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Development of Hybrid Adaptive Neural Fuzzy Inference System-Based Evolutionary Algorithms for Flexural Capacity Prediction in Corroded Steel Reinforced Concrete Beam

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Abstract
The damages in reinforced concrete (RC) beams due to reinforcement corrosion is a major problem in the RC industry. Accurate prediction of the residual bearing capacity of RC beams can effectively prevent structural failures or unwanted over-costs of inspections and rehabilitations. This paper proposes a novel machine learning-based prediction framework that combines the adaptive neural fuzzy inference system (ANFIS) with several metaheuristic algorithms for the effective estimation of the flexural strength capacity. Five optimization algorithms are employed for auto-selection of the optimum ANFIS parameters, including differential evolution (DE), genetic algorithm, particle swarm optimization, artificial bee colony, and firefly algorithm (FFA). A comprehensive experimental database of the flexural capacity of corroded steel reinforced concrete beams obtained from the literature, consisting of 177 tests, is used as a case study to evaluate the prediction performance of the proposed hybrid models. The results demonstrate that the proposed hybrid models transcend the previously developed models, while the optimized ANFIS using FFA represents the highest accuracy and strong stability among the proposed models. It is concluded that the proposed framework using ANFIS-FFA can be effectively employed as a useful tool for the accurate estimation of the flexural strength capacity of corroded reinforced concrete beams.

Keywords Flexural strength capacity · Prediction · Machine learning · Adaptive neural fuzzy inference system · Nature-inspired algorithms · Firefly algorithm

Abbreviations

X, Y	Input variables
f_1, f_2	Output
A_1, A_2, B_1, B_2	Membership functions
a_1, a_2, b_1, b_2, r_1, r_2	Linear output parameters
E	Experimental values
P	Predicted values
f	Concrete strength
b	Beam section width
h	Beam section depth
ρ_l	Section ratio of the longitudinal steel reinforcement
ε_y	Steel yield strength
λ	Beam shear span-to-depth ratio
h_{wt}	Weight loss ratio due to corrosion
h_{sn}	Section loss ratio due to corrosion
$M_{fx,\,exp}$	Ultimate flexural strength
$P_{fx,exp}$	Ultimate concentrated load
RC	Reinforced concrete
CRC	Corroded reinforced concrete
AI	Artificial intelligence
ML	Machine learning
ANFIS	Adaptive neural fuzzy inference system
FL	Fuzzy logic

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ANN	Artificial neural network
DE	Differential evolution
GA	Genetic algorithm
PSO	Particle swarm optimization
ABC	Artificial bee colony
FFA	Firefly algorithm
RMSE	Root mean square error
MAE	Mean absolute error
MAPE	Mean absolute percentage error
NSE	Nash and Sutcliffe efficiency index
R^2	Coefficient of determination
AE	Average error
FB	Fractional bias
IA	Index of agreement
FE	Fractional error
$r(I_k, O)$	Relevancy factor

1 Introduction

It is well understood that reinforced concrete (RC) beams are important components in the construction industry for several structures such as buildings and bridges. However, the durability of RC beams is highly influenced by corrosion phenomena [1–3]. This means that deterioration may occur which could result in excessive cost of inspections, maintenance, or rehabilitation operations [4–6]. Several experimental studies have been conducted to investigate the behavior of RC beams under reinforcement corrosion, including the flexural behavior by Almusallam et al. [7], the bending resistance at different rates of reinforcement corrosion and stirrup spacing by Rodriguez et al. [8], the residual bending strength under the influence of corrosive environments by Mangat and Elgarf [9], the residual flexural capacity of corroded reinforced concrete (CRC) beams, and the related failure modes by Hui et al. [10]. Most of these studies are focused on three main aspects: the steel reinforcement, concrete, and the bond performance between concrete and steel. In addition, previous studies have indicated that the corrosion reduces the mechanical properties of steel reinforcement and decreases the concrete effective areas. Thus, increased corrosion would highly decrease the bond performance between concrete and steel [11]. Therefore, it is crucial to provide an accurate quantification of the residual bearing capacity of RC beams under deterioration caused by corrosion.

In recent years, various models have been proposed to calculate the residual flexural strength capacity for CRC beams based on experimental procedures. There are three different methods utilized for carrying out these experiments in the laboratory; (a) using accelerated corrosion, including electrochemical or salt corrosion, (b) using a beam exposed to the natural environment, and (c) using damaged components of beams removed, from the structure. Most of the experimental tests carried out in the literature have used the first method, due to the higher cost and processing time associated with the other alternatives. Moreover, according to the existing empirical correlations used for the estimation of the residual flexural strength capacity of CRC beams, two main strategies are followed during their developments. The first is to use results from experimental tests to determine the bending moment of the CRC beam following the corresponding specification, which will be multiplied by a reduction factor that takes into account the effect of the corrosion. The second strategy consists of first multiplying the yield stress of the longitudinal steel reinforcement by a reduction factor to account for the corrosion influence, with the consideration of the cross-sectional areas. Thereafter, the ultimate bending moment is determined according to its specification.

Among the drawbacks of the existing empirical correlations for modeling the flexural strength capacity of CRC beams are the followed analytical development basis and the used techniques for fitting, including linear or nonlinear regression methods. Moreover, according to a recent study by Zhao-Hui et al. [12], the previously developed models may exhibit an over- or under-estimation for cases of data other than the ones used for the model development. Thus, these models become less accurate when a new dataset is used which was not included in the original database for developing the models. Therefore, there is need to introduce advanced techniques which are more powerful and robust for the estimation of the flexural strength capacity of CRC beams [13]. In recent years, machine learning (ML) approaches have gained significant attention for solving engineering problems, including modeling the behavior of the shear strength of reinforced concrete beams [14–16], predicting the corrosion phenomena in different steel components [17–19], and other applications, such as prediction problems, failure modes classification, and life assessment in structural engineering [20–22]. For these applications, the artificial neural network (ANN), adaptive neural fuzzy inference system (ANFIS), and support vector regression (SVR) are among the most well-known and widely used machine learning techniques. The ANFIS model has become very popular lately, due to its simplicity and its capability of dealing with uncertainty when a large database is used during the modeling process [23–25]. However, most of the known ML models suffer from the lack of an appropriate and efficient approach for the optimum selection of their parameters, which makes the prediction process less accurate [26]. Therefore, to deal with this problem, hybrid models are proposed, in which metaheuristic algorithms are combined with the main ML models for the auto-selection of the optimum parameters. This suggests that combining the ANFIS model with metaheuristic algorithms may be a robust and efficient technique to solve the problem of estimation of the flexible strength capacity of CRC beams.

This paper aims at introducing new frameworks for the accurate and reliable estimation of the flexural strength capacity of CRC beams using advanced machine learning techniques. A set of novel hybrid models are developed by combining the ANFIS and five metaheuristic algorithms, including differential evolution (DE), genetic algorithm (GA), particle swarm optimization (PSO), artificial bee colony (ABC), and firefly algorithm (FA). The ANFIS approach is employed due to its excellent performance in dealing with modeling problems with high surrounding uncertainties, whereas the metaheuristic algorithms are used as powerful algorithms for the auto-selection of the optimum parameters. Moreover, real experimental tests including the flexural strength capacity are used from the open literature for creating and validating the proposed hybrid models. The present study is structured as follows: Sect. 2 describes the employed methodology, which is based on a hybrid ANFIS and metaheuristic model (i.e., DE, GA, PSO, ABC, and FFA), as well as the evaluation metrics. Section 3 contains information about the CRC beams flexural capacity database. Section 4 analyzes the results obtained with the proposed framework, followed by a detailed discussion, comparison, and the variables influence analysis. Section 5 contains the conclusions of the study, as well as limitations and recommendations.

Figure 1 illustrates the structure of the proposed study for using hybrid machine models to solve the flexural capacity prediction problem in corroded steel reinforced concrete beams.

2 Methodology

2.1 Hybrid Predictive ANFIS Models

This section presents the theoretical details of the novel models proposed in this paper for the estimation of the flexural strength capacity (M_{fx}). A recall of the theoretical background related to the ANFIS and the five metaheuristic algorithms is detailed.

