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Modelling the deflection of reinforced concrete beams using the improved artificial neural network by imperialist competitive optimization

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Abstract. This study proposed a robust artificial intelligence (AI) model based on the social behaviour of the imperialist competitive algorithm (ICA) and artificial neural network (ANN) for modelling the deflection of reinforced concrete beams, abbreviated as ICA-ANN model. Accordingly, the ICA was used to adjust and optimize the parameters of an ANN model (i.e., weights and biases) aiming to improve the accuracy of the ANN model in modelling the deflection reinforced concrete beams. A total of 120 experimental datasets of reinforced concrete beams were employed for this aim. Therein, applied load, tensile reinforcement strength and the reinforcement percentage were used to simulate the deflection of reinforced concrete beams. Besides, five other AI models, such as ANN, SVM (support vector machine), GLMNET (lasso and elastic-net regularized generalized linear models), CART (classification and regression tree) and KNN (k-nearest neighbours), were also used for the comprehensive assessment of the proposed model (i.e., ICA-ANN). The comparison of the derived results with the experimental findings demonstrates that among the developed models the ICA-ANN model is that can approximate the reinforced concrete beams deflection in a more reliable and robust manner.

Keywords: artificial neural network; deflection of RC beam; ICA-ANN; modelling; optimization algorithm

1. Introduction

Concrete beams are indispensable components of buildings and civil engineering structures. Many types of existing concrete can be used in construction, such as steel-reinforced concrete, plain concrete, bamboo-reinforced, steel-concrete composite, fibre-reinforced concrete, and fibre-reinforced polymers, to name a few (Bischoff 2005, Yuan *et al*. 2016, Venkateshwaran and Tan 2018, Mishra *et al*. 2019). Of those, steel-reinforced concrete beam is the most widely used since it has an advantage of load-carrying capacity, simplicity and economic efficiency (Cai *et al*. 2003, Nie *et al*. 2008, Kim *et al*. 2011, Xing *et al*. 2016). However, the corrosion of steel and the deflection of reinforced concrete beams are the main concerns of engineers (Melchers *et al*. 2008, Shin *et al*. 2009, Lemonis *et al*. 2022). Corrosion of steel is also thought to be related to the deflection of reinforced concrete beams (Zhang *et al*. 2009). Therefore, the deflection of beams is of particular concern in civil works given the gravity of its impact on buildings and infrastructures, and the safety of the occupants in the long run (Lapko and Urbański 2015). Moreover, excessive loads and large deflections in beams have been associated with crack propagation and deformation on these structures (Ghali *et al.* 2018, Visintin *et al.* 2018, Al-Kamyani *et al.* 2019). Besides, errors in the deflection computation of flexural members, loading of flexural members, vibration, flexural stiffness, factors affecting fixity, and construction variations of flexural members, are also the factors which affect deflections of beams in reinforced concrete structures (Mohamedbhai 1971, Kaklauskas 2004, Ahmed 2007, Issa *et al.* 2011, Pakar and Bayat 2012, Mahmoud Bayat *et al.* 2013, M Bayat *et al.* 2013, Pakar and Bayat 2013). An accurate prediction of concrete beam deflection thus becomes imperatively challenging to construction engineers, especially concerning the design and construction optimization of structures.

In recent years, artificial intelligence (AI) techniques promised a remarkable entrance as a robust tool for modelling and predicting, as well as an excellent optimization approach (Asteris *et al.* 2016, Gao *et al.* 2018, Attouch and Cabot 2019, Bui *et al.* 2019, Eckstein and Kupper 2019, Gao *et al.* 2019, Kennedy and Ward 2019, Moayedi *et al.* 2019a, Moayedi *et al.* 2019b, Neumayer *et*

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al. 2019, Nguyen *et al.* 2019b, Nguyen *et al.* 2019c, Nguyen *et al.* 2019d, Nguyen *et al.* 2019e, Vila and Gauchi, 2019, Zhang *et al.* 2019). These techniques have been successfully employed in many fields with promising results, i.e., prediction of the compressive strength of concrete (Nikoo *et al.* 2015, Asteris *et al.* 2016, Chopra *et al.* 2016, Khademi and Behfarnia 2016, Asteris and Plevris 2017, Khademi *et al.* 2017, Asteris *et al.* 2018, Hosein Naderpour *et al.* 2018, Yaseen *et al.* 2018, Asteris and Kolovos 2019, Asteris and Nikoo 2019, Asteris *et al.* 2019), detection of beam structures (Asteris and Cotsovos 2012, Cha and Buyukozturk 2015, Gerist and Maheri 2016, Chatterjee *et al.* 2017, Asteris and Nikoo 2019), prediction of shear resistance of concrete beams associated with a high level of confidence (Chou *et al.* 2015, Mohammadhassani *et al.* 2015, Asteris *et al.* 2016, Safa *et al.* 2016, Naderpour *et al.* 2018), detection of structural damage (Facchini *et al.* 2014, Betti *et al.* 2015, Abdeljaber *et al.* 2017, Alkayem *et al.* 2018, Avci *et al.* 2021), composite structures in aircraft manufacturing technology (Ai *et al.* 2021), to name a few. Regarding the prediction of beam deflection, Hegazy *et al.* (1998) did pioneer research in 1998, where they used an ANN to predict the deflection of concrete slabs. Subsequently, Flood *et al.* (2001) also adopted ANN to analyse the performance of externally reinforced beams, aimed at providing the best solutions of overcoming the damage leading to cracks and breaks in concrete structures. Moreover, with ANN, Sakr and Sakla (2008); (2009) modelled and predicted the long-term deflection of cracked composite beams, whereas Tadesse *et al.* (2012) successfully developed an ANN model to predict the deflection of composite bridges with high reliability. Darain *et al.* (2015) applied an adaptive neuro-fuzzy inference system (ANFIS) to simulate and predict the deflection and cracking behaviour of near-surface mount, which is a promising strengthening approach. They concluded that their ANFIS model gave a significant improvement to the accuracy of the predictions. Furthermore, Mishra *et al.* (2019) applied ANN to predict the deflection of steel-reinforced, plain and bamboo-reinforced concrete beams.

