm

fuzzy layer, fuzzy layer, normalized layer and total output layer. Considering the input/output data for a set of parameters, ANFIS models a FIS[8] whose membership function parameters are adjusted by applying either a backpropagation algorithm alone or in permutation with a least-squares type of method. The major purpose of ANFIS is to delineate the optimal variables of equivalent FIS parameters by using a learning algorithm. The parameter optimization is performed across the training session in a way that the error between the target and actual output is minimized.

[8] fuzzy inference system

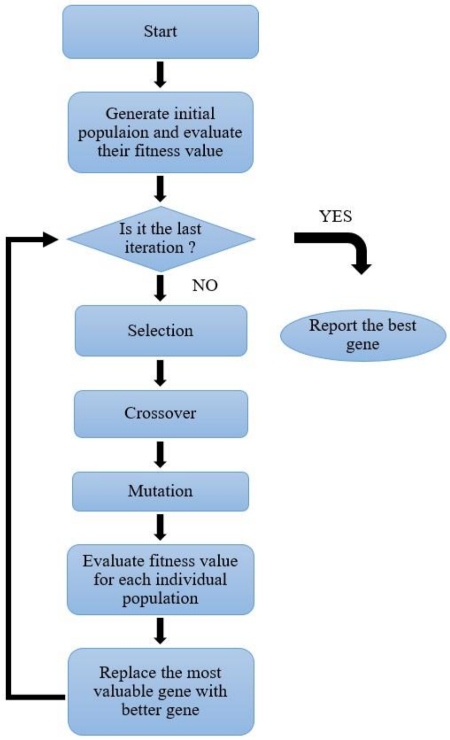

Fig. 5 the flowchart of sequential steps of GA algorithm

A hybrid algorithm is utilized for the optimization, which is the combination of least square estimate and gradient descent method. Those parameters optimized in ANFIS are the premise parameters, defining the shape of membership functions. For decreasing the error measure, any several optimization routines could be used after constituting MFs. The parameter set of an adaptive network allows fuzzy systems to learn from the modeled data. It is assumed that the adaptive system under consideration has two inputs *V1* and *V2* and one output *f*. Let us scrutinize a first-order Takagi, Sugeno and Kang (TSK) FIS containing two rules:

Rule 1: If (v is V1) and (d is D1) then $f_1 = p_1 v + q_1 d + r_1$

Rule 2: If (v is V2) and (d is D2) then $f_2 = p_2 v + q_2 d + r_2$

p1, p2, q1, q2, r1, *r2* = linear parameters
V1, V2, D1, D2 = nonlinear parameters
V1 , *D1* = the membership functions of ANFIS (antecedent)
p1, q1, r1 = the following parameters

Circle and square are used to reflect the adaptive capabilities, while a circle represents a fixed node and square shows an adaptive node, say parameter(s) could be altered during adapting or training. ANFIS is developed from the integration of neural network (NN) and fuzzy logic. During the ANFIS designing, the number of membership functions, the number of training epochs and the number of fuzzy rules should be accurately tuned. The mapping of those parameters is highly important for the system because it might take the system to over fit the data or is not able to fit the data. This adjusting could be gained by applying a hybrid algorithm with the combination of the least-squares method and the gradient descent method with a mean square error method. The latest difference between ANFIS output and the desired objective means an accurate ANFIS system. Thus, it’s tended to decline the training error in training process. The integration of fuzzy logic and NN as FNN[9] has been built and typically ANFIS. NN has many inputs and multiple outputs, however, the fuzzy logic has many inputs and one single output, thus the combination of these two is called ANFIS (Walia *et al.* 2015). ANFIS as a FIS is used in the adaptive networks’ framework (Jang 1993, Shariati *et al.* 2019d) including five layers (Fig. 7). The central core of ANFIS network is a FIS. The first layer receives inputs and converts them to fuzzy values by the membership functions (Toghroli *et al.* 2014, Sedghi *et al.* 2018, Shariati *et al.* 2019e).
Every node in first layer is selected as an adaptive node with a node function

$$O_i^1 = \mu A_i(x) \tag{9}$$

A_i = a linguistic label
O_i^1 = the membership function of A_i

Bell-shaped membership function is usually selected due to its high capacity for the regression of nonlinear data (Sari *et al.* 2019), also it functions with the maximum value of *1* and minimum value of *0*

$$\mu(x) = bell(x; a_i, b_i, c_i) = \frac{1}{1 + \left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}} \tag{10}$$

[9] fuzzy neural network

$\{a_i, b_i, c_i, d_i\}$ = parameters set

x = the input

The parameters of first layer are known as *premise parameters*.

The second layer multiplies the incoming signals and sends their product to the next layer

$$w_i = \mu A_i(x) \times \mu B_i(y), \qquad i = 1,2 \tag{11}$$

Each output of the nodes shows the firing strength of a rule. In the rule layer (third one), the ratio of i^{th}node firing strength of rule to other nodes is calculated

$$w_i^* = \frac{w_i}{w_1 + w_2} \qquad i = 1,2 \tag{12}$$

The outcomes w_i^* are known as *normalised firing strength.* In defuzzification layer (forth layer), each node has a node function as below

$$O_i^4 = w_i^* f_i = w_i^*(p_i x + q_i y + r_i) \tag{13}$$

where w_i^*= the output of the third layer
$\{p_i, q_i, r_i\}$ = the parameters of forth layer known as *following parameters*.
The 5th layer includes the output layer in which the overall output is calculated by summing all the incoming signals

$$O_1^5 = f = \sum_i w_i^* f_i \tag{14}$$

In this process, a threshold value between the actual value and the output is set, then, the following parameters are obtained by the least-squares model, and an error for each data is obtained. If this value is larger than the considered threshold, the premise parameters are updated through the gradient descent method. This procedure continues until the error becomes lower than the threshold. Since the parameters are simultaneously obtained by the two algorithms (least squares and decent gradient algorithm), the used algorithm is known as *a hybrid algorithm.*

3.1.2 Particle Swarm Optimization (PSO)

PSO is another vital member of swarm intelligence algorithm initially built by Kennedy and Eberhart (1995) while motivated by the social behavior of fish schooling or birds flock. It shares many similar features with the evolutionary computation techniques like GA. Like other population-based intelligence systems, PSO needs a primary population of random solutions. The search for optima is gained by updating generations without evolution operators like mutation and crossover. The potential resolutions are generally called *particles in PSO.* These particles fly by the resolution space through their own experience(s) and the current optimal particles. Thus, PSO is functionally comparable and might be alternatively used for GA. In last decade, PSO is frequently applied as an optimization algorithm due to its effectiveness in performing rigorous optimization tasks. Also, the scheme gains better outcomes in a costly and faster method in comparison with few models with less parameter to adjust. Application could be used in the problem solving of multi-objective integer programming, optimization, clustering, classification, combinatorial optimization, and min-max drawbacks, or more engineering applications. There are M agents (particles) applied in PSO algorithm. Each agent is treated as a particle with infinitesimal volume with its properties explained by the current position vector, its personal best position vector and velocity vector including N-dimensional vectors with the properties according to N decision values. At the n^{th} iteration, the three vectors explaining the properties of particle i $(1 \le i \ \le M)$ are:

1. The current position vector: $X_{i,n} = \left(X_{i,n}^1, X_{i,n}^2, \ldots, X_{i,n}^j, \ldots, X_{i,n}^N\right)$, in which every component of the vector shows a decision variable of problem and $1 \le j \ \le N$

2. The velocity vector: $V_{i,n} = \left(V_{i,n}^1, V_{i,n}^2, \ldots, V_{i,n}^j, \ldots, V_{i,n}^N\right)$, denoting the current position increment when $1 \le j \ \le N$

3. The personal best position vector: $P_{i,n} = \left(P_{i,n}^1, P_{i,n}^2, \ldots, P_{i,n}^j, \ldots, P_{i,n}^N\right)$ $1 \le j \ \le N$