2.1.1 Adaptive Neural Fuzzy Inference System (ANFIS)

The ANFIS model was first proposed by Jang in 1993 [27]. It is generally considered as a useful tool for solving prediction problems by providing low uncertainties [28]. Unlike other approaches that deal with linear correlation, the ANFIS model is a powerful approach for situations where prediction problems present a highly nonlinear form [29]. As a fast-learning algorithm, ANFIS integrates the ANN as a soft computing approach with the fuzzy logic (FL) as an inference system, where the role of the first part is the pattern recognition of the immediate environment, while the role of the second part is to mimic the human-like expertise. Several nodes are used as directional connectors between the ANN and FL algorithm in order to estimate the fuzzy parameters. This allows the ANFIS model to combine the advantages of both the ANN and the FL in a single framework. It should also be noted that the operation mechanism of the ANFIS model is based on Takagi–Sugeno fuzzy inference system [30]. Various parameters are normally employed as inputs to estimate one output where several rules are defined based on the membership functions to stipulate the input–output. These rules can be given for a two-variable example (X and Y) as follows:

$$\text{Rule 1}: \text{If } X \text{ is } \boldsymbol{A}_1 \text{ and } Y \text{ is } \boldsymbol{B}_1, \text{ then } f_1 = a_1 X + b_1 Y + r_1 \tag{1}$$

$$\text{Rule 2}: \text{If } X \text{ is } \boldsymbol{A}_2 \text{ and } Y \text{ is } \boldsymbol{B}_2, \text{ then } f_2 = a_2 X + b_2 Y + r_2 \tag{2}$$

where A_1, A_2, B_1, and B_2 are the membership functions for the inputs X and Y. f_1 and f_2 denote the related output from the respected rule, while the linear output parameters from the first and second rules are represented by a_1, a_2, b_1, b_2, r_1, and r_2. In this study, the ANFIS approach consists of five layers, which are connected using nodes as illustrated in Fig. 2. These layers can be briefly described as follows [31]:

- *Layer 1* Using the membership functions described in Eqs. (3) and (4), X and Y (input variables) are transformed into linguistic terms, noting that the membership's grades are created using square nodes, whereas the Gaussian membership function [29] is used in this work.

$$O_{1,i} = \mu_{\text{Ai}}(X) \tag{3}$$

$$O_{1,i} = \mu_{\text{Bi}}(Y) \tag{4}$$

In the above, the linguistic terms and their related membership functions are represented by $A_{i(X)}$, $B_{i(Y)}$ and $\mu_{\text{Ai}}(X)$, $\mu_{\text{Bi}}(Y)$, respectively.

- *Layer 2* The output of this layer, $O_{2,i}$ is calculated by using Eq. (5) as follows:

$$O_{2,i} = w_i = \mu_{Ai}(X)\mu_{Bi}(Y) \tag{5}$$

- *Layer 3* The normalization of the output, $O_{3,i}$ is determined in this layer as follows:

$$O_{3,i} = \overline{w_i} = \frac{w_i}{\sum_{j=1}^{2} w_j} \tag{6}$$

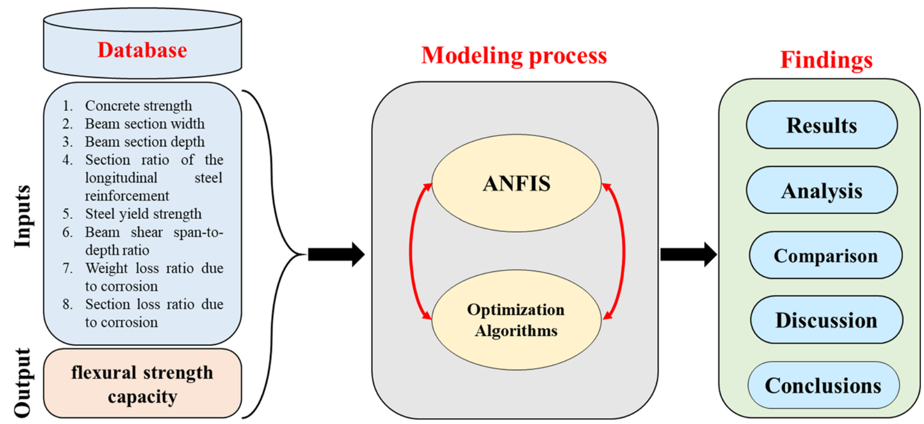

Fig. 1 Proposed hybrid machine learning framework

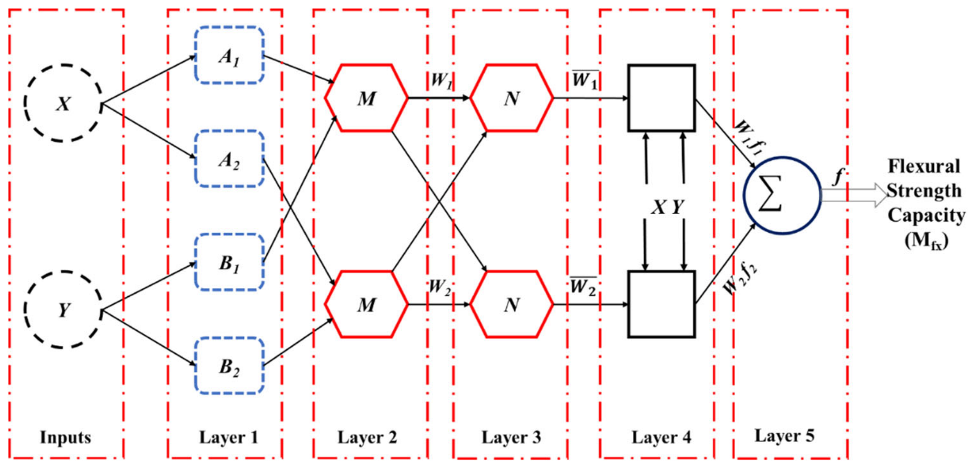

Fig. 2 The structure of adaptive neuro-fuzzy inference system (ANFIS) technique for modeling flexural strength capacity (M_{fx})

- *Layer 4* The nodes become adaptive nodes in this layer, $O_{4,i}$, and can be calculated as illustrated in Eq. (7):

$$O_{4,i} = \overline{w_i} f_i = w_i(a_i X + b_i Y + r_i) \tag{7}$$

- *Layer 5* The final output is computed in this layer based on the previous outputs in each layer, as incoming single nodes that have gathered, using Eq. (8) as follows:

$$O_{5,i} = \sum_i \overline{w_i f_i} = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{8}$$

2.1.2 Metaheuristic Algorithms

Differential Evolution (DE) The DE algorithm is a sophisticated metaheuristic that utilizes genetic operators such as selection, recombination, and mutation to solve optimization problems. It was first introduced by Storn and Price [32]. Since then, it has been extensively used for the solution of optimization problems in various scientific areas, including applications in structural engineering [33, 34]. DE is utilized in this work to determine the optimum ANFIS parameters, referred to as ANFIS-DE. The process starts with the initialization of the population and the DE control parameters. The fitness function is used to evaluate each individual, and then, the stopping criterion is checked to determine whether convergence has been achieved. In case the termination criterion is not met, three steps are repeated. First, by applying the mutation operation using the following equation:

$$\mathrm{TX}_{i,j} = X^k_{a_1,j} + F\left(X^k_{a_2,j} + X^k_{a_3,j}\right) \quad \forall j \text{ and } \forall i \tag{9}$$

where a_1, a_2, anda_3 are selected random indices from the population size, while F is the mutation factor.

Second, by applying the crossover operation on the mutated individual by using Eq. (10):

$$U_{i,j} = \begin{cases} TX_{i,j} & \text{if } rand \leq \mathrm{CR} \quad \text{or} \quad j = I_{rand} \\ X^k_{i,j} & \text{if } rand > \mathrm{CR} \quad \text{or} \quad j \neq I_{rand} \end{cases} \tag{10}$$

where *rand* stands for a random value uniformly distributed between 0 and 1, while *CR* denotes the crossover probability and $I_{rand} \in (1, 2, \ldots, d)$ is a random selected index.