Based on the perspectives of the authors of this study, the applications of AI techniques in this field are very sketchy. The primary technique employed in the above-cited studies is ANN. Modern AI techniques are considered powerful methods because of their remarkable ability to predict the deflection behaviour of concrete beams (Mohammadhassani *et al.* 2013a, Mohammadhassani *et al.* 2013b, Kaczmarek and Szymańska 2016, Parsajoo *et al.* 2021). As such, this study presents a novel intelligence model for the prediction of the deflection of reinforcement steel-concrete beams (DRSCB) based on evolutionary social intelligence of imperialist competitive algorithm (ICA) and artificial neural network (ANN), namely ICA-ANN model. It is worth mentioning that although the ICA-ANN model has been developed and applied in other areas/fields; nevertheless, it has not been investigated and developed for modelling the deflection of RC beams.

Furthermore, the performance of the ICA-ANN models with different problems, as well as the different database is not similar. Therefore, in this study, a total of 120 experimental datasets in terms of loads applied, tensile reinforcement strength and the reinforcement percentage were performed and gathered for the aim of predicting the deflection of steel-reinforced concrete beams in smart buildings. Besides, five other artificial intelligence models, such as ANN, SVM (support vector machine), GLMNET (lasso and elastic-net regularized generalized linear models), CART (classification and regression tree) and KNN (k-nearest neighbours), were also taken into account and developed for the similar purposes and compared with the proposed ICA-ANN technique.

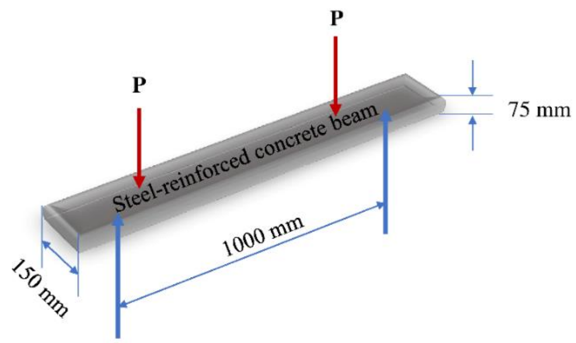

Fig. 1 Data collection experiments for the present study

Considering the above, the manuscript is organized into six sections, including this introductory section. In section 2, the database used and background of the ICA and ANN is presented; Section 3 presents detailed and in-depth the proposed novel ICA-ANN model for the prediction of DRSCB. In section 4 the methods that are applied to evaluate the predictive models are presented. Sections 5 and 6 present the results of the work presented herein and conclusions of the current research, respectively.

2. Material and methods

In this section, the database used for the training and development of the proposed forecast models is presented followed by a detailed and in-depth presentation and discussion of the methodologies of the soft computing models proposed and developed in the work presented herein.

2.1 Material

The majority of researchers that are occupied with the training and the development of computational modals pay more attention on the credibility of the computational techniques used and less attention on the database that is used for their training. However, the reliability of a proposed mathematical model depends mainly on the reliability of the database that is used for the training. By using the Reliability terms it actually means that the database used is consisted of an adequate number of data that describe the full length of the issue in research. Specifically, sufficient number of reliable data is required

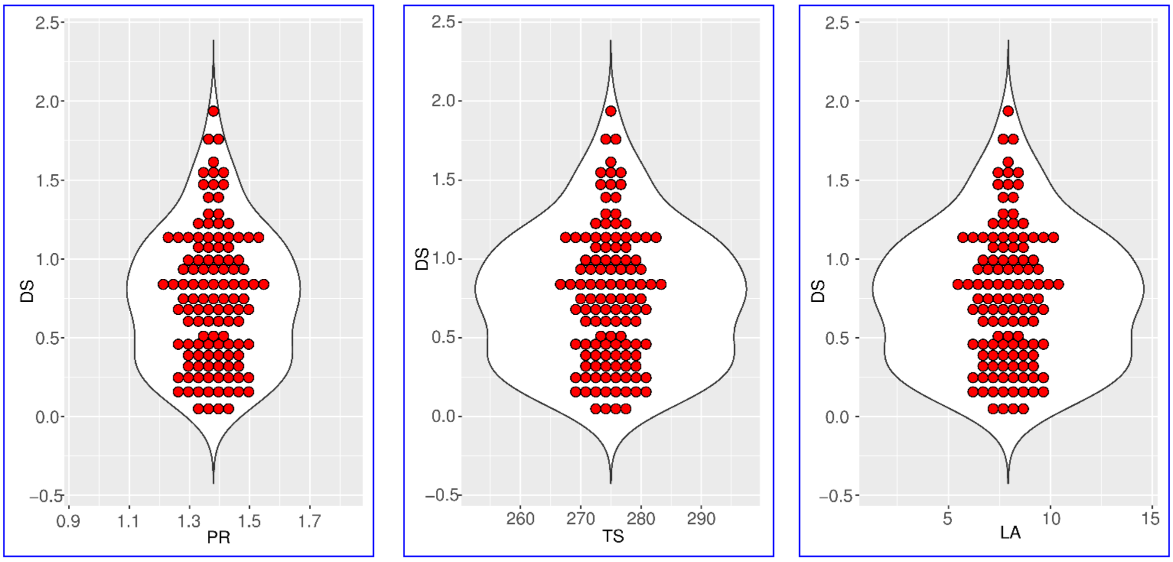

Fig. 2 Kernel probability density of the dataset used at different values by violin plots

Table 1 Experimental datasets used in this study

Elements	PR	TS	LA	DRSCB
Min.	1.060	250.0	0.547	0.024
Mean	1.373	276.2	6.631	0.757
Max.	1.700	300.0	15.322	1.937

that evenly covers the full length of any possible outcomes that a parameter might take that is an input of the issue in research.