The personal best position vector denoted as *pbest* in pseudo-code notation and applied to return the best objective performance variable or fitness value in the subsequent iterative procedure. The primary approximation of $X_{i,0}$ is mightily produced within the search domain $\left[X_{min}^j, X_{max}^j\right]$ $(1 \ \le j \ \le N)$, in which X_{min}^j and X_{max}^j are the upper limit and the lower limit of particle positions in j^{th} dimension. Typically, the uniform distribution on $\left[X_{min}^j, X_{max}^j\right]$ in j^{th} dimension has been applied to make the primary current position vector. Likewise, the initial velocity vector $V_{i,0}$ might be initialized by selecting its j^{th} component randomly on $\left[-V_{max}^j, V_{max}^j\right]$ $(1 \ \le j \ \le N)$ in which V_{max}^j is the upper limit of velocities in j^{th} dimension. The initial approximation of $P_{i,n}$ could be set as the initial current position vector. At the n^{th} iteration, the particle with its personal best position which returns the best objective function value among all the particles is named *the global best particle*. This personal best position is denoted as $P_{g,n}$ recorded in the position vector $G_n = \ (G_n^1, G_n^2, \ldots, G_n^N)$ known as *the global best position.* Here δ is the global best particle index. The update of $P_{i,n}$ is given by

$$P_{i,n} = \begin{matrix} X_{i,n} & if\ f\left(X_{i,n}\right) \ < f\left(P_{i,n-1}\right) \\ P_{i,n-1} & if\ f\left(X_{i,n}\right) \ \ge \ f(P_{i,n-1}) \end{matrix} \tag{15}$$

and thus G_n can be found by
$G_n = P_{\delta,n}$, where

$$\delta = \arg \min_{1 \le i \le M} \left[f\left(P_{i,n}\right)\right].$$

At the $(n+1)^{\text{th}}$ iteration

$$V_{i,n+1}^j = \ V_{i,n}^j + C_1 r_{i,n}^j\left(P_{i,n}^j - X_{i,n}^j\right) + C_2 R_{i,n}^j\left(G_n^j - X_{i,n}^j\right), \tag{16}$$

$$X_{i,n+1}^j + \ X_{i,n}^j + \ V_{i,n+1}^j \tag{17}$$

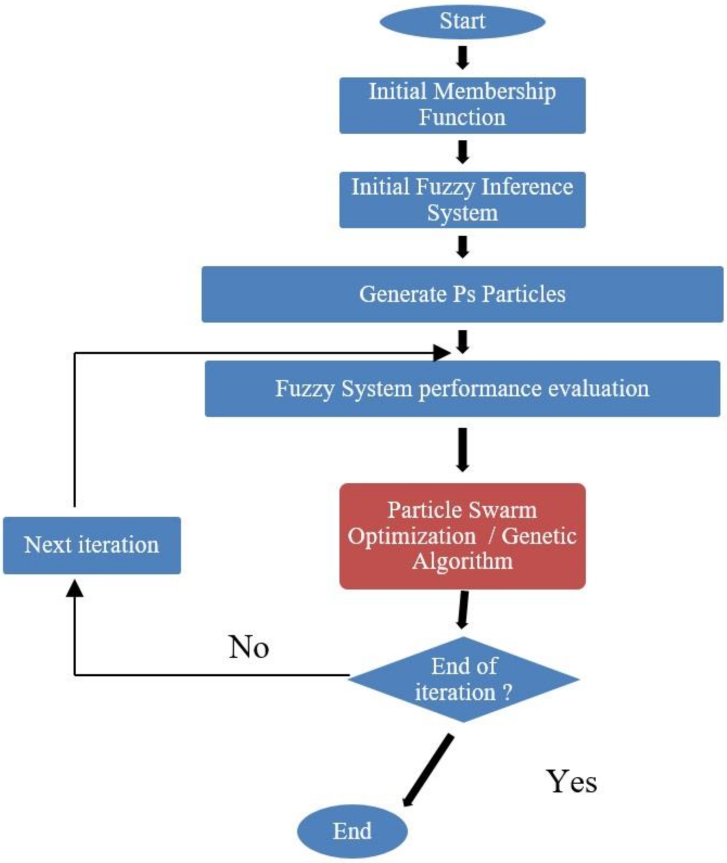

Fig. 6 The flowchart of sequential combination of ANFIS-PSO and ANFIS-GA algorithm

3.1.3 Genetic Algorithm (GA)

GA is a metaheuristic algorithm belonging to the larger class of EA[10] as an evolutionary algorithm that mimics the principles of biological evolution in nature. GA is commonly utilized to make high quality resolutions to the search of shortcomings and optimization by relying on bio-inspired operators such as mutation, crossover and selection followed by Holland (1960) to introduce GA and Goldberg (1989) (Sadeghi *et al.* 2014, Suhatril *et al.* 2019). In GA, the variables of a problem are encoded as chromosomes initially selected, then overlapped and mutated in an evolutionary procedure. After many evolution times, the best individual is gained. Regarding the convergence and robustness of GA, it takes much less time and more accuracy in finding an optimal solution.

GA has three operators 1) selection, 2) crossover, and 3) mutation which are applied on the population of all possible resolutions for developing their fitness function in each iteration or generation. A string describes each solution like the original chromosomes. At first, the population is randomly produced and continued until the achievement of terminating criterion like the exceeding of a given limit of generations. Align with the purpose of this study, GA code is rewritten in MATLAB (version 2019). Thus, a uniform crossover is applied while genes are randomly selected by one of Roulette wheel selection, Tournament selection and Random selection methods. GA implementation has included 5 primary steps 1) Setting the structure of gene, (2) deciding the evaluation criteria of gene (objective function), (3) generating an initial population of genes, (4) selecting an offspring generation mechanism, and (5) coding the procedure in a computer program (Fig. 5).

3.1.4 Extreme Learning Machine (ELM)

Huang *et al.* (2006) has provided the extreme learning machine as an AI tool for SLFN[11] architecture. In ELM, the weights of SLFN input are randomly selected, while the output weights are analytically determined. The main advantage of ELM is its breakneck speed in finding the weights of network, also systematically determines all the network factors and prevents unnecessary interference of humans. This is a different method from ANN, ANFIS, and SVM due to the use of ELM in finding the weights of SLFN. ELM is a recent applicable tool compared to the intelligence methods due to it benefits in different study fields. Three steps are involved in developing of ELM 1) a SLFN is constructed, 2) the weights and biases of network are randomly selected, 3) the output weights are estimated

[10] Evolutionary algorithms

[11] Single-layer feed-forward neural network

by inverting the hidden layer output matrix. For a dataset including d-dimensional vectors for $i = 1, 2, 3, \ldots, N$ training sample, a SLFN with L hidden nodes is mathematically defined as follows

$$f_L(x) = \sum_{i=1}^{L} \beta_i G(a_i, b_i, x), \qquad x \in R^n, \qquad a_i \in R^n \tag{18}$$

a_i, b_i = learning parameters of hidden nodes
β_i = the output weight matrix between the output neurons and hidden neurons
G (a_i, bi, x) = the output value of i^{th} hidden node with input x
$G(a_i, b_i, x)$, $g(x): R \to R$ is a non-linear piecewise continuous performance that should satisfy the ELM approximation theorem by using various activation performances used in NN based modelling. A sigmoid equation is used to develop ELM

$$G(a_i, b_i, x) = \frac{1}{1 + exp(-a_i x + b_i)} \tag{19}$$

ai & bi ∈ R

The approximation error should be reduced for solving the weights that connect the hidden and output layer (β) through the least square fitting

$$\min \|H\beta - T\|^2 \quad \beta \in R^{L \times m} \tag{20}$$

Accordingly, $\|H\beta - T\|$ is the Frobenius norm and H is the randomized hidden layer output matrix as

$$H = \begin{bmatrix} G(a_1, b_1, x_1) & \cdots & G(a_L, b_L, x_1) \\ \vdots & \cdots & \vdots \\ G(a_1, b_1, x_N) & \cdots & G(a_L, b_L, x_N) \end{bmatrix}_{N \times L} \tag{21}$$

Thus, the target matrix in data training period is explained as

$$T = \begin{bmatrix} t_1^T \\ \vdots \\ t_L^T \end{bmatrix}_{N \times m} = \begin{bmatrix} t_{11} & \cdots & t_{1m} \\ \vdots & & \vdots \\ t_{N1} & \cdots & t_{Nm} \end{bmatrix}_{N \times m} \tag{22}$$

An optimum resolution can be determined by solving the following system of linear equations

$$\beta = H^{\dagger} T \tag{23}$$

$H^{\dagger}$ = Moore-Penrose generalized inverse function
β = the output weights of network

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{L \times m} = \begin{bmatrix} \beta_{11} & \cdots & \beta_{1m} \\ \vdots & & \vdots \\ \beta_{L1} & \cdots & \beta_{Lm} \end{bmatrix}_{L \times m} \tag{24}$$

The output weight β can be used to estimate the targets of problem for any given input vector (x).