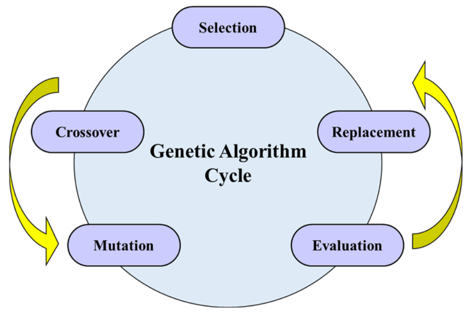

Fig. 3 The genetic algorithm's cycle process

Third, by calculating the trial fitness, the mutation is determined on the trial solution as follows:

$$X_{i,j}^{k+1} = \begin{cases} U_{i,j} \ if \quad f\left(U_{i,j}\right) \le f\left(X_i^k\right) \\ X_{i,j}^k \ \text{otherwise} \end{cases} \tag{11}$$

Finally, the process continues until the selected convergence (stopping) criterion is satisfied.

Genetic Algorithm (GA) GA is a very well-known optimization technique that was inspired by the theory of evolution and proposed by Holland and his colleagues [35]. Over the years, GA has been extensively utilized to solve various types of complex optimization problems, including applications in structural engineering [36], given its efficiency and accuracy [37]. In this study, the GA is combined with the ANFIS model as an auto-optimized framework which starts with the random generation of the initial population called chromosomes. The main goal of the optimization process for this study is to select the best outperforming chromosomes for solving the flexural strength capacity problem. To do so, the fitness function is used to evaluate the performance of each individual. In every iteration (generation), three main operations are used to update the chromosomes by better ones, starting with the roulette wheel process (selection operation), then the crossover and mutation operations are followed successively, and the fitness function is evaluated again. The process is repeated, while the convergence (stopping) criterion is not met. Figure 3 depicts the cycle process of the GA.

Particle Swarm Optimization (PSO) PSO is a metaheuristic optimization algorithm inspired from the swarm behavior and animal dynamic movement of birds and fish, proposed originally by Eberhart and Kennedy [38]. PSO has been utilized by many researchers to solve complex engineering problems [39–41]. In this study, PSO is coupled with the ANFIS model as a novel solution for the problem of CRC beams. The PSO algorithm normally starts with the random generation of the initial population. Each member of the population (particle) is characterized by two factors, namely its location in the search space and its velocity. Similar to GA, the fitness function is employed to evaluate the performance of each particle. Until the convergence criterion is satisfied, the velocity and the location of each particle in the population are updated using Eq. (12) and Eq. (13), respectively, as follows [42, 43]:

$$V_{i+1} = \omega V_i + c_1 r_1 (P_{i\text{best}} - X_i) + c_2 r_2 (g_{i\text{best}} - X_i) \tag{12}$$

$$X_{i+1} = X_i + V_{i+1} \tag{13}$$

where X_i, V_i, X_{i+1}, and V_{i+1} denote the particle location and velocity at the ith and $(i+1)$th iterations, respectively. c_1 and c_2 are learning factors, while r_1 and r_2 are two random numbers with uniform distribution in the range [0, 1]. ω represents a weighting factor to accelerate the algorithm convergence. The next step is to evaluate the performance of the new particles using the fitness function and the process continues until the optimum results are achieved.

Artificial Bee Colony (ABC) The ABC is a swarm intelligence algorithm that mimics the behavior of honeybees during the collecting of nectar sources in the area of their hives, proposed by Karaboga in 2005 [44]. This algorithm has been gaining much interest recently for solving complex optimization problems [45]. Similar to the previous algorithms, the ABC is also used for the optimum selection of the ANFIS parameters in this work. The algorithm starts with the generation of the initial population of food sources, whereas each bee is designated to a food source. The fitness function is evaluated for each solution, and three steps are considered during the iterations of the method. The first step is to renew the position of the bees to discover a new food source (Employed bees' step). To do so, Eq. 14 is employed [46].

$$x_{j,t+1} = x_{j,t} + \xi_j \left(x_{j,t} - x_{\eta t}\right) \tag{14}$$

where η denotes an arbitrary number from (1, 2, …, colony size) and distinct from j, while ξ_j is a random variable in the range [0, 1]. The new positions replace the old ones using the fitness function, in case they contain more nectar. The second step consists of changing the nectar information using onlooker bees, according to the fitness function values. The probability P of the solution selection can be given as:

$$P_j = \frac{\text{fit}_j}{\sum_{j=1}^{\text{NE}} \text{fit}_j} \tag{15}$$

where the number of the employed bees is represented by NE, and the fitness values of the jth bee are denoted by fit_j. The same process as the first stage is used by onlooker bees for the actual position. The last step is introduced when there is no amelioration in the food sources. The employed bees become scout bees and search for new random solutions and then turn to employed bees again if a better solution is achieved. These stages continue until the stopping criterion is fulfilled and the optimum solution is achieved.

Firefly Algorithm (FFA) The FA is a new population-based algorithm, which mimics the dynamic movements of fireflies and was introduced by Yang [47]. FA has been proven to be a powerful technique to tackle numerous optimization problems [48]. Similar to the previously mentioned techniques, FA is used to find the optimal ANFIS parameters for the estimation of the flexural strength capacity of CRC beams and the corresponding model is denoted as ANFIS-FA model. The FA is initialized with the random generation of the initial fireflies' population in terms of original light intensity (β_0), adsorption coefficient (γ), and attractiveness. According to the concept of this algorithm, each firefly moves toward the brighter ones, and using this mechanism, the population moves to "brighter" locations of the search space, i.e., locations with better values of the objective function which symbolizes the brightness. This is a repeated, iterative process which stops when the convergence (stopping) criterion is met and the optimum solution has been obtained. The update of the fireflies' location is made using Eq. (16):

$$\boldsymbol{X_i} = \boldsymbol{X_i} + \beta_0 e^{-\gamma r_{i,j}^2}\left(\boldsymbol{X_i} - \boldsymbol{X_j}\right) + \alpha\left(\boldsymbol{rand} - \frac{1}{2}\right) \tag{16}$$

In the above formula, $\beta_0 e^{-\gamma r_{i,j}^2}$ denotes the attractiveness, $\alpha\left(rand - \frac{1}{2}\right)$ indicates the randomization in a range of [−0.5, 0.5] where α stands for the randomization coefficient, β_0 represents the intensity of light, and γ is the coefficient of adsorption. Moreover, the Cartesian distance is used to determine the distance $r_{i,j}$ between the fireflies X_i and X_j, as shown in Eq. (17):

$$r_{i,j} = \sqrt{\sum_{k=1}^{D}\left(X_{i,k} - X_{j,k}\right)^2} \tag{17}$$

Thereafter, the fireflies are ranked based on their fitness values and the process continues until the stopping condition is fulfilled and the optimum solution has been found.

2.2 Implementation Procedure

2.2.1 Proposed Framework

The framework proposed for the novel hybrid ANFIS models in this study for the flexural strength capacity (M_{fx}) prediction is illustrated in Fig. 4. The framework is programmed using the MATLAB programming language. It should be noted that for all optimization algorithms, the maximum number of iterations has been set to 100, which was proven enough in order to achieve stable results (e.g., convergence) and can serve as a comparison point between the different hybrid ML models. For the same reason, the five optimization algorithms listed above were assigned the same initial population size (i.e., 50 members). Furthermore, Table 1 reports the proper control parameters obtained by the tuning method for each nature-inspired algorithm used in this study (i.e., GA, DE, PSO, ABC, FFA).

2.2.2 Performance Evaluation Metrics

In this section, the accuracy and efficiency of the results obtained from the proposed ML techniques (i.e., ANFIS-FFA, ANFIS-ABC, ANFIS-PSO, ANFIS-GA, and ANFIS-DE) are evaluated. Nine statistical indices are used to verify the performance of the developed models for the prediction of the flexural strength capacity of CRC beams ($M_{\text{fx,exp}}$). The adopted evaluation criteria include five indices for comparing the models' performance, which are the root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), Nash and Sutcliffe efficiency index (NSE), and coefficient of determination (R^2) [49, 50]. In addition, another four criteria are used to verify the models' performance, which are the average error (AE), fractional bias (FB), index of agreement (IA), and fractional error (FE). The mathematical formulas of these indices are given as described in Eqs. 18–25 as [51, 52]:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(E_i - P_i)^2} \tag{18}$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}|(E_i - P_i)/E_i| \times 100\% \tag{19}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|E_i - P_i| \tag{20}$$

$$R^2 = \frac{\sum_{i=1}^{n}\left(P_i - \overline{P}\right)\left(E_i - \overline{E}\right)}{\sqrt{\sum_{i=1}^{n}\left(P_i - \overline{P}\right)^2 . \sum_{i=1}^{n}\left(E_i - \overline{E}\right)^2}} \tag{21}$$

