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Committee integration of optimized models for prediction of compressive strength of masonry structures

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Abstract

An accurate computation of the compressive strength of masonry structures (CSMS) is an overarching factor in design and construction of masonry structures (MS). This considerable significance compels researchers to propose an appropriate, reliable and, more generalized method whereby the precise value of CSMS is calculated. In the current study, a committee machine (CM) with optimized elements is constructed, thereby extracting a non-linear relationship between CSMS with compressive strength (CS) of mortar and brick. In order to accomplish this objective, three intelligent models viz. neural network (NN), fuzzy inference system (FIS), and support vector regression (SVR) are firstly optimized with bat-inspired algorithm (BA), and these improved models are subsequently applied for estimation of CSMS. BA is hybridized with intelligent models for extracting the best values of weights and biases of NN, membership's functions of FIS, and user-defined parameters of SVR. Then, CM is utilized for amalgamating the outputs of three optimized models (OMs) incl. optimized neural network (ONN), optimized fuzzy inference system (OFIS), and optimized support vector regression (OSVR). BA is also embedded in the structure of CM, thereby determining the optimal contribution of each optimized model in

the final prediction. Data sets including 96 records accessible in the literature are used to learn and evaluate the constructed models. Appraisal of the accuracy based on statistical parameters verified that the CM could effectively improve the prediction accuracy of the OMs and also has a better performance compared to commonly well-known predictive correlations. This study also proved that CM with optimized elements is a very convenient approach for mapping nonlinear functions between CSMS and CS of brick and mortar.

Keywords: Compressive strength (CS), Masonry structures (MS), Optimized model (OM), Committee machine (CM), Bat-inspired algorithm (BA).

1. Introduction

Masonry walls are construction regularly used in masonry buildings. Advances in using this type of wall have motivated civil engineers to understand the different parameters that impact on at a detailed level and provide improvement in it based on this understanding. Existing parameters that impact the design of MS are bifurcated in quantitative parameters (e.g. brick CS) and other more qualitative parameters (e.g. construction process). The combination of these parameters complicates the evaluation of MS. MS made of clay bricks (CB) and cement mortar (MC) is one of the most important parameters which is used in the evaluation of MS. Heretofore, three types of methodology are used for modeling of CSMS of CB and MC. The first group belongs to the analytical model that obtains the CS of the brick and mortar combination of theoretical principles, based on a series of mechanical hypotheses and applying equilibrium and compatibility equations [1-5]. Although these categories of model help identification of effective parameters on CS of the brick and mortar, it poses some flaws, these models are also highly complex, as well as require a variety of parameters (geometry, CS of brick and mortar, elasticity modulus, and Poisson coefficient) [6]. Empirical models are another type of models used for modeling CSMS which are

made by CB and MC. In recent years, significant efforts have been made by different scholars with a view to achieving accurate empirical models for this subject and therefore developing several correlations [8-14]. This type of model is simple and shows the acceptable result in the modeling of CSMS made by CB and MC. Recently, intelligent-based models have been emerging in civil engineering and numerous researchers have attained outstanding results in solving complicated problems where underlying relationships are unknown or hard to define. The superiority of intelligence models over empirical approaches for dealing with prediction problems has been demonstrated in the literature. In terms of CS prediction, only Garzón-Roca et al. study has been conducted based on inputs, including CS of CB and CS of MC [15]. They applied two data-driven approaches (NN and FL) to determine the CS of a masonry structure commingled of CB and MC, as a function of the CS of the mortar and that of the bricks. These models have useful results, but the quest for superior intelligent models is always feasible. Recently CM has emerged as a novel method for integrating different experts and producing a model that uses the benefits of each of the experts [16-20]. In this study, CM with optimized elements is used for finding functional dependency between CSMS made of CB and MC and CS of the mortar and that of the brick. Firstly, three intelligent based models viz. NN, FIS, and SVR are optimized by BA and then these optimization methods are used for the prediction of CSMS made by CB and MC. Then, the outputs of the aforementioned OMs are combined through CM. BA is included in the CM structure for finding how much each optimized model contributes in the final prediction. Fig. 1 demonstrates the flowchart of the roadmap that is employed for quantitative estimation between CSMS and CS of mortar and brick. As shown in Fig. 1, the developed strategy generally comprises two steps: optimizing intelligence models by BA, and combining the outputs of OMs by virtue of CM. In the end, the results of CM compared OMs in terms of accuracy based on statistical indexes.