3.2 Hybrid ANFIS-PSO/GA Architecture

The diagram of sequential PSO/GA and ANFIS combination is shown in Fig. 8. In PSO, swarm begins with a group of random solutions named *a particle* while si⇀ shows the particle's position. Likewise, a particle swarm moves in the problem space in which vi⇀ shows the particle's velocity. Function *f* is verified at each time slap by the input si⇀. Each particle records its best position associated to the best fitness obtained to this point in pi⇀ vector. pig⇀ tracks the most appropriate position defined by any neighborhood member. In a standard PSO, pig⇀ shows the most proper point within the whole population. A new velocity is gained for any particle *i* in each iteration based on the best individual positions, pi(*t*)⇀, and p⇀ig(*t*) neighborhood, thus the new velocity could be represented by

$$v_i \rightharpoonup (t+1) = wv_i \rightharpoonup (t) + c_1 \emptyset_1 \rightharpoonup . \left(p_i \rightharpoonup (t) - x_i \rightharpoonup (\mathrm{t})\right) + c_2 \emptyset_2 \rightharpoonup . \left(p_i \rightharpoonup (t) - x_i \rightharpoonup (\mathrm{t})\right)$$

w = inertia weight

The positive acceleration coefficients are depicted by *c1* and *c2*. *Ø1⇀*, while *Ø2⇀* shows the uniformly-distributed random vectors as (0,1) in which a random value is tried for every dimension. *vi⇀* limited in the *[-vmax⇀, vmax⇀]* series rely on the problem provided that the velocity has sometimes exceeded the mentioned limit, and rearranged in its suitable curbs. Based on their velocities, every particle has changed its position as

$$s_i \rightharpoonup (t+1) = s_i \rightharpoonup (t) + v_i \rightharpoonup (t+1) \tag{25}$$

Regarding *vi⇀* and *si⇀*, the particle population tends to cluster around the best.

3.3 Performance evaluation

To evaluate the function of all developed models, *RMSE*[12], *r*[13], *and* R^2 [14] are used

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (P_i - O_i)^2}{n}} \tag{26}$$

[12] root mean squared error
[13] Pearson correlation coefficient
[14] determination coefficient

Table 2 Details of the input variables

Inputs	Variables	Minimum	Maximum	Mean Value	Std*
Input 1	Width (mm)	150.00	400.00	202.94	33.92
Input 2	Height (mm)	140.00	400.00	208.30	34.22
Input 3	Shear Span Ratio (a/d)	1.00	10.71	2.42	1.61
Input 4	Concrete Compressive Strength (Mpa)	18.30	158.00	38.67	17.11
Input 5	Fibre Fraction Ratio (%)	0.00	3.00	0.92	0.67
Input 6	Fibre Yielding Strength (Mpa)	0.00	1600.00	581.49	344.87
Input 7	Maximum Lateral force (kN)	13.50	636.50	138.73	79.24

* Std = Standard Deviation

Table 3 Inputs and Outputs of database

Inputs and Outputs	Variables	Minimum	Maximum	Mean Value	Std*
Input 1	Width (mm)	150.00	400.00	202.94	33.92
Input 2	Height (mm)	140.00	400.00	208.30	34.22
Input 3	Shear Span Ratio (a/d)	1.00	10.71	2.42	1.61
Input 4	Concrete Compressive Strength (Mpa)	18.30	158.00	38.67	17.11
Input 5	Fibre Fraction Ratio (%)	0.00	3.00	0.92	0.67
Input 6	Fibre Yielding Strength (Mpa)	0.00	1600.00	581.49	344.87
Input 7	Maximum Lateral force (kN)	13.50	636.50	138.73	79.24
Output 1	Concrete Compressive Strength (Mpa)*	18.30	158.00	38.67	17.11
Output 2	Maximum Lateral force (kN)	13.50	636.50	138.73	79.24

* Compressive Strength and Lateral load were employed both as input and output according to their order in the database

$$r = \frac{n\left(\sum_{i=1}^{n} O_i \cdot P_i\right) - \left(\sum_{i=1}^{n} O_i\right) \cdot \left(\sum_{i=1}^{n} P_i\right)}{\sqrt{\left(n\sum_{i=1}^{n} O_i^2 - \left(\sum_{i=1}^{n} O_i\right)^2\right) \cdot \left(n\sum_{i=1}^{n} P_i^2 - \left(\sum_{i=1}^{n} P_i\right)^2\right)}} \tag{27}$$

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(O_i - \overline{O_i}\right)\cdot\left(P_i - \overline{P_i}\right)\right]^2}{\sum_{i=1}^{n}\left(O_i - \overline{O_i}\right)\cdot\sum_{i=1}^{n}\left(P_i - \overline{P_i}\right)} \tag{28}$$

P_i , O_i = the predicted and observed variables
n = total number of considered data

Comparing the performance of ANFIS-PSO, ANFIS-GA and ELM have been performed through MATLAB (version 2019), adding that all the codes run in one computer system with no external compiler or toolbox.

3.4 Statistical data

To analyse the characteristics affecting the flexural response of specimens exposed to high temperatures, the selected nine structural parameters has predicted the deflection and flexural capacity of specimens to more accuracy. The selected attributes are gained based on the importance and quality of the experimental data in the next section. The collected database is composed of 317 datasets. Experimental data of Width (mm), Height (mm), Fiber Fraction Ratio (%), Maximum Lateral force (kN), Maximum Lateral force (kN), fiber tensile Concrete Compressive Strength (Mpa), Fiber Yielding Strength (Mpa), Shear Span Ratio (a/d) and Concrete Compressive Strength (Mpa) are used as inputs in each model for prediction and optimization (Table 2).

4. Models development

As prior mentioned, the purpose of this article is to gain the most compelling algorithm optimizing and to predict the seismic response. Thus, by the use of each five sub database, the impact of a critical portion of fibre-reinforced concrete could be analysed. Thereafter, by comparing the obtained results from their placement in AI models, the quality of their impact and determination have been gained (Table 3). The characteristics of temperature fibre have to be presented in all datasets due to its important in FRC properties. Therefore, database has been set for the hardened concrete variables, beside the lateral seismic load and compressive strength directly related to each other due

Table 5 Parameter characteristics used for ANFIS-PSO in this study.

FIS Clusters	Population Size	Iterations	Inertia Weight	Damping Ratio	Learning coefficient	
					Personal	Global
10	300	150	1.00	0.99	1	2

Table 6 Analytical prediction results through ANFIS-PSO algorithm

	Test		Train	
Lateral load prediction	Std	11.19545547	Std	9.823105383
	e mean	0.607023834	e mean	0.07197157
	R^2	0.8756	R^2	0.9019
	r	0.935723509	r	0.949682397
	RMSE	11.20264199	RMSE	14.99834454
	Test		Train	
Compressive Strength prediction	Std	4.06790175	Std	3.058751324
	e mean	0.000881726	e mean	-0.08208611
	R^2	0.609	R^2	0.8078
	r	0.780358665	r	0.898755692
	RMSE	4.064532983	RMSE	4.671791712