Based on the above special care has been taken during the preparation of the database used in the work presented herein. Namely, the experimental data of the present study consists of 120 laboratory test datasets of the reinforcement steel-concrete beams, in which a two-point load was applied to the beams, as depicted in Fig. 1. Each beam is 1000 mm long, 150 mm wide and 75 mm thick or has a cross-sectional area of 150 mm × 75 mm.

It is worth writing that all beams were prepared and testing in accordance with international codes and standards. The materials used for beam designs were Fe 250 and FE 300 grade bars with tensile strength (TS) values of 250 and 300 N/mm2, respectively. Four steel strips corresponding to total areas of 100, 120, 140 and 160 mm^2, respectively, were used for reinforcement of the beams. These areas, in turn, corresponded to reinforcement percentages (PR) of 1.06%, 1.28%, 1.49% and 1.70%. The loading was applied stepwise through a 100 kN capacity servo-hydraulic machine in a force-controlled mode by a load step equal to 1 kN. Test results showed that these loads applied ranged from 0.547 to 15.322 kN. Finally, DRSCB was recorded using a dial gauge. The experimental datasets used in DRSCB estimation are summarised in Table 1. The kernel probability density of the datasets used at different values by violin plots is shown in Fig. 2.

2.2 Methodology: background of the ICA and ANN

As introduced in the introduction section, ICA-ANN, ANN, KNN, CART, SVM, and GLMNET are the AI techniques used in the present study, where ICA-ANN is the proposed hybrid model. The details of both the ANN and ICA, as well as the development of the ICA-ANN model, are highlighted in the succeeding sections, whereas information on KNN, CART, SVM and GLMNET are found in previous studies (Friedman *et al.* 2010, Ogutu *et al.* 2012, Bui *et al.* 2019, Nguyen 2019, Nguyen *et al.* 2019a, Asteris *et al.* 2021a, Asteris *et al.* 2021b, Kardani *et al.* 2022).

Imperialist Competitive Algorithm (ICA)

1. Initialize parameters;
2. Generate the population randomly;
3. Initialize the empire:
   For $i = 1$ to N_{pop} (N_{pop} = population size)
   Compute the evaluation cost c_i;
   Sort the computed cost c_i in descending order for the entire population;
   Select N_{imp} (number of imperialist countries) out of N_{pop};
   Normalize the cost of each imperialist C_n;
   Compute the normalized power of each imperialist P_n;
   Assign N_{col} remained countries to the imperialists;
   End Loop
4. Assimilation, Revolution, Imperialist Competition Processes;
   For $j = 1$ to N_{imp}
   Move the colony toward the relevant imperialist (assimilation);
   Compute the costs of assimilated countries;
   Perform revolution on new colony;
   If the cost of new colony is less than cost of imperialist
   Then exchange the position of colony and imperialist;
   Pick the weakest colony (colonies) from the weakest empire and assign it (them) to the empire that has most likelihood to possess it;
   End Loop
5. Elimination Process;
   If there is imperialist with no colonies
   Then eliminate the imperialist;
6. Until stopping condition is reached.

Fig. 3 ICA pseudocode (Hosseini and Al Khaled 2014)

2.2.1 ICA

ICA was introduced by Atashpaz-Gargari and Lucas (2007) as a robust evolutionary algorithm based on the inspiration from a social phenomenon. It is widely applied to

optimal problems, especially nonlinear integer programming, e.g., dynamic programming (Hammer and Rudeanu, 2012). Based on the evolutionary behaviour of human society, ICA employs evolutionary procedures to

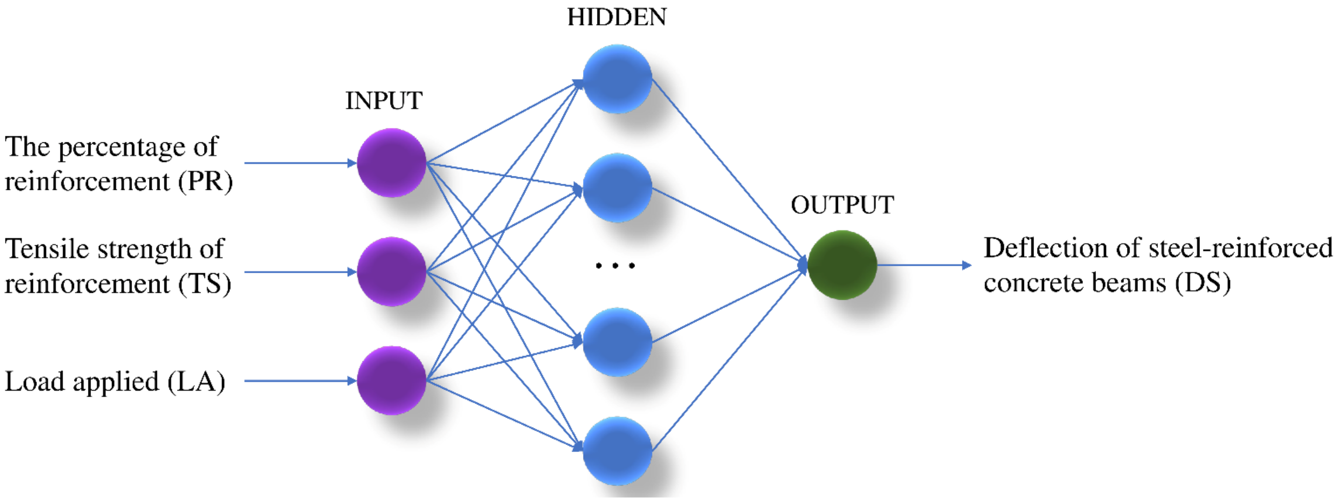

Fig. 4 ANN framework for modelling the deflection of the reinforced concrete beam in this study

find optimal problems. Human development, social needs, imperial competition and colonial rivalry, are the fundamental behaviours considered by ICA for any optimisation problem.