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{n}(E_i - P_i)^2}{\sum_{i=1}^{n}\left(E_i - E_{rate}^{avg}\right)^2} \quad -\infty \le \text{NSE} \le 1 \tag{22}$$

$$\text{AE} = \frac{1}{n}\sum_{i=1}^{n}(P_i - E_i) \tag{23}$$

$$\text{FB} = \frac{2}{n}\sum_{i=1}^{n}(P_i - E_i)/(P_i + E_i) \tag{24}$$

$$\text{IA} = 1 - \frac{\sum_{i=1}^{n}(E_i - P_i)^2}{\sum_{i=1}^{n}\left(\left|P_i - \overline{E}\right| + \left|E_i - \overline{E}\right|\right)} \tag{25}$$

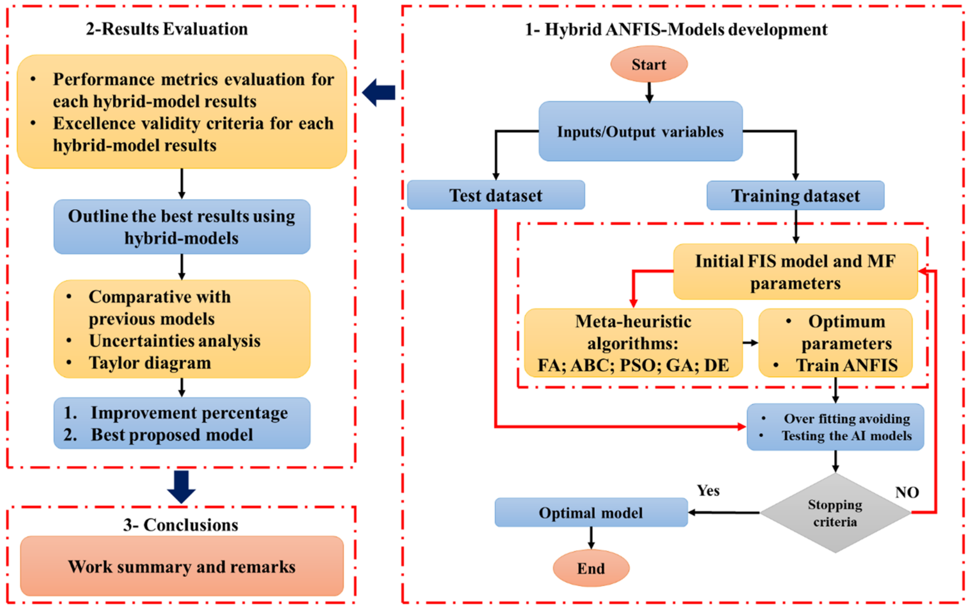

Fig. 4 The detailed structure of the proposed hybrid machine learning model framework implementation and evaluation

$$\mathrm{FE} = \frac{2}{n}\sum_{i=1}^{n}|P_i - E_i|/(P_i + E_i) \tag{26}$$

In the above equations, E_i and P_i denote the ith experimental and predicted values of the flexural strength capacity (M_{fx}) of CRC beams, respectively, and n indicates the sample size. It is worth mentioning that the best predictive model is the one with the lowest values of RMSE, MAE, MAPE, AE, FB, and FE. In addition, the closer the values of R^2 and IA are to unity, the more efficient the model is in predicting the experimental values.

3 Description of the CRC Beams Flexural Capacity Database

A comprehensive experimental database of CRC beams is used for the computation, which consists of 177 tests, gathered from several references and collected systematically by Zhao-Hui et al. [12]. It has to be noted that these experimental tests were carried out using CRC beams subjected to concentrated loads with residual flexural capacity (M_{fx}). Considering that, the latter (i.e., M_{fx}) is significantly influenced by the beams state under corrosion phenomena and the applied load. The CRC beams characteristics collected during the experimental tests include the concrete strength (f), the beam section width b and depth h, the section ratio of the longitudinal steel reinforcement (ρ_l), the steel yield strength (ε_y), the beam shear span-to-depth ratio (λ), and the weight and section loss ratios due to corrosion (i.e., η_{wt} and η_{st}). Besides, for the recorded tests results at failure, the ultimate flexural strength capacity (M_{fx}) and the ultimate concentrated load (P_{fx}) are utilized.

In this study, eight parameters are used as inputs for the modeling process, namely the parameters: f, b, h, ρ_l, ε_y, λ, η_{wt}, and P_{fx}. Since η_{wt} and η_{st} are strongly correlated with each other, only the weight loss ratio η_{wt} due to corrosion is used as a parameter, as suggested in [12]. Statistical information about the database, including the mean, maximum, minimum, range, median, and standard deviation values is reported in Table 2.

Due to the fact that there are no specific guidelines in machine learning modeling for splitting the database between a training and a testing set, researchers have taken different approaches for different problems. In general, the portion of data points used for training the model should be sufficiently larger than the portion for testing it as machine learning models require more comprehensive data to understand and replicate the phenomenon. In our study, we used the trial-and-error method to determine the best data splitting. Thus, the data were divided as 90–10%, 80–20%, 75–25%, and 70–30% between training and testing, respectively. We then ran the modeling, and based on the results, a balance between training and testing with superior results was obtained by the 75–25% splitting scheme, which was finally chosen.

4 Results and Discussion

This section presents the results obtained using the proposed machine learning-based algorithms. The performance of the models is evaluated based on the prediction effectiveness, the model's efficiency and accuracy, and the uncertainties related to the predicted results obtained from the proposed

Table 1 Setting parameters of the metaheuristic optimization algorithms

Optimization algorithm	Parameters	Setting values
GA	Population size	50
	Crossover's probability	90%
	Mutation's probability	10%
	Type of replacement	Elitism (10% of the population)
	Type of selection	Roulette wheel
	Maximum number of iterations	100
DE	Population size	50
	Crossover's constant	0.95
	Maximum number of iterations	100
PSO	Number of particles	30
	C_1, C_2	2.05
	$\omega_{\max}$	1.2
	$\omega_{\min}$	0.1
	Maximum number of iterations	100
ABC	Number of employer bees	50
	Number of onlooker bees	50
	Number of iterations to the scout bees	6
	Maximum number of iterations	100
FFA	Number of fireflies	50
	α	0.5
	β	5
	γ	1
	Maximum number of iterations	100

ML models and compared to the pre-existing correlations in the literature. The obtained results from the hybrid ANFIS models are evaluated firstly by the aforementioned four statistical indices, namely RMSE (kN m), MAE (kN m), MAPE (%), and NSE. The obtained results during the training, testing, and overall phases are reported in Table 3. It should be noted that the closer the RMSE, MAE, and MAPE values are to zero, the more the predicted results agree with the experimental results, and the more accurate the prediction model is. The results reported in Table 3 show that, as expected, the error associated with the training data is in most cases lower that the error associated with the test data, but the differences are not very big, which shows the validity of the methodology. The highest relative difference (i.e., training to testing) is recorded in the ANFIS-DE model with an $\mathrm{RMSE}_{\mathrm{Diff}}$ (%) = 35.53% and $\mathrm{MAE}_{\mathrm{Diff}}$ (%) = 40.87%. The ANFIS-PSO shows the lowest relative differences between the training and testing phases results with $\mathrm{RMSE}_{\mathrm{Diff}}$ (%) = 12.51% and MAE_{Diff} (%) = 13.12%.

Among others important findings, Table 3 shows that the ANFIS-FFA model shows the best results for predicting the flexural strength capacity M_{fx} of CRC beams, in both training and testing phases compared to the other ANFIS-based hybrid models. The provided metrics values by utilizing the ANFIS model coupled with the FFA algorithm for auto-selection of its optimum parameters are RMSE = 2.3049 kN m, MAE = 1.7755 kN m, MAPE = 11.9696%, and NSE = 0.9667 for the overall performance (training and testing).