*Std = standard deviation

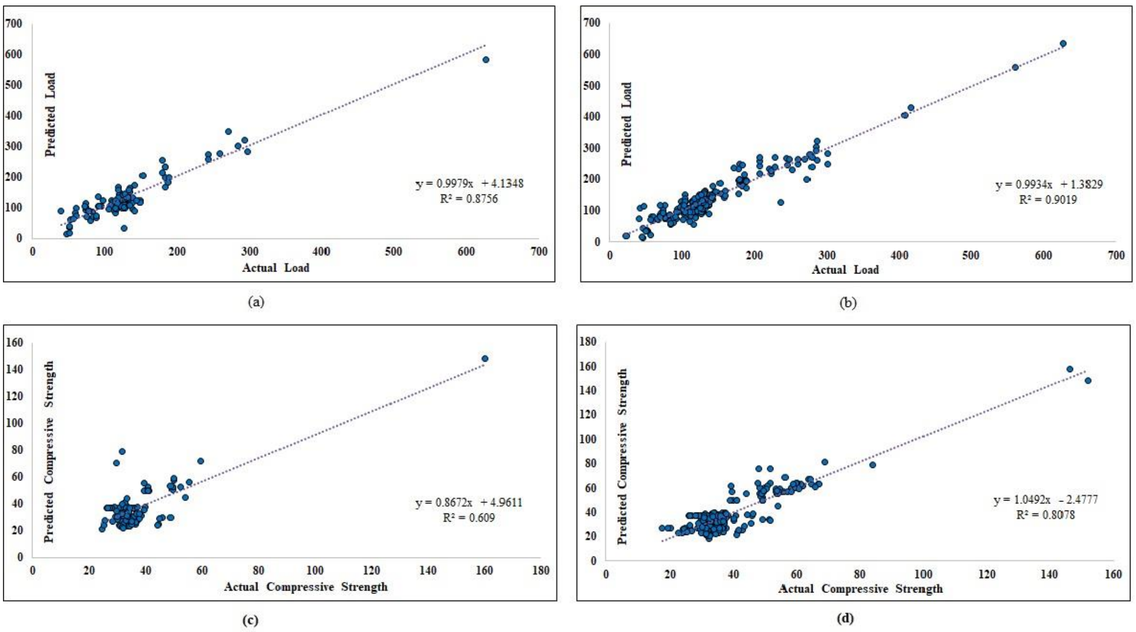

Fig. 7 ANFIS-PSO prediction vs experimental results regression for (a) lateral load test phase, (b) lateral load train phase, (c) compressive strength test phase and (d) compressive strength train phase

to the experimental study. On the other hand, load and strength could be substituted as either input or output.

5. Results

All the three employed algorithms of this study are separately tuned. In order to optimise the coefficients of the

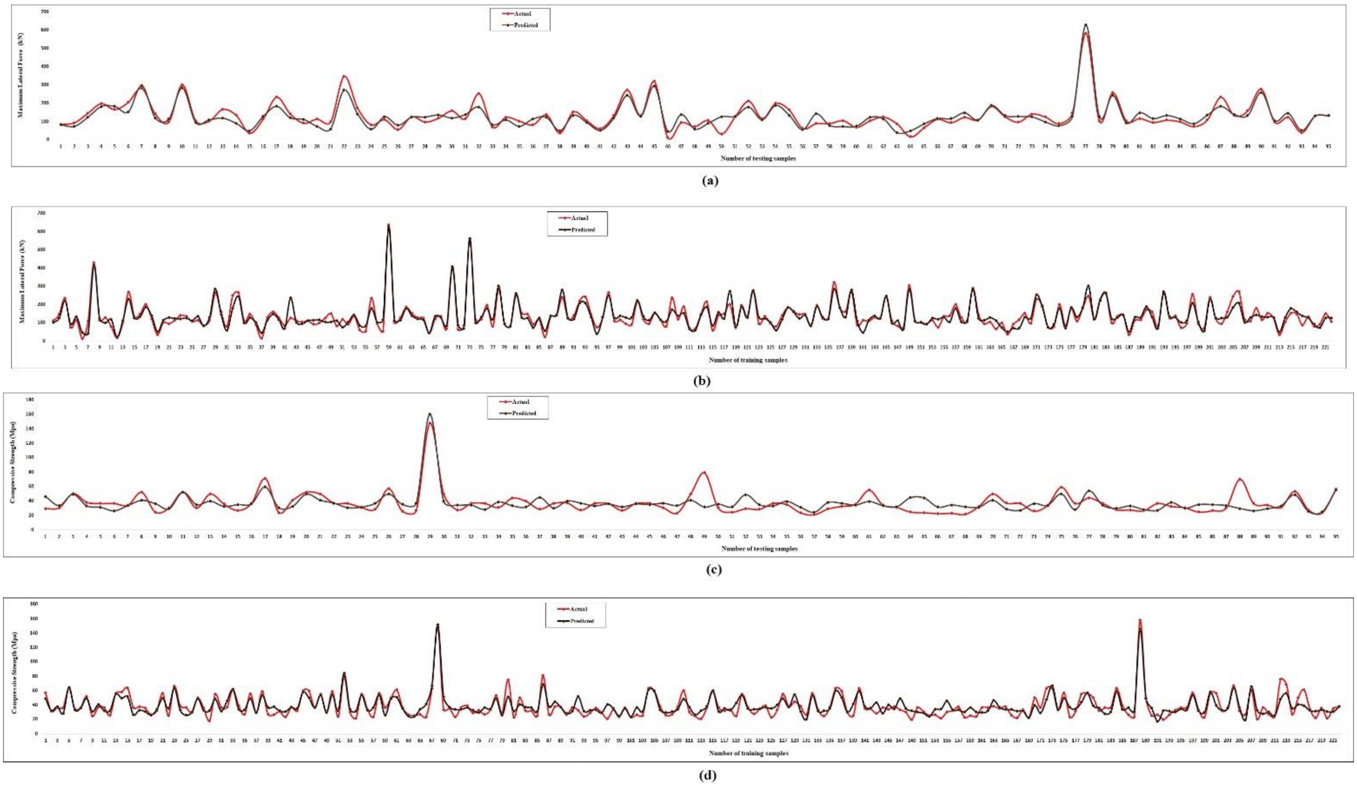

Fig. 8 ANFIS-PSO prediction vs experimental diagram for (a) lateral load test phase, (b) lateral load train phase, (c) compressive strength test phase and (d) compressive strength train phas

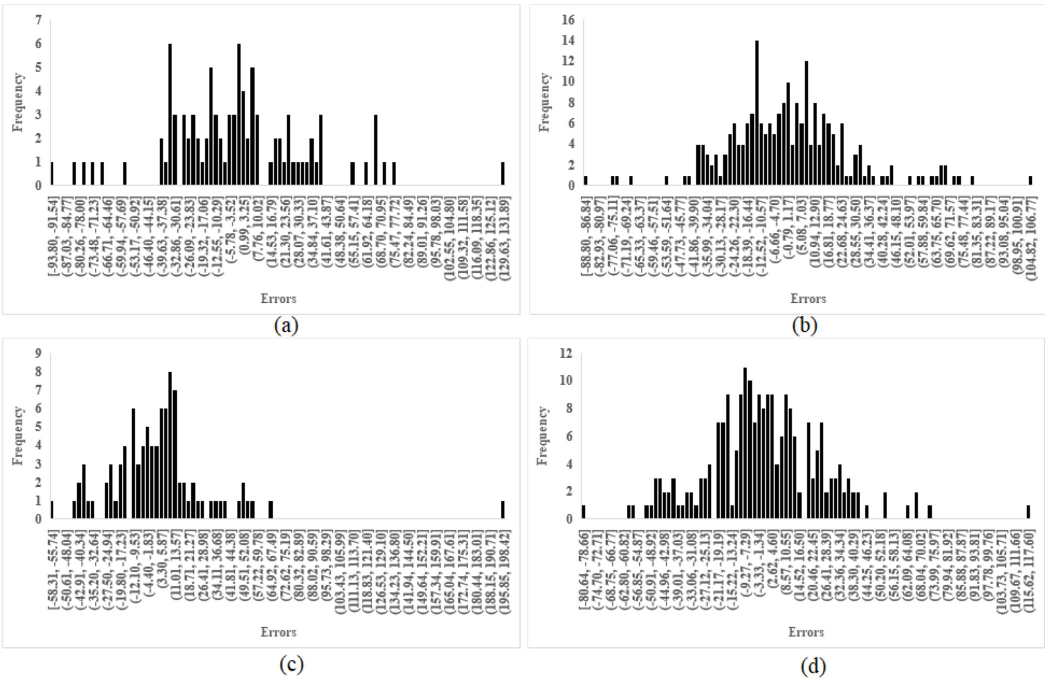

Fig. 9 ANFIS-PSO error histogram for (a) lateral load test phase, (b) lateral load train phase, (c) compressive strength test phase and (d) compressive strength train phase

parameters related to each algorithm, other parameters are kept constant. By changing the coefficient, the best value is delineated and continued to other parameters. In this case, algorithms have been repeatedly implemented and revised until being developed, finally, to provide the following results:

Table 7 Parameter characteristics used for ANFIS-GA in this study.