Practically, ICA consists of three main principles, e.g., assimilation policy, imperialistic competition and revolution (Mikaeil *et al.* 2018). The procedure used to find the optimal values with this algorithm is illustrated using pseudocode in Fig. 3. ICA remains a contemporary approach to solve problems in different fields, such as mining, civil engineering, mechanics and electrical engineering, to name a few (Kaveh and Talatahari 2010, Mokhtari *et al.* 2012, Shabani *et al.* 2013, Rad *et al.* 2014, Xu *et al.* 2014, Hajihassani *et al.* 2015, Abd-Elazim and Ali 2016, Gerist and Maheri 2019). Here, ICA was used to optimise an ANN model in estimating the deflection of steel-reinforced concrete beams.

2.2.2 ANN

ANN is a nervous system designed based on the structure of the human brain. It is a subfield of AI or data-mining (Frankish and Ramsey, 2014) with powerful data processing and analysis capabilities. ANN's primary goal is to develop a computing system that is capable of learning based on the biological model of the brain. According to a university survey from a database article, ANN has been used in 27,736 articles from 1985 to 2000 and 203, 328 articles from 2001 to 2016 (Walczak 2019), indicating the strong applicability of ANN in real life, which tends to increase.

The ANN has three layers: input, hidden and output. Independent variables are represented by independent vectors, to represent parts from the input initially, and then processed and transferred to the hidden layers. The number of hidden layers can be one or more depending on the complexity of the problem to be processed (Russell and Norvig 2016). Accordingly, weights express interconnections between the layers and the neurons are considered as the main parameter of an ANN model. Node bias in each hidden layer or output layer is calculated to determine the accuracy of the container of the value (Ritter *et al.* 2017). Ultimately, the output values are estimated and considered as dependent variables in each ANN model. Based on this study's review of related works, ANN is also a commonly used technique for predicting DS and has been successful in similar purposes in other engineering structures (Cascardi *et al.* 2017, Fathalla *et al.* 2018, Abdelkarim *et al.* 2019, Cao *et al.* 2019, De Granrut *et al.* 2019, Xu *et al.* 2019). The architecture of an ANN model for DS prediction in this work is described in Fig. 4.

3. ICA-ANN model for modelling the deflection of reinforced concrete beam

The DS prediction algorithm of ICA-ANN was developed based on the procedure as follows: (1) First, an initialisation ANN model was developed, and (2) then, its weights and biases were optimised by the ICA. More specifically, the ICA pseudocode in Fig. 3 was applied to find out the optimal values for the weights and biases of the established ANN framework. (3) A fitness function (i.e. root-mean-squared error (RMSE)) was applied to measure the fitting level of the optimised ANN model (i.e. ICA-ANN). In the optimal case, the optimal ICA-ANN model was corresponded by the lowest RMSE. The ICA-ANN framework is shown in Fig. 5.

4. Measurement systems of the model performances

The performance of the proposed ICA-ANN model, as well as that of the five other models (i.e., ANN, CART, KNN, SVM and GLMNET), was evaluated using five performance indices, namely, MAPE, RMSE, VAF, MAE and R^2, which are expressed as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{1}$$

$$\mathrm{R}^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2} \tag{2}$$

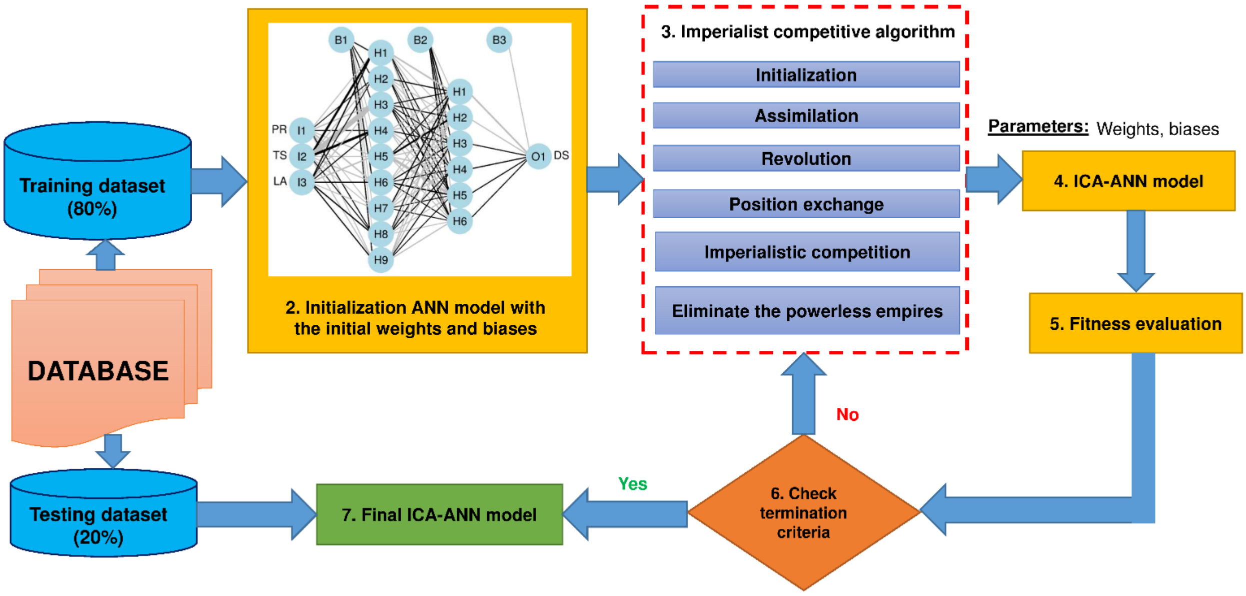

Fig. 5 ICA-ANN framework for DS estimation

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \quad (3)$$

$$\text{VAF} = \left(1 - \frac{\text{var}(y_i - \hat{y}_i)}{\text{var}(y_i)}\right) \times 100 \quad (4)$$

$$\text{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (5)$$

where n stands for the number of instances and $\overline{y}$, y_i and $\hat{y}_i$ denote the average, calculated and modelled values of the response variable.