Besides, the ANFIS-DE outcome is RMSE = 4.5318 kN m, MAE = 3.3952 kN m, and MAPE = 19.9448%, which shows the worst performance, compared to the other models. Moreover, the ANFIS-ABC, ANFIS-PSO, and ANFIS-GA models achieved RMSE values equal to 2.9116 kN m, 3.2454 kN m, and 3.89 kN m, respectively. Comparing the best performer (ANFIS-FFA) with the other four algorithms in terms of the RMSE values and the overall performance, we end up that the results of ANFIS-FFA show a relative improvement of 26.32%, 40.8%, 68.77%, and 96.61%, in comparison with the corresponding results of ANFIS-ABC, ANFIS-PSO, ANFIS-GA, and ANFIS-DE. These results indicate the very good performance of ANFIS-FFA for the accurate prediction of the flexural strength capacity (M_{fx}) of CRC beams.

The results related to the excellence validity criteria are listed in Table 4 including the training and testing phases, as well as the overall results for both of them for each hybrid model.

An in-depth analysis of the obtained results from the various methods can reveal the following findings:

- Unlike the first group of criteria presented in Table 3, the ones of the second group compare the effectiveness of the hybrid models performance in terms of predicted results to experimental tests as fractions. Thus, the performance of the hybrid ANFIS models is compared to reference values (i.e., zero for the AE, FB, and FE criteria and one for IA). The obtained responses using the hybrid ANFIS models' performances are clearly different from one model to another, depending on the used metric. It is shown that among all the different models, ANFIS-FFA gives the best result for the AE, FB, and FE metrics.
- By taking into consideration the IA metric, it is shown that ANFIS-DE exhibits the best overall value (closest to one) with $\mathrm{IA}_{\text{ANFIS-DE}} = 0.7671$, followed by ANFIS-FFA with $\mathrm{IA}_{\text{ANFIS-FFA}} = 0.7626$ and ANFIS-ABC with $\mathrm{IA}_{\text{ANFIS-ABC}} = 0.7614$. The ANFIS-PSO model yielded an IA value

Table 2 Statistical information of the used database for the flexural capacity (M_{fx}) prediction

Parameter	Notation	Unit	Minimum	Maximum	Range	Mean	Median	Std
Concrete strength	f	MPa	22.13	62.62	40.49	33.78	33.4	9.45
Beam section width	b	mm	120	200	80	156.37	150	25.70
Beam section depth	h	mm	150	315	165	207.29	200	46.26
Section ratio of the longitudinal steel reinforcement	ρ_l	%	0.58	1.84	1.26	1.21	1.22	0.34
Steel yield strength	ε_y	MPa	293	593	300	481.76	500	101.14
Beam shear span-to-depth ratio	λ		1.35	4.88	3.53	2.87	2.78	0.91
Weight loss ratio due to corrosion	h_{wt}	%	0	34.8	34.8	7.71	5.84	7.18
Section loss ratio due to corrosion	h_{sn}	%	0	47.77	47.77	10.40	7.16	10.06
Ultimate flexural strength	$M_{\mathrm{fx,exp}}$	kN m	2.84	65.98	63.14	21.13	19.5	12.82
Ultimate concentrated load	$P_{\mathrm{fx,exp}}$	kN	7.1	188.51	181.41	49.16	35.62	35.54

StD denotes the standard deviation

Table 3 Performance indices' values for the ANFIS-based hybrid models in the training, testing, and overall phases

Model	Phase	RMSE	MAE	MAPE	NSE
ANFIS-DE	Training	4.1620	3.0805	19.4314	0.8869
	Test	5.6411	4.3395	21.4848	0.8360
	Overall	4.5318	3.3952	19.9448	0.8742
ANFIS-GA	Training	3.9502	2.9405	17.5475	0.9126
	Test	3.7093	2.9102	22.2550	0.8684
	Overall	3.8900	2.9329	18.7244	0.9015
ANFIS-PSO	Training	3.1470	2.4500	15.8471	0.9397
	Test	3.5408	2.7716	18.2943	0.9224
	Overall	3.2454	2.5304	16.4589	0.9354
ANFIS-ABC	Training	2.7164	2.0799	12.9908	0.9542
	Test	3.4969	2.5924	15.8086	0.9289
	Overall	2.9116	2.2080	13.6952	0.9479
ANFIS-FFA	Training	2.1587	1.7088	11.2934	0.9723
	Test	2.7435	1.9755	13.9983	0.9498
	Overall	**2.3049**	**1.7755**	**11.9696**	**0.9667**

The best results among the others, for each index, are indicated in bold

of 0.7605, while the worst performance was the one of ANFIS-GA (0.7496).

- The values of both the fractional bias (FB) and the fractional error (FE) metrics are closest to zero for the ANFIS-FFA model, equal to − 0.0005 and 0.1148, respectively. In the case of FB, the value has a negative sign, indicating an under-estimation.
- For the case of the AE metric, ANFIS-FFA shows the best overall performance with a value equal to 0.0941, while the lowest value is the one of ANFIS-DE, equal to − 0.5209.
- According to the results shown in Table 4, the proposed hybrid ANFIS-based models show valid prediction results of the flexural strength capacity (M_{fx}) for CRC beams, while the ANFIS-FFA model shows the best performance in terms of the validation criteria of AE, FB, FE, and IA.

Figure 5 depicts the scatter plots of the estimated results versus the experimental values of the flexural strength capacity (M_{fx}) using the data of the training (75%) and testing (25%) phases. Figure 5 includes the coefficient of determination (R^2) and the linear relationship between the target values and output results, formulated using the equation $y = ax + b$ and illustrated in the figures by the dashed red line. This equation indicates a perfect match between the estimated and observed results when $a = 1$ and $b = 0$. Based on Fig. 5, it is shown that the estimated and experimental values are in most agreement using the ANFIS-FFA model, in comparison with the other models. The highest recorded coefficient of determination value is yielded by using the ANFIS-FFA model, with $R^2 = 0.9725$ and 0.9503 in the training and testing sets, respectively. The lowest recoded

Table 4 Results of the excellence validity criteria of the flexural strength capacity (M_{fx}) prediction using the hybrid ANFIS models

Model	Phase	AE	FB	IA	FE
ANFIS-DE	Training	– 0.0296	– 0.0386	0.7599	0.2097
	Test	– 1.9949	– 0.0827	0.7886	0.2223
	Overall	– 0.5209	– 0.0496	**0.7671**	0.2128
ANFIS-GA	Training	0.0752	– 0.0247	0.7592	0.1813
	Test	1.0418	0.0075	0.7209	0.2197
	Overall	0.3169	– 0.0167	0.7496	0.1909
ANFIS-PSO	Training	0.2264	– 0.0054	0.7581	0.1576
	Test	0.2833	0.0156	0.7675	0.1753
	Overall	0.2406	– 0.0012	0.7605	0.1621
ANFIS-ABC	Training	0.2731	0.0092	0.7580	0.1263
	Test	0.8042	0.0502	0.7716	0.1469
	Overall	0.4059	0.0195	0.7614	0.1314
ANFIS-FFA	Training	0.0333	– 0.0078	0.7549	0.1119
	Test	0.2765	0.0213	0.7636	0.1236
	Overall	**0.0941**	**– 0.0005**	0.7626	**0.1148**

The best results are indicated in bold

Table 5 Comparison between the performance of the developed hybrid models and the existing correlations

Model	RMSE	R^2
Previous models		
Azad et al.'s model [53]	7.56	0.65
Sun's model [54]	6.27	0.756
Azad et al.'s modified model [55]	6.03	0.777
Torres-Acosta et al.'s model [56]	5.53	0.813
Xu's model [57]	5.50	0.815
Zhang et al.'s model [58]	4.48	0.847
Zhao-Hui et al. [12]	3.87	0.908
Proposed models		
ANFIS-DE	4.53	0.881
ANFIS-GA	3.89	0.909
ANFIS-PSO	3.25	0.936
ANFIS-ABC	2.91	0.950
ANFIS-FFA	**2.30**	**0.967**

The best results among the others are indicated in bold

R^2 is the one using the ANFIS-DE model, which is equal to 0.8869 (training phase) and 0.8651 (testing phase). Using the best R^2 value ($R^2_{ANFIS-FFA} = 0.9725$, the improvement in the prediction accuracy is 1.8%, 3.2%, 6.0%, and 8.9% compared to the values of ANFIS-ABC, ANFIS-PSO, ANFIS-GA, and ANFIS-DE models, respectively. Overall, the proposed hybrid machine learning approaches based on combining the ANFIS approach with metaheuristic algorithms indicate a good performance in terms of prediction effectiveness compared to the real experimental values of the flexural strength capacity (M_{fx}) for CRC beams, especially using the ANFIS-FFA model.