FIS Clusters	Population Size	MAX-iteration	Cross over percentage	Mutation percentage	Mutation rate	Selection pressure
10	180	200	1.00	0.5	0.1	8

Table 8 Analytical prediction results through ANFIS-GA algorithm

	Test		Train	
Lateral load prediction	Std	13.28704509	Std	12.38533298
	e mean	-0.928540841	e mean	-0.282863646
	R^2	0.8560	R^2	0.8300
	r	0.925213544	r	0.911058857
	RMSE	13.30847329	RMSE	18.91489176
	Test		Train	
Compressive Strength prediction	Std	5.353261106	Std	3.669653297
	e mean	-0.076964023	e mean	0.021877075
	R^2	0.5069	R^2	0.6715
	r	0.711978515	r	0.819432184
	RMSE	5.34938145	RMSE	5.602935407

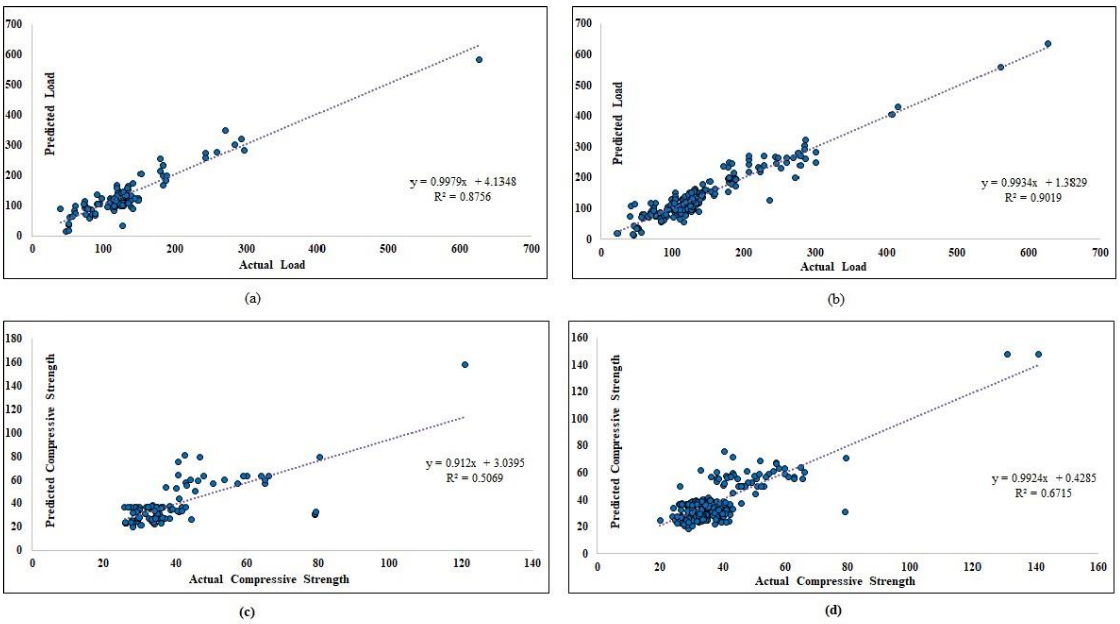

Fig. 10 ANFIS-GA prediction vs experimental results regression for (a) lateral load test phase, (b) lateral load train phase, (c) compressive strength test phase and (d) compressive strength train phase

5.1 ANFIS-PSO

The parameters of ANFIS-PSO are adjusted and tabulated (Table 5). Also, the inputs of dataset were initially defined and predicted while separately predicting the lateral load and compressive strength through different analysis. The results of regression graphs and comparative graphs are shown (Figs. 7 and 8). The processing results analysis is also presented (Table 6). According to Fig 7 and Table 6, ANFIS-PSO is more successful in predicting the lateral load than the compressive strength due to its properties or in principle to more predictable output. Also, the test results in

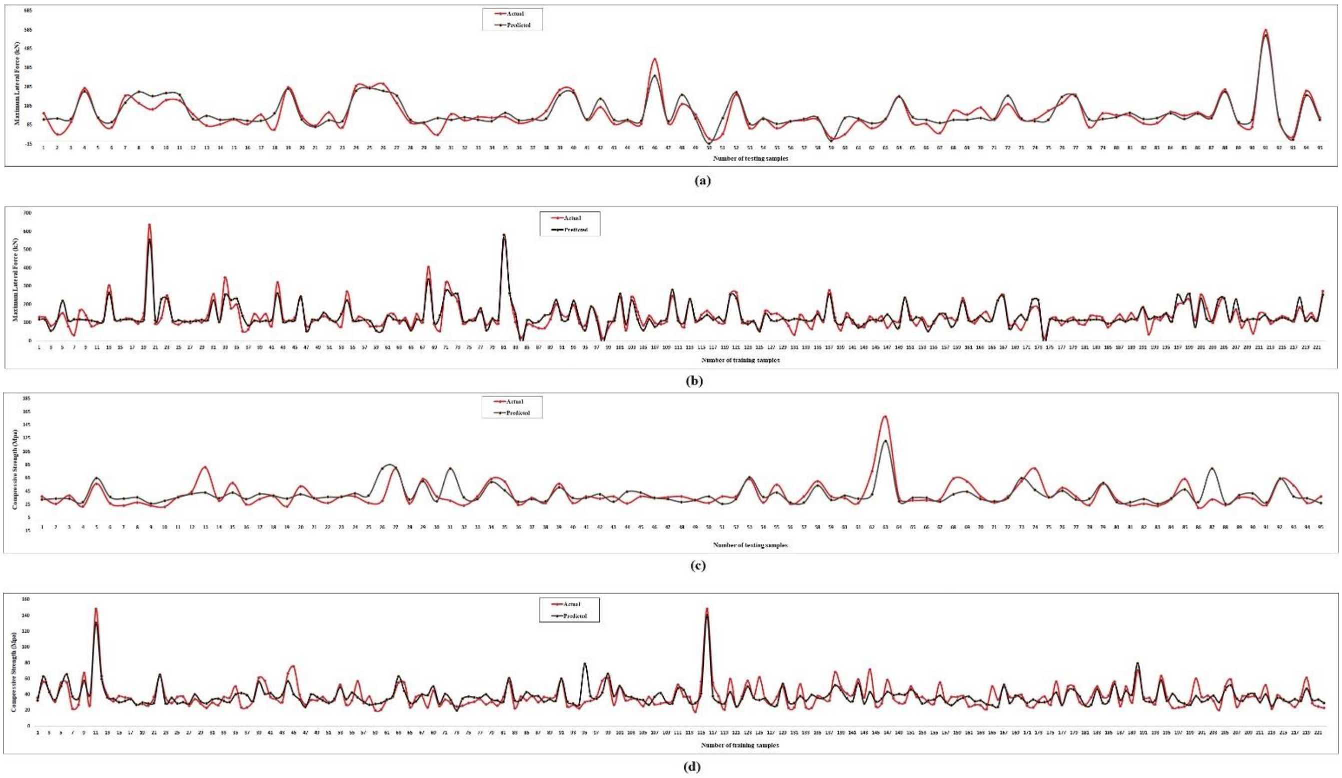

Fig. 11 ANFIS-GA prediction vs experimental diagram for (a) lateral load test phase, (b) lateral load train phase, (c) compressive strength test phase and (d) compressive strength train phase