In addition, the colour intensity and Taylor diagram were also used to evaluate the performance of the deflection predictive models.

Imperialist Competitive Algorithm (ICA)

1. Initialize parameters;
2. Generate the population randomly;
3. Initialize the empire:
   For $i = 1$ to N_{pop} (N_{pop} = population size)
   Compute the evaluation cost c_i;
   Sort the computed cost c_i in descending order for the entire population;
   Select N_{imp} (number of imperialist countries) out of N_{pop};
   Normalize the cost of each imperialist C_n;
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4. Assimilation, Revolution, Imperialist Competition Processes;
   For $j = 1$ to N_{imp}
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   Perform revolution on new colony;
   If the cost of new colony is less than cost of imperialist
   Then exchange the position of colony and imperialist;
   Pick the weakest colony (colonies) from the weakest empire and assign it (them) to the empire that has most likelihood to possess it;
   End Loop
5. Elimination Process;
   If there is imperialist with no colonies
   Then eliminate the imperialist;
6. Until stopping condition is reached.

Fig. 6 The architecture of the selected ANN model for DS prediction

5. Results and discussion

In order to model the deflection of a reinforced concrete beam, the framework in Figure 5 was applied. The dataset collected from 120 experimental tests was divided into two subsets, one for training and another for testing. The training dataset comprised 80% (96 experimental tests) of the entire data and was used to develop the ICA-ANN model, whereas the remaining 20% (24 experimental tests) was used to evaluate its performance. The same data subsets were applied into the other models (ANN, CART, KNN, SVM and GLMNET), merely for comparison purposes.

An initialisation ANN model (Fig. 5) was first developed for the optimisation process by the ICA. To save time and to minimise work complexity, an ANN model (developed without optimisation) was considered for the optimisation process. In this respect, we determined the number of hidden layers and neurons that is best for the ANN model. Nguyen *et al.* (2018a) argued that too many hidden layers/neurons would lead to overfitting; by contrast, too few would lead to underfitting. Nonetheless, an ANN model with one or two hidden layers can solve most of the problems (Nguyen *et al.* 2018b). On account of these concerns, a 'trial and error' procedure with two hidden layers was implemented to define the optimal ANN model in this case study. Additionally, the ANN model was developed using a backpropagation algorithm, acknowledging a repetition count of 200 to determine the initial weights and biases. To avoid overfitting with the scale, data scale method was applied in the scale of [−1,1]. Eventually, the optimal ANN model, that is, ANN 3-9-6-1 (Fig. 6), was found.

Subsequently, the ICA was applied to optimize further

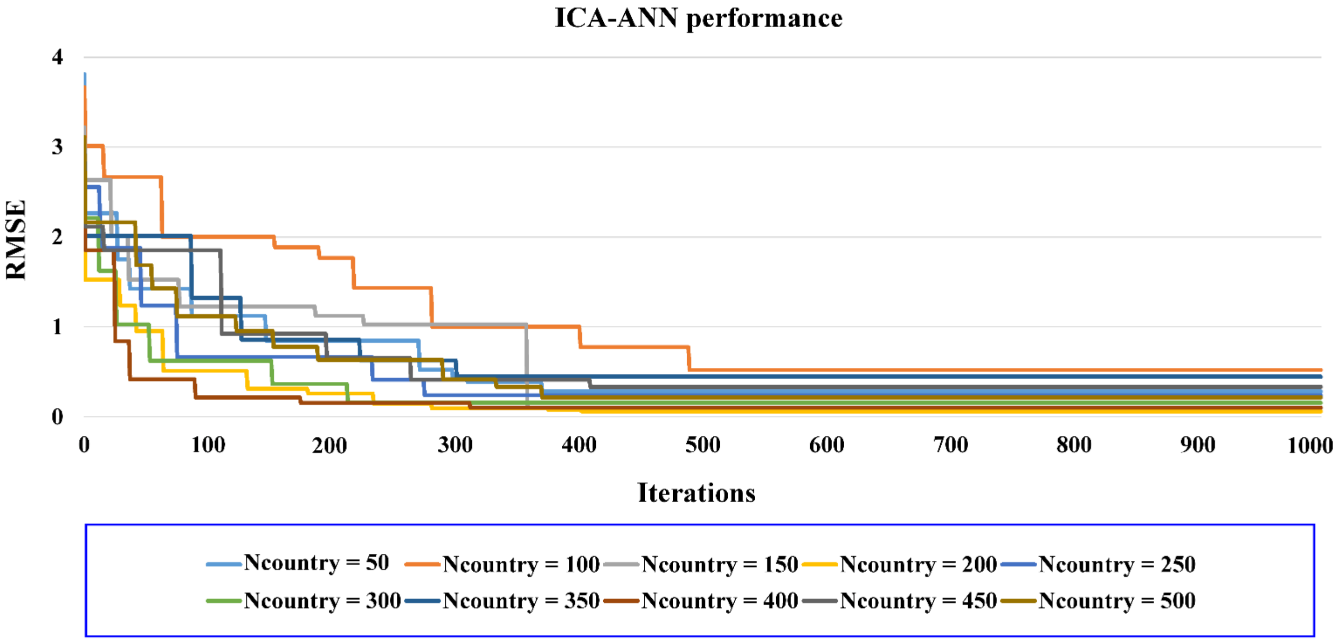
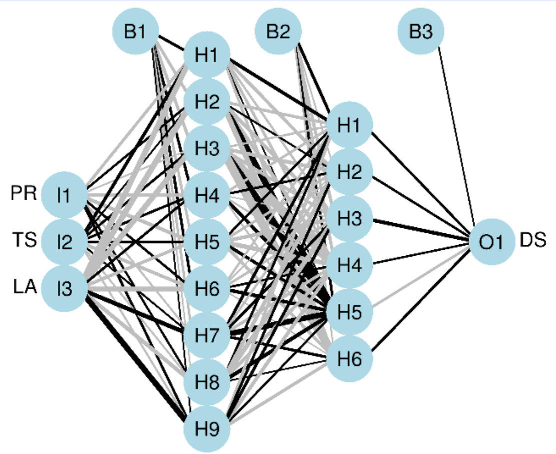