Although the above results indicate that the proposed ANFIS models show promising results for the accurate and efficient modeling of M_{fx}, it is crucial to compare these models to those in the literature. Next, the performance of the hybrid ANFIS models will be compared with existing models from the literature, in the terms of the RMSE and R^2 statistical indicators. Zhao-Hui et al. [12] conducted a study based on the database used here, where a comparative investigation between their model and the previous correlations is carried out. The same results are extracted and used in the present study, for comparison purposes. Table 5 shows the comparison of the results from the five hybrid models based on ANFIS and the previous correlations from the literature. It is shown that four out of five of the proposed hybrid models (i.e., ANFIS-FFA, ANFIS-ABC, ANFIS-PSO, and ANFIS-GA) outperform the existing ones, in terms of accuracy and efficiency, with lower values of RMSE and higher R^2 results (closer to one). The proposed model by Zhao-Hui et al. [12] is the only model that shows better results than the ANFIS-DE (i.e., the one with the worst performance among the proposed ANFIS-based models). The performance improvements of the four models (ANFIS-FFA, ANFIS-ABC, ANFIS-PSO, and ANFIS-GA) over the one of Zhao-Hui et al. [12]) are 53.95%, 29.53%, 15.94%, and 0.52% in terms of RMSE values and 6.21%, 4.48%, 3.08%, and 0.11% in terms of R^2 values, respectively. Subsequently, the proposed approaches are more efficient

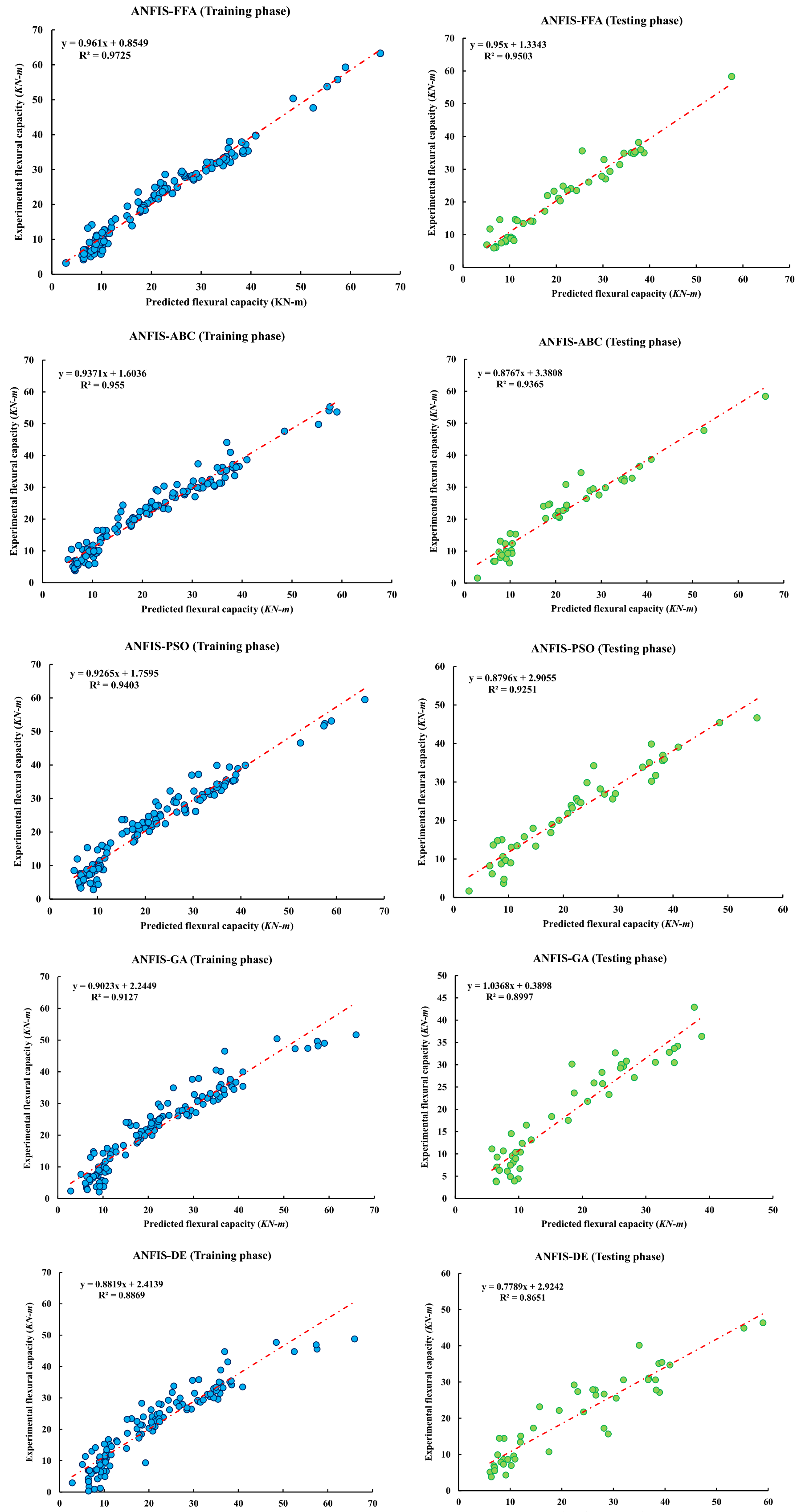

Fig. 5 Scatter plots of experimental values vs predicted results using the proposed hybrid models for training (left column) and testing (right column)

than previous models developed by researchers for modeling the flexural strength capacity (M_{fx}) of CRC beams.

To investigate the uncertainties related to the modeling process, two graphical illustrations are used as time series plot (Fig. 6) during the training and testing phases and the error histograms (Fig. 7) for the entire dataset. It can be seen from Fig. 6 that the plotted prediction results are very close to the experimental values using the proposed models, while the best agreement is the one of the ANFIS-FFA model, for both the training and the testing sets. Moreover, the modeling process using the ANFIS-DE model is clearly showing the highest uncertainty, compared to the other models.

It is worth mentioning that the error histograms exhibited in Fig. 7 correspond to the difference between the predicted results using the proposed ML models and the experimental values of the flexural strength capacity (M_{fx}), i.e., the values $P_i - E_i$. In addition, the mean and standard deviation are calculated and reported in each sub-figure, where the lower the values of the mean and the standard deviation are, the less uncertainty is provided by the model.

According to the results shown in Fig. 7, the prediction of the flexural strength capacity (M_{fx}) using the ANFIS-FFA model exhibits the lowest uncertainty during the modeling process compared to the experimental values. The overall recorded mean and standard deviation values using the ANFIS-FFA model are 0.0941 and 2.3234, respectively. The ANFIS-DE model exhibited the highest overall errors compared to the other models, with mean = 0.5029 kN m and Std = 4.56. The difference between the estimated results using the ANFIS-FFA and the worst model (i.e., ANFIS-DE) is around 40.9% in terms of the mean value and 49.1% in terms of the standard deviation, respectively. It is proven based on the above results that the ANFIS-FFA-based machine learning model is the most suitable choice for modeling the flexural strength capacity (M_{fx}) of CRC beams using real experimental data.

In the final step, the Taylor diagram plot is illustrated in Fig. 8 using the five hybrid models' results against the real experimental values of the flexural strength capacity (M_{fx}). It should be noted that in these figures, the black (radius) lines refer to the Pearson correlation coefficient R, whereas the circles correspond to circumferences with equal standard deviations, while the dash lines are for circumferences with equal centered normalized root mean square errors (*NRMSE*). Thus, the predictive ML models accuracies are compared based on the correlation coefficient, the standard deviation, and the *NRMSE* using the overall data. It is clear from the plotted results of the Taylor diagram that the ANFIS-FFA model (red circle) exhibits the best performance as it is closest to the experimental data point (green circle), compared to the others models.

The relevancy factor analysis is a sensitivity analysis process that allows the evaluation of the influence of the variables considered in the construction of the hybrid ML models for predicting the flexural strength capacity (M_{fx}) of CRC beams. According to Chen et al. [59] and Hajirezaie et al. [60], the higher the obtained relevancy factor value, the stronger the relationship between the model's output and that variable. The relevancy factor is calculated using the following formula:

$$r(I_k,\ O) = \frac{\sum_{i=1}^{N}\left(I_{k,i} - \overline{I_k}\right)\left(O_i - \overline{O}\right)}{\sqrt{\sum_{i=1}^{N}\left(I_{k,i} - \overline{I_k}\right)^2 \sum_{i=1}^{N}\left(O_i - \overline{O}\right)^2}} \tag{27}$$

In the above equation, I represents the sample index, whereas I_k is the *kth* input variables with an average value $\overline{I_k}$. O and $\overline{O}$ are the predicted value and its average, respectively.