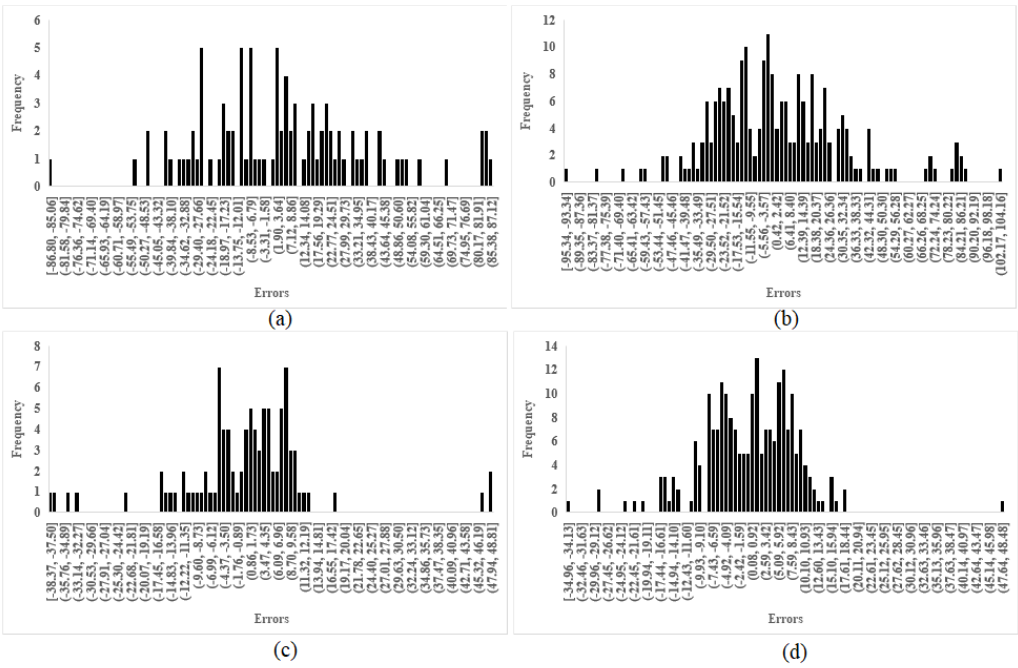

Fig. 12 ANFIS-GA error histogram for (a) lateral load test phase, (b) lateral load train phase, (c) compressive strength test phase and (d) compressive strength train phase

lateral load prediction are very close to the Train results, while the compressive strength output is more significant, indicating that it is more reliable for predicting the lateral load. Though, the outputs of other type are acceptable, the discrepancy of test results and train results has reduced our confidence over the outputs.

Table 9 Parameter characteristics used for ELM in this study

Classifier	Regression	Hidden nuerons	Activation function
1.0	0.0	350	Hard Limited

Table 10 Analytical prediction results through ELM algorithm

	Test		Train	
Lateral load prediction	Std	15.37184851	Std	10.66578843
	e mean	-0.462510647	e mean	7.35656E-14
	R^2	0.8502	R^2	0.8442
	r	0.922063022	r	0.918794552
	RMSE	15.36608044	RMSE	16.28455228
	Test		Train	
Compressive Strength prediction	Std	5.472551655	Std	2.301456853
	e mean	0.263004755	e mean	-1.69063E-14
	R^2	0.6574	R^2	0.8620
	r	0.810771741	r	0.928414563
	RMSE	5.474340963	RMSE	3.513870042

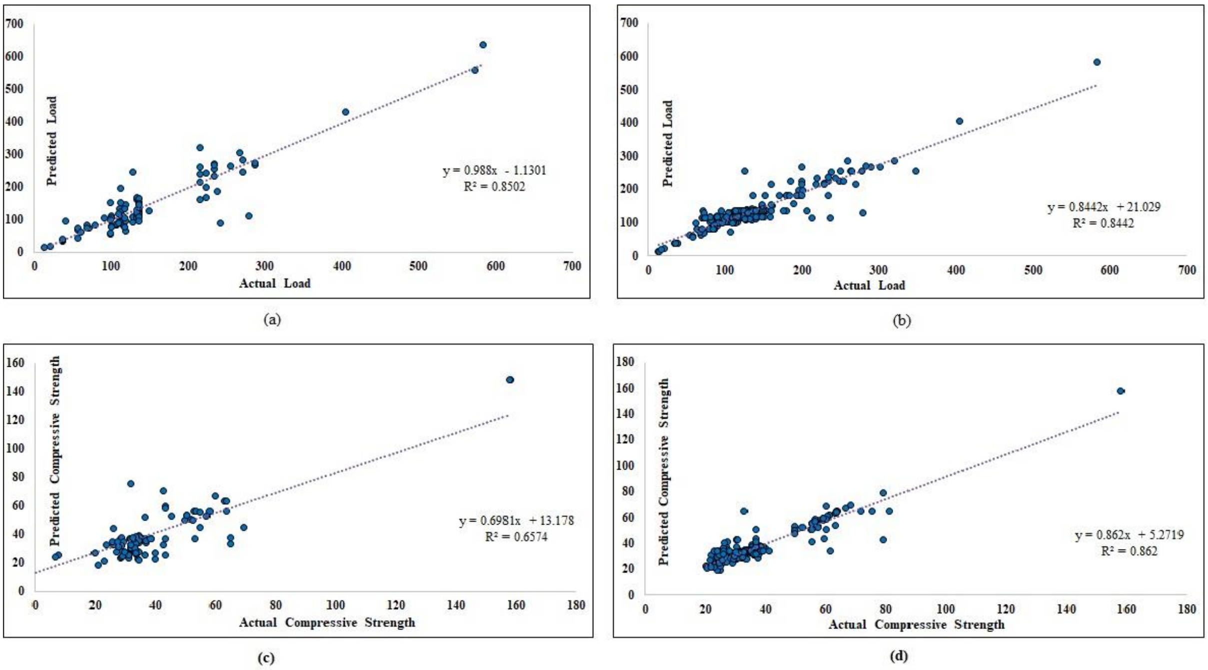

Fig. 13 ELM prediction vs experimental results regression for (a) lateral load test phase, (b) lateral load train phase, (c) compressive strength test phase and (d) compressive strength train phase

According to Fig. 7, another point deduced from the regression diagram (c) is that the low results of the compressive strength output test are due to 2 to 3 points with high error rates and to the other samples that provide acceptable results, also to the standard deviation results for this output. While the Std difference in two phases of Test and Train for the lateral load is 14%, this difference for the compressive strength is 33%, indicating less concentration of errors in the second output than the first output (Fig. 9).

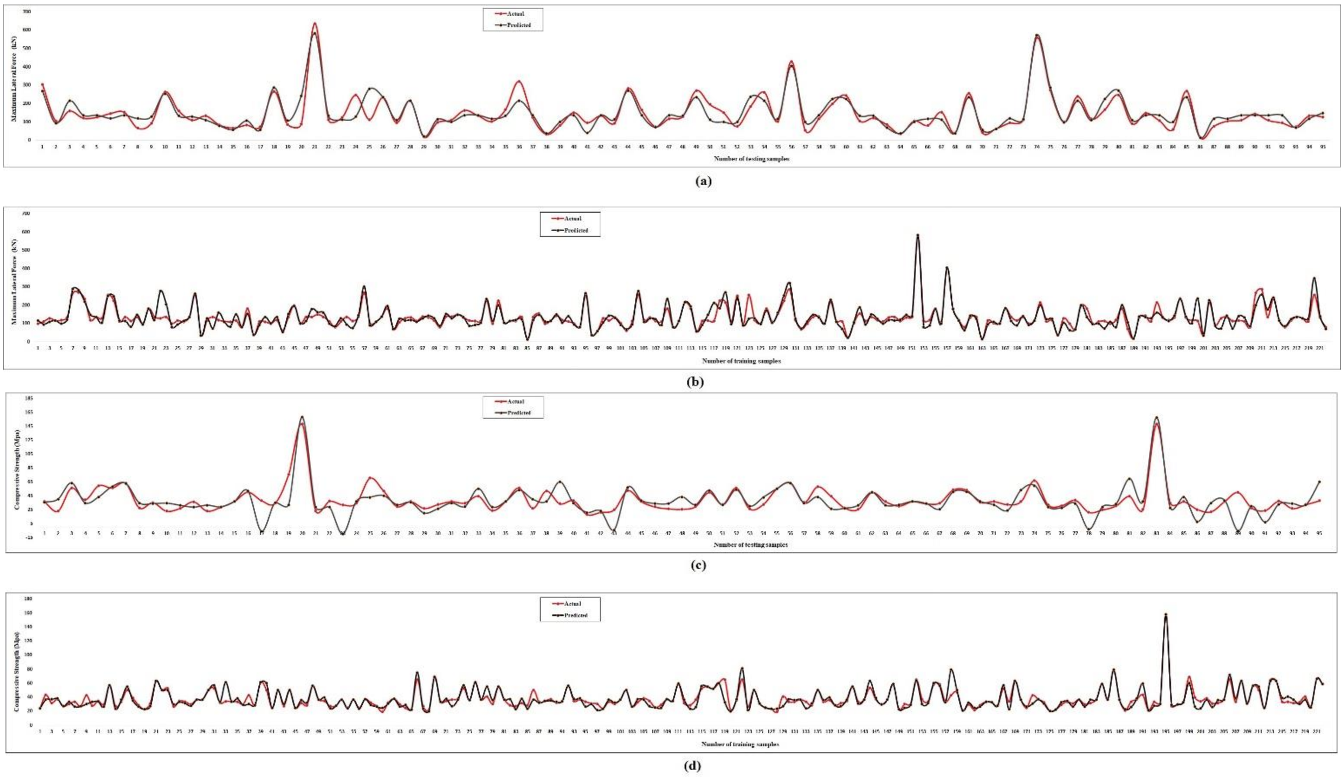

Fig. 14 ELM prediction vs experimental diagram for: (a) lateral load test phase, (b) lateral load train phase, (c) compressive strength test phase and (d) compressive strength train phase