Fig. 7 Optimisation of the training dataset of the ANN model by the ICA



Positive weights are represented by black lines, and negative weights by grey lines. The thickness of the lines is proportional to the magnitude of the weights relative to all others. The input variables (PR, TS, LA) are presented by I1 to I3, respectively. The number of hidden neurons in each hidden layer are presented by H1 to H9, respectively. The DS is the output parameter, which illustrated by O1. The biases applied as constant values to the nodes are presented by B1, B2, and B3.

Fig. 8 ANN model optimised by the ICA (i.e., ICA-ANN model)

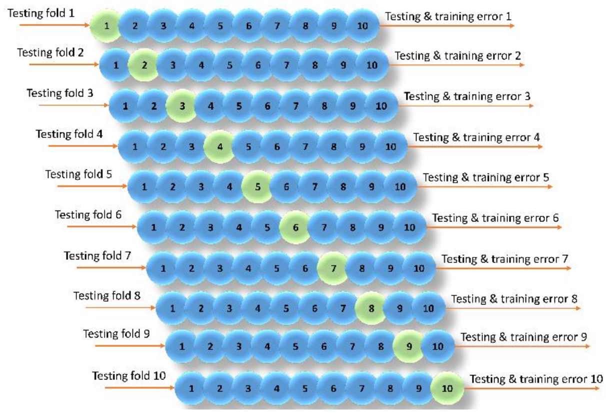


Fig. 9 Resampling technique of 10-fold cross-validation

the selected ANN model aiming to improve its accuracy. Weights and biases computed in the selected ANN model were used as a precursor to improving the model's performance using evolutionary algorithms. The ICA performed a global search of the optimal values for the weights and biases of the ANN model, after which the feasibility and performance of the ICA-ANN model were considered and assessed. More importantly, to optimise the ANN, the ICA needed a series of pre-parameters, namely, the number of initial countries ($N_{country}$), initial imperialists (N_{imper}), the maximum number of iterations (N_i), lower-upper limit of the optimisation region (L), assimilation coefficient (As) and revolution of each country (r). Such optimisation task was implemented simultaneously with a TAE procedure for $N_{country}$, in which $N_{country}$ was set equal to a 50-500 range at a stepwise of 50; N_{imper} was set equal to 20, 30 and 50; L was set in the $[-10,10]$ interval; As was set to 3; r was set to 0.5 and N_i was set to 1000. After the ICA parameters were corrected, the global search for the colonies by the empires was conducted, or rather, the established ICA optimised the weights and biases of the ANN model. The performance of the proposed ICA-ANN model DS estimation during the optimisation process (only provided for the training dataset) is shown in Fig. 7.

Accordingly, the optimal ICA-ANN model was obtained at $N_{country}$ = 200 and 404 iterations, with the lowest RMSE of 0.060. After the optimisation process was satisfied, the search was stopped, and the optimal values of weights and biases were extracted. The ICA-ANN framework with the optimal weights and biases is presented in Fig. 8. Relative to Fig. 6 (i.e., ANN model), the structure in Fig. 8 (i.e., ICA-ANN model) was similar, but with different weights and biases, as indicated by the grey and black lines in Figs. 6

Table 2 Performance on the testing dataset of the developed models

Model	RMSE	MAE	R^2	VAF	MAPE	Rank for RMSE	Rank for MAE	Rank for R^2	Rank for VAF	Rank for MAPE	Total ranking
ICA-ANN	0.047	0.033	0.991	99.051	0.185	6	6	6	6	4	28
ANN	0.063	0.049	0.984	98.329	0.121	5	5	5	5	6	26
KNN	0.078	0.053	0.980	97.521	0.196	3	3	3	3	3	15
CART	0.119	0.072	0.945	93.989	0.262	2	2	2	2	2	10
SVM	0.235	0.086	0.778	77.409	0.267	1	1	1	1	1	5
GLMNET	0.066	0.052	0.983	98.192	0.162	4	4	4	4	5	21