Figure 9 depicts the results of the relevancy factor analysis in the form of bar and pie charts using the best outcome hybrid model (i.e., ANFIS-FFA). A negative value is a strong indication of an opposite influence on the outcome; in other words, an increase in the variable values will result in a decrease in the outcome (the flexural strength capacity of CRC beams). The obtained results clearly show an interesting finding, with the beam section depth (h) having the highest relevancy factor value (0.81), indicating a high impact on the flexural strength capacity, followed by the beam section width (b) with 0.59, and then the steel yield strength (ε_y) with $r = 0.44$. This is a logical result because the dimensions of the beam are important factors, particularly the beam depth to resist corrosion penetration, where a decreasing value will eventually reduce the strength of the beam. In addition, the greater the yield strength value, the greater the flexural strength capacity of CRC. The weight and section loss ratios due to corrosion (i.e., η_{wt}andη_{st}) and the beam shear span-to-depth ratio (λ) on the other hand indicated a negative impact on the flexural strength capacity, which means that increasing the values of these variables will result in a decrease in the output result (the flexural strength capacity). In general, the relevancy factor analysis revealed that the developed hybrid ANFIS model in conjunction with FFA yielded logical and coherent sensitivity analysis results.

5 Conclusions

An accurate prediction of the flexural strength capacity (M_{fx}) of CRC beams will provide engineering or field operators with valuable information not only about the state of the structure, but also on the most suitable inspection procedures to follow using cost-effective strategies for maintenance and rehabilitation. However, obtaining reliable predictions for the flexural strength capacity is a very challenging task due to the influence of various parameters such as the corrosion rate and the applied loads on the CRC beams. In this paper, five

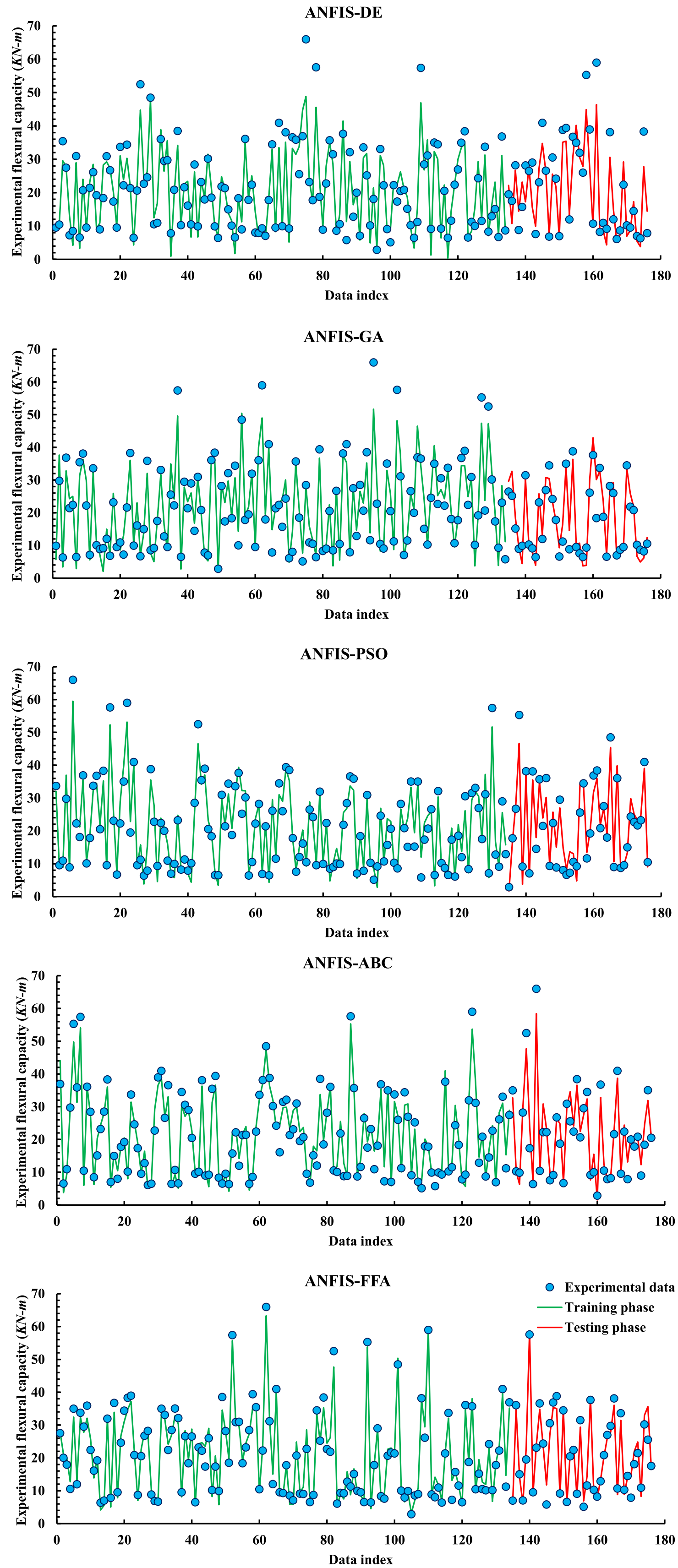

Fig. 6 Time-series plots of the experimental values versus the estimated results using the proposed machine learning models in the training and testing phases