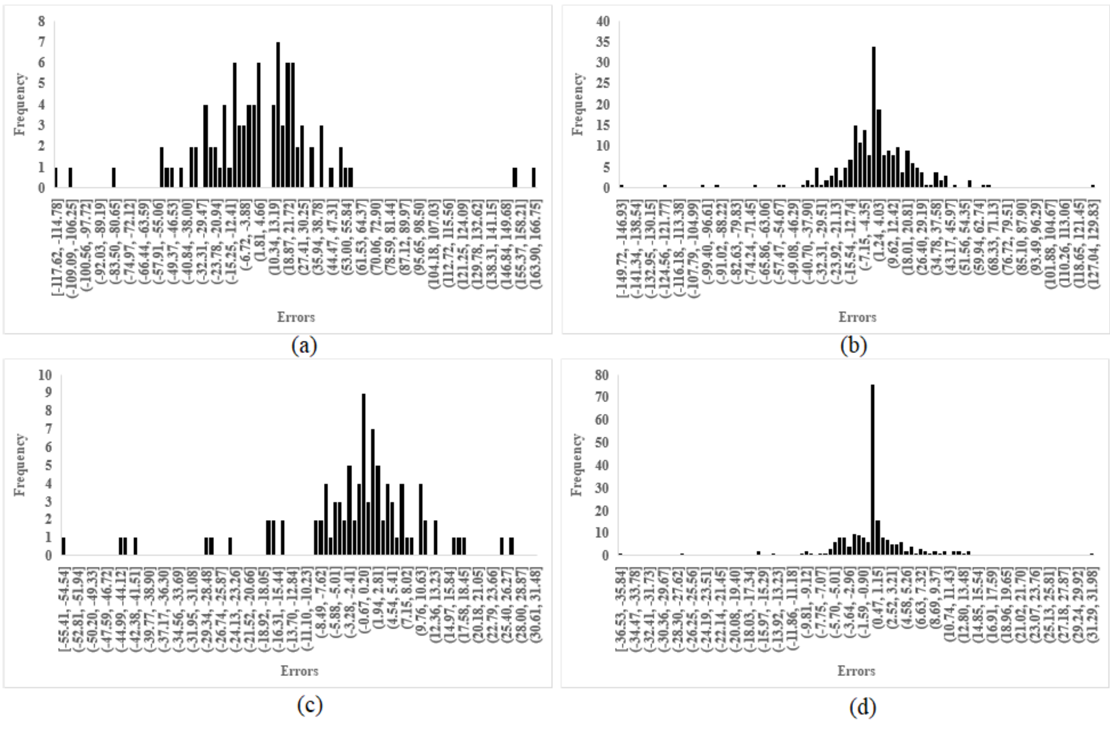

Fig. 15 ELM error histogram for (a) lateral load test phase, (b) lateral load train phase, (c) compressive strength test phase and (d) compressive strength train phase

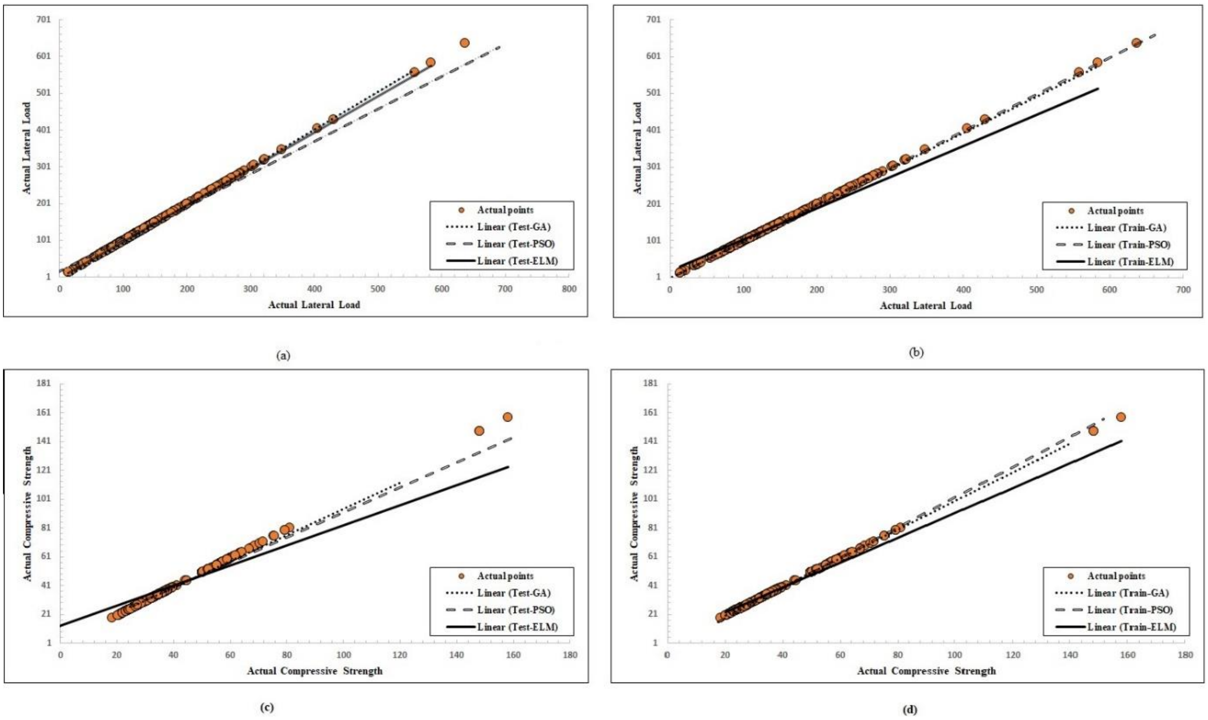

Fig. 16 the comparisons between (a) flexural load test phase, (b) flexural load train phase, (c) deflection test phase and (d) deflection train phase

5.2 ANFIS-GA

The results of ANFIS-PSO neural network are presented in Table 8 and Figs. 10 and 11. Also, the combination settings used for this hybrid grid are shown in Table 7.

In this method, the results for the lateral load output are much better than the compressive strength, and the difference between the test and train phase results for the first output is very close.

Given the low result for R^2 , average result for r and considering the regression graph (c) and (d) of Fig. 12, the approximation NN results for the second output at the boundary are unacceptable. Higher error results are likely occurred particularly during the testing phase. According to the graphs, lower error for the compressive strength data below 40 Mpa and higher error for the data above 40 Mpa are observed. During the test phase, it seems that NN for the second output with a value higher than 40 Mpa is not well trained due to a large number of samples below 40 Mpa (Fig. 12).

5.3 ELM

ELM as the final NN is used in the settings shown in Table 9. The obtained results are also acceptable for both outputs. However, as shown in Table 10, it is found that by comparing the lateral load output performance parameters to the compressive strength, and by comparing the Test and Train results, the Lateral load outputs are very close, while it is much different for the other output.

By examining the standard deviation as well as the error histogram diagram (Fig. 15), errors with a greater focus on the lateral load makes the outputs more reliable. Compressive strength outputs might provide good results, however, due to the lack of focusing on center-axis of errors, an unprecedented response could likely provide high and unacceptable errors.