Note: The best model is shown in bold type

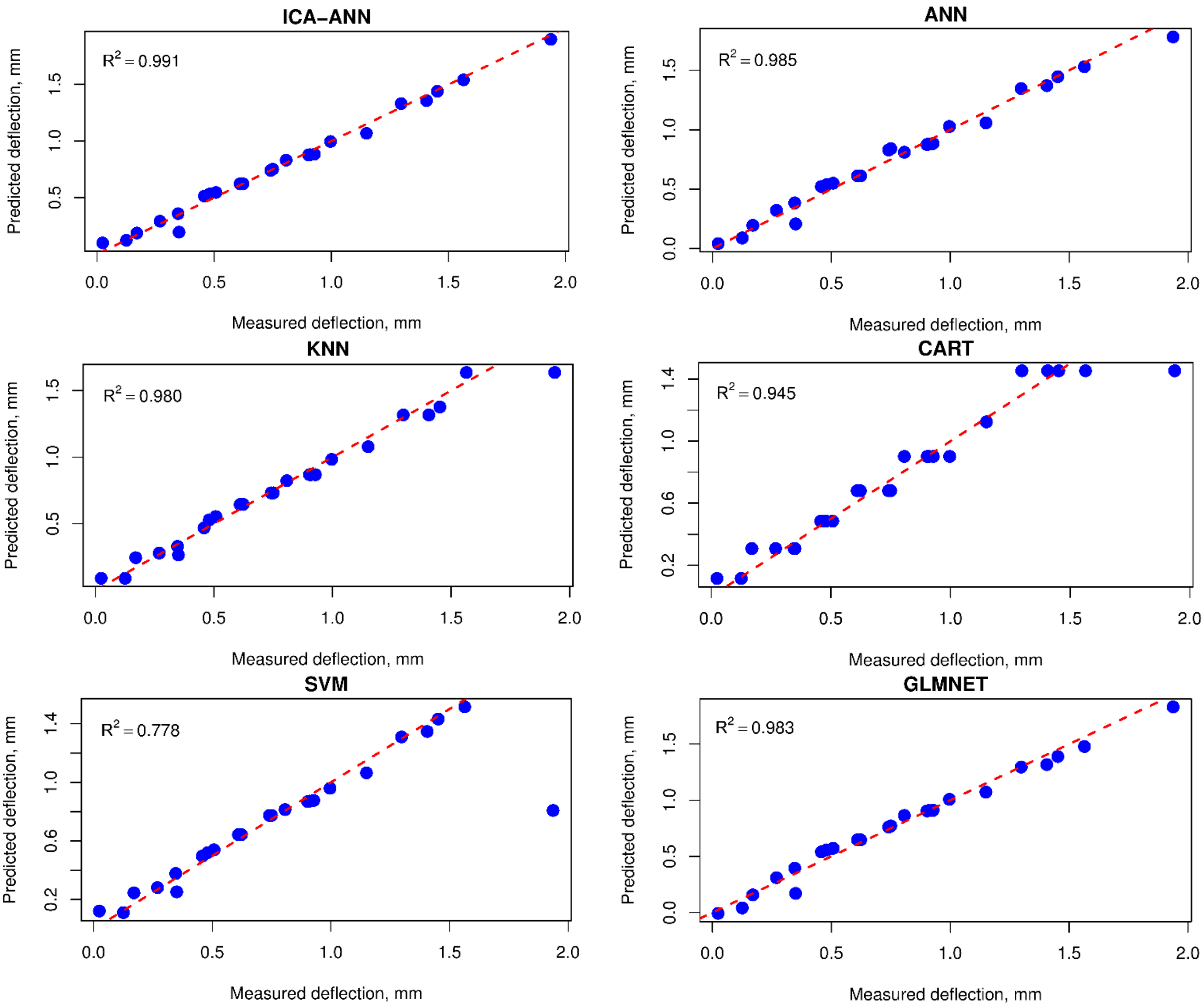


Fig. 10 Correlation analysis results of the models for DS prediction

and 8.

After designing ANN and ICA-ANN, the remaining four models (i.e., CART, SVM, KNN and GLMNET) were developed in the same fashion using the same training dataset. A ten-fold cross-validation resampling technique (Fig. 9) was applied for these models during development to avoid overfitting. Eventually, their hyper-parameters were defined as the optimal models for DS prediction. Accordingly, the accuracy level quality of all models, including ICA-ANN, was evaluated through the use of the testing dataset (from the 24 experimental tests), where DS was predicted on account of the performance metrics (i.e. RMSE, MAE, VAF, MAPE and R^2). The corresponding results are shown in Table 2. In addition to the performance metrics, colour intensity was evaluated to rank the accuracy of the models. Apparently from Table 2, the ICA-ANN provided the best prediction as regards colour intensity. Most performance indicators for the proposed ICA-ANN model were maximised, particularly RMSE = 0.047, MAE = 0.033, R^2 = 0.991, VAF = 99.051, MAPE = 0.185 and