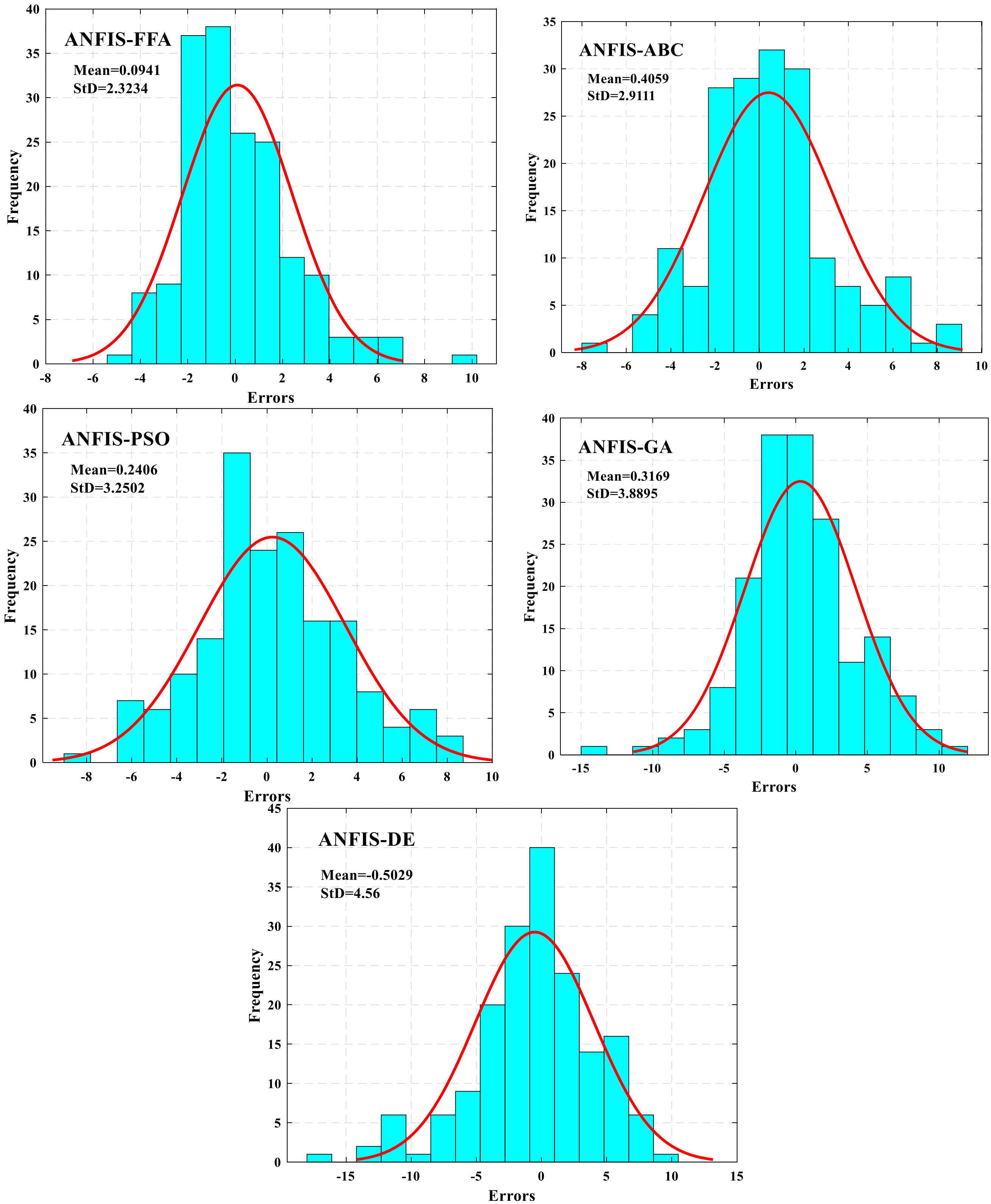

Fig. 7 The prediction error related to the ANFIS-based hybrid models using the overall data

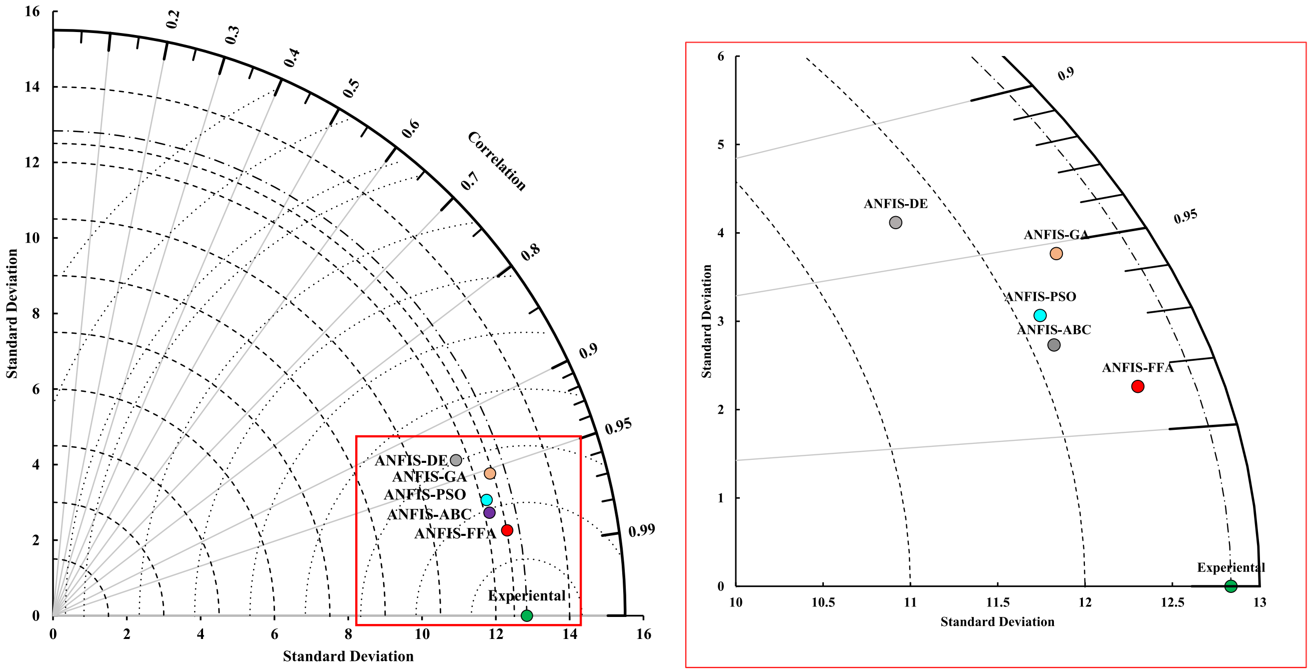

Fig. 8 Statistical comparison of the proposed hybrid models based on the ANFIS approach with the experimental values, using the Taylor diagram

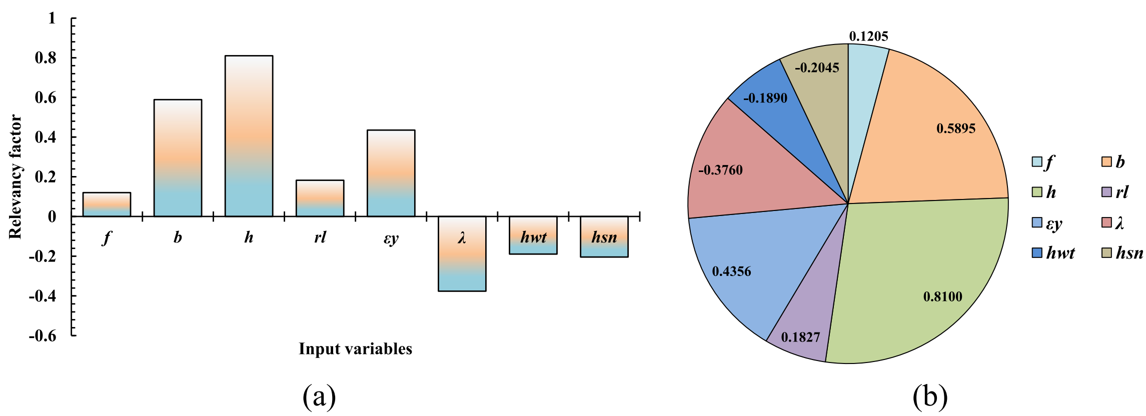

Fig. 9 Sensitivity analysis using the relevancy factor. **a** Bar chart, **b** pie chart results

novel predictive hybrid models based on the ANFIS approach are proposed to introduce an accurate and stable prediction framework for the flexural strength capacity of CRC beams. A comprehensive database including 177 real experimental tests is employed to illustrate the proposed methodologies. Multiple evaluation criteria are utilized to evaluate the validity and the performance of the novel hybrid models. Based on the results presented in the paper, the following conclusions can be drawn:

- Results of the performance accuracy metrics (i.e., RMSE, MAE, MAPE, and NSE) indicated acceptable results during the testing phase with different outcomes using the proposed models based on the hybrid ANFIS and the five metaheuristic algorithms. Specifically, a performance pattern was noticed as ANFIS-FFA > ANFIS-ABC > ANFIS-PSO > ANFIS-GA > ANFIS-DE, where " > " denotes the better performance. Besides, the respective R^2 values were estimated as 0.9503, 0.9365, 0.9251, 0.8997, and 0.8651 during the testing phase.
- Excellence validity results indicated a similar pattern for the hybrid models' performance. Again, ANFIS-FFA yielded the highest excellence among the other developed hybrid models with FB and FE values equal to − 0.0005 and 0.1148, respectively.
- The proposed hybrid models proved to outperform previous models that have been developed by researchers, in terms of accuracy and efficiency. The results revealed that four out of five hybrid ANFIS-based models (namely

ANFIS-FFA, ANFIS-ABC, ANFIS-PSO, and ANFIS-GA) achieved superior results, with 53.95%, 29.53%, 15.94%, and 0.52% improvements in terms of RMSE and 6.21%, 4.48%, 3.08%, and 0.11% in terms of R^2 compared to the best previous model (i.e., Zhao-Hui et al. [12]), respectively.
- All the hybrid models show low uncertainties related to the modeling process, with ANFIS-FFA model exhibiting the best performance in this criterion. Besides, the Taylor diagram confirms the superior performance of ANFIS-FFA model for the accurate estimation of the flexural strength capacity of CRC beams.

Finally, given its performance ability in M_{fx} prediction, the newly developed ML framework can serve as a useful engineering tool. However, it should be noted that this study is based on a limited number of samples (i.e., 177 samples) and input variables (i.e., eight factors). It is strongly recommended that future works investigate the applicability of the proposed hybrid models using a larger database with the examination of additional influencing factors, such as the age of the CRC beams, and others. Furthermore, comparing the obtained results with other machine and deep learning approaches can provide different insights into the prediction of CRC beam flexural strength capacity and the behavior of the factors that influence it the most.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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