6. Discussion

ANFIS is trained for each input in order to separately delineate the inputs of RMSE, R^2 and r to define the effect of every input on the output. The input with the smallest training RMSE has the most significant effect or relevance to output. Testing RMSE is applied to track the overfitting between training and testing data. A higher testing RMSE means that the regression of data is not useful. Thus the combination of two inputs in order to gain the most potent combinations of inputs on the output could be further studied. The training and testing RMSE for the combinations of two inputs are shown (Table 2). According to the training RMSE, the combination of inputs 2 and 3 forms the optimal combination with the most substantial effect on the output parameter. The quality of the estimations made by the algorithms and used in this paper beside the actual points used in paper (Cai and Degée 2017) along with the regression lines of each algorithm are presented in Fig 16. Comparing the regression results obtained from the Test section, GA and ELM algorithms are closer than PSO algorithm, even if the PSO regression covers more data range (Fig. 16 a). Respectively, regarding the results of the Train section, the PSO regressions are closer to the main points than the other regressions (Fig. 16

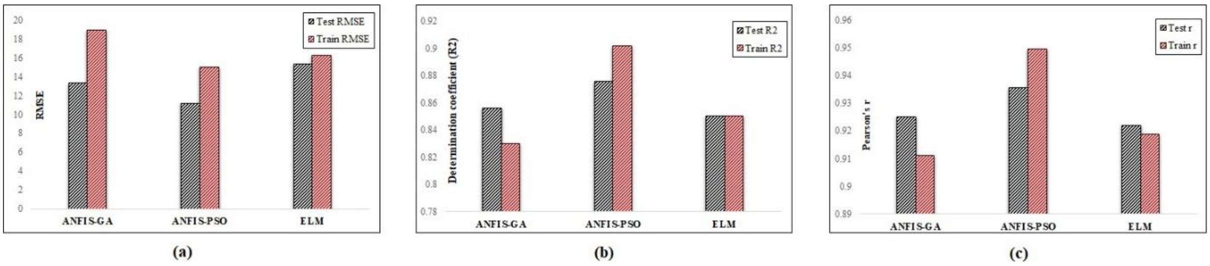

Fig. 17 The comparisons between performed algorithms results of lateral load based on analytical parameters as (a) RMSE, (b) determination coefficient and (c) Pearson's correlation value

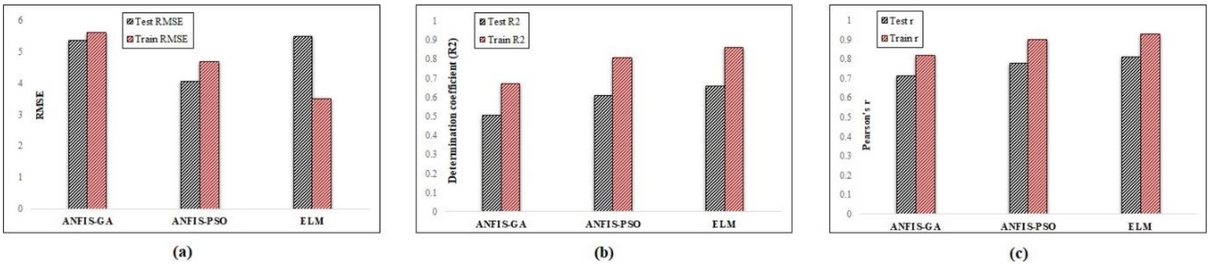

Fig. 18 The comparisons between performed algorithms results of compressive strength based on analytical parameters as (a) RMSE, (b) determination coefficient and (c) Pearson's correlation value

b and d). Finally, the most significant difference of regressions with the main points is seen in Fig. 16(c). In Fig. 16(c), the alignment of the regression lines with the real points is highly different from the other parts. Also, ELM shows the highest difference among the other algorithms, while GA and PSO show consistent regressions.
By examining the responses of all methods, the lateral load is excessively predictable than the compressive strength, which might be due to the type of inputs or type of NN. For the lateral load output, the best result for ANFIS-PSO method is with the performance parameters of *R^2 = 0.8756 r = 0.935723509, and RMSE = 11.20264199.* Other approaches have provided close and acceptable responses (Fig. 17). By looking at the histogram of test phase error (Figs. 9, 11, 15), in terms of concentration, all three graphs have a good concentration around the center, while due to the smaller error interval in ANFIS-PSO method, it is concluded that the probability of receiving a high error response in this method is lower than the other methods.
For the compressive strength output, ELM method also provides the best response (Fig. 18). The Tethys phase performance parameters for this method are *R^2 = 0.6574, r = 0.810771741, and RMSE = 5.474340963. Thus*, the response presented by ANFIS-GA method in test phase is almost unacceptable. Although it is reliable for data with less than 40 networks, high errors in data over 40 has caused system failure, therefore, the test phase error diagrams at this output are not significantly different except the ANFIS-PSO diagram that has the widest range and no centralization. However, considering that only one output with an error is high, the diagram of this method can be taken close to other two methods.

7. Conclusions

The prediction of most influenced factor on ultimate strengths of FRC rectangular columns adjusted to the simulated seismic loading is complex because of many parameters. Thus, the current research has performed a soft computing method to overcome this prediction difficulty by eliminating some extra input parameters. ANFIS is applied to choose the most dominant parameters for the prediction of most influenced factor on the ultimate strengths of FRC rectangular columns adjusted to the simulated seismic loading. In this paper, ANN and backed-up data from the experimental results of 317 rows Width (mm), Height (mm), Fiber Fraction Ratio (%), Maximum Lateral force (kN), Maximum Lateral force (kN), fiber tensile Concrete Compressive Strength (Mpa), Fiber Yielding Strength (Mpa), Concrete Compressive Strength (Mpa), and Shear Span Ratio (a/d) are related to the prediction values of the two types of outputs as lateral load and compressive strength. Three types of NN are used in this study as follows: In two fuzzy models, ANFIS neural network characteristics are the same and the only difference is in the algorithm optimization type.

- ANFIS-PSO which operates based on the random population generation and based on the modelling and simulation of avian mass flight behavior or mass movement of fish. A global minimization method that deals with the shortcomings whose answer is a point or surface in *n*-dimensional space. In such a space, a random population is assumed, and an elementary velocity is assigned as well as the channels of communication between the particles which move through the response space, and followed by the results that are calculated on a "merit basis" after each time interval. Particles accelerate toward the particles of higher competence in the same communication group during the time. Despite good performance of each method toward the problems, there is a great success in solving continuous optimization problems. This combinational results for the lateral load output in the test phase are R^2 = *0.8756 and r = 0.935723509,* and *RMSE = 11.20264199*. Also the results for the compressive strength are R^2 = *0.5069, r = 0.711978515,* and *RMSE = 5.34938145.*

- ANFIS-GA neural network is examined. Also, GA is a special type of evolutionary algorithm to gain the optimal formula for the prediction or pattern matching. GA is a good option for the regression-based prediction techniques, also a programming technique in problem solving including inputs that are transformed into solutions during a patterned process of genetic evolution. Then the solutions are verified candidates by the Fitness Function, and algorithm is terminated if the problem exit condition is provided. Generally, it is an iteration-based algorithm that many parts are randomly selected. The results of this method for the lateral load are R^2 = *0.856, r = 0.925213544, and RMSE = 13.30847329,* which is not the best answer, but satisfactory. The results of compressive strength are R^2 = *0.5069, r = 0.711978515, and RMSE = 5.34938145* which is not acceptable.
- The extreme learning machine as an authenticate algorithm is a feedforward NN for the clustering, regression, classification, sparse approximation, compression and feature learning (with a single layer or multiple layers of hidden nodes) in which the parameters of hidden nodes is not tuned and used to firmly verdict the other results. These hidden nodes could be randomly assigned and never updated, or can be inherited from their ancestors without alteration. In most cases, the output weights of hidden nodes are generally learned in a single step, which significantly amounts to learn a linear model.

The results of Lateral load prediction are R^2 = *0.8502, r = 0.922063022,* and *RMSE = 15.36608044* which is not the best, but acceptable. For the compressive strength, ELM provides the best results *as* R^2 *=0.6574, r = 0.810771741,* and *RMSE = 5.474340963.*

To sum up, though the prediction results of lateral seismic loads by all three methods are outstanding, ANFIS-PSO method has provided the best results. Moreover, for the compressive strength, the best results belong to ELM neural network. Though the results of this output are not as reliable as the first output results, the results of ANFIS-GA method can be also unacceptable. Consequently, the methods are suitable for the lateral load prediction and compressive strength due to the abysmal results, recommending using ELM method in case of neural network with better results.

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