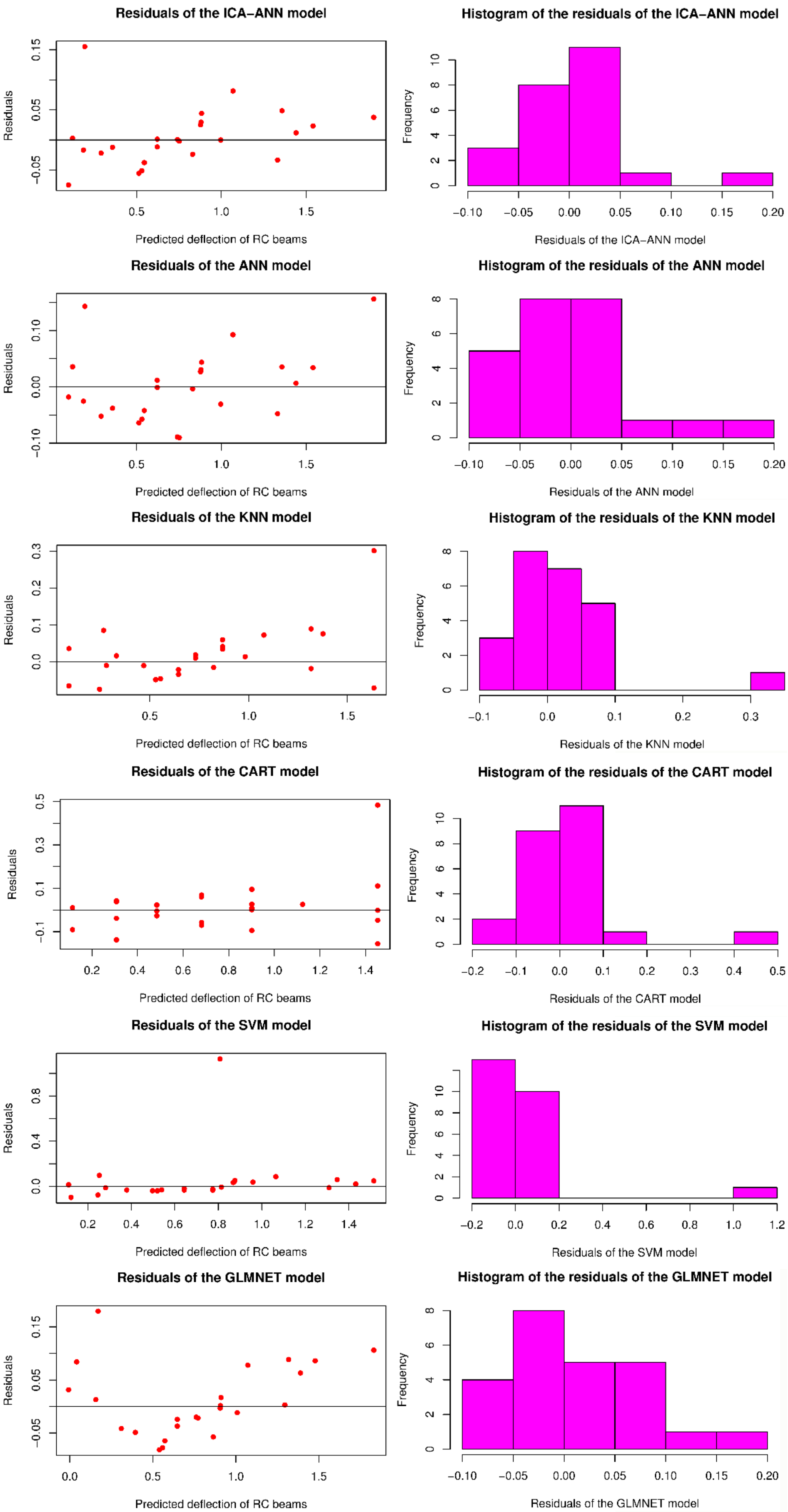


Fig. 11 Residuals of the individual models in estimating DS

total ranking = 28. On the contrary, the ANN model (not optimised) displayed a lower accuracy, RMSE = 0.063, MAE = 0.049, R^2 = 0.984, VAF = 98.329, MAPE = 0.121 and total ranking = 26. On the basis of the results, the ICA demonstrated a significant role of optimising the ANN model. KNN, CART, SVM and GLMN*Et al*so yielded lower performance than the proposed ICA-ANN model in deflecting the steel-reinforced concrete beams with the respective metric results: RMSE = 0.078, 0.119, 0.235 and 0.066; MAE = 0.053, 0.072, 0.086 and 0.052; R^2 = 0.980, 0.945, 0.778 and 0.983; VAF = 97.521, 93.989, 77.409 and 98.192; MAPE = 0.196, 0.262, 0.267 and 0.162 and total ranking = 15, 10, 5 and 21. The results of correlation analysis of the models for DS prediction is shown in Fig. 10.

Based on Fig. 10, we can see that the proposed ICA-ANN provided the best fit values with most of the DS predictions are in the regression line. The other models provided slightly lower performances, and the CART model seems to provide the lowest performance. However, taking a closer look at Fig. 10 for the SVM model andperformance measures for the SVM model in Table 2, it can be seen that the performance measures of the SVM model in Table 2 are lowest. It was evaluated as the weakest model through the performance metrics. However, in Fig. 10, the overall performance of the SVM model even better than the CART model, and only one data point made the performance metrics of the SVM model decreased. These results are further demonstrated through the residuals of the individual models in Fig. 11.

As illustrated in Fig. 11, the results of the SVM model are in agreement with the observations in Fig. 10, and we can see that the residual of the SVM model is very high, i.e., greater 1.0 for the outlier sample point. Another critical point in evaluating the performance of the models is the consideration of the histogram of the residuals, as plotted in Fig. 11. Accordingly, it is clear that the proposed ICA-ANN model provided the residuals to follow a roughly normal distribution, and it is acceptable as a valid model. The ANN model without optimization provided a little skew of the normal distribution. However, it can be accepted with lower accuracy and reliability than the proposed ICA-ANN model. In contrast, the other models, especially the SVM model, look not normal, and they are considered as the not valid model for predicting DS.

6. Conclusions

Optimisation of the bearing capacity and accurate calculation of concrete beam deflection are among the major challenges faced by construction engineers. An accurate estimation of the deflection of concrete beams based on essential parameters enables engineers to calculate and design buildings optimally, as well as to ensure their safety in the long run. The ICA-ANN framework, the hybrid AI technique proposed in this study, demonstrated prediction of deflection in reinforced concrete beams at an excellent accuracy of up to 99%. Through the model, the TS of reinforcement and the percentage of reinforcement can be calculated to minimise the deflection of the beam and consequently reduce the structural damage of a building or infrastructure.

Moreover, this study showed ANN's position as a robust technique providing high reliability in DS prediction, whose accuracy could be significantly improved with the incorporation of an evolutionary algorithm, i.e., ICA. The practicality of ICA-ANN as a technique could be applied in civil engineering objectives, especially in calculating and optimising the load capacity of reinforced concrete beams.

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Contributions of authors

Ning Li, Panagiotis G. Asteris: Conceptualization, Data curation, Visualization, Writing- Original manuscript.

Trung-Tin Tran, Biswajeet Pradhan: Methodology, Software, Modelling, Visualization, Prepare the revised manuscript.

Hoang Nguyen: Modelling, Visualization

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