2. Model description

2.1. Optimized neural network

The NN is a brain-inspired computational model which was developed to capture the logic relationship between input and output parameters of complex and nonlinear problems without a priori assumption about the properties of those data [21]. Due to the outstanding problem-solving ability of this type of model in tackling difficult estimation problems, it gains the attention of researchers in different fields [22-23]. Training of the ANN model means that the values of those weights and biases are being adjusted, meanwhile the MSE between the model estimated values and target values are minimized. In developing NN, finding global minima has a great significance on the efficiency of constructing models mainly because of the premature convergence phenomenon that happens when the model traps in local optima. This importance led to the inclusion of the optimization approach in formulating NN for extracting the most suitable value of those weights and biases. Recently, there have been many attempts to integrate and utilize different types of optimization methods in NN and satisfactory results are attained [24]. In the current paper, BA is adopted to explore the value of weights and biases that meet the condition of trapping in the global minima. Fig. 2 shows the mechanism that is employed by BA for the optimization of the ANN parameters.

2.2. Optimized fuzzy inference system

The FIS is a mathematical model that was firstly developed by Zadeh (1965) for handling uncertainty based on fuzzy sets [25]. Under the condition of absence of any prior knowledge about the relationship between input parameters and output, this methodology can fully capture the subtle functional dependency between the aforementioned relationship. Hence, there has been growing interest in solving difficult regression problems [17]. Two recognized types of FIS systems are

Mamdani and Sugeno. In this study, Sugeno model is used as the FIS framework. In this theory, a membership function (MF) corresponds to every fuzzy set. For solving a problem through this approach, input data is firstly mapped into values ranging from 0 to 1 by virtue of a set of input MF. Then the inference engine which includes a fuzzy rule is applied to the mapped data and those outputs are determined. Finally, the outputs that are calculated from the last step are integrated through an output MF in the defuzzifier process to get one fuzzy output distribution and also transfer it into a crisp output. The gaussian membership function is defined as input MF ($MF_{in}(I)$) and a linear polynomial function is proposed as output MF ($MF_{out}(I)$) as following equations:

$$MF_{in}(I) = \exp(-(\frac{I-m}{\sqrt{2}\sigma})^2) \tag{1}$$

$$MF_{out}(I) = \beta_0 + \beta_1 I_1 + ... + \beta_n I_n \tag{2}$$

m, σ and β_n are coefficients of MFs and in the formulation of FIS, these values have a critical role in the completeness of the model that implies the use of optimization algorithm in its formulation has a desirable impact [17]. In the current study, the membership function embedded in the structure of the Sugeno type is optimally tuned by virtue of BA.

2.3. Optimized support vector regression

Recently, a pioneering approach, namely SVR was innovated by Vapnik based upon statistical learning theory [26]. This method can identify nonlinear patterns effectively and therefore achieve satisfactory results in practical application [27]. The most important advantage of SVR over ANN is that, SVR uses the principle of structural risk minimization in its formulation, the upper bound on expected risk is minimized meanwhile ANN employs the empirical risk minimization principle for diminishing the error on the training data [26]. In the SVR method, the original data are mapped

into a high-dimensional feature space via considering a kernel function to construct a linear model in this space. In this study a radial basis kernel function, $k(x_i, x_j)$, the following mathematical expression is used.

$$k(x_i, x_j) = \exp(-\gamma \left\| x_i - x_j \right\|^2) \tag{3}$$

Where γ is the kernel parameter and, x_i, x_j are training vectors. An error tube with a radius of epsilon is defined to control the model in this space. The other important SVR parameter is the cost parameter (C) which defines a trade-off between model complexity and error minimization. γ, epsilon and C are critical parameters of SVR construction. Because of the dependency of SVR efficiency for the accuracy of these free parameters, the finding of the best values of these parameters becomes essential in this research field. The survey in former papers indicated that by including the optimization method in the formulation of SVR, its penalty parameters are extracted accurately and therefore the performance of the model is increased [27-29]. Based on this result, in current work, the BA is assigned to optimize the free value incorporated in SVR, which is ordinarily adjusted by the user and therefore improves its performance in the estimation of CSMS.

2.4. Committee machine

CM is a novel methodology that was originally developed to fuse the outputs of predictive models into a single one [16-18]. Hence, when various solutions for a specific problem exist, this methodology can be utilized for combining these solutions and construct unique responses. Hence, compared with the individual model, the prediction precision by the CM is improved due to taking advantage of individual models [17]. Two different structures are employed by CM for combining results of individual models. The first is the static structure in which the outputs of different experts are linearly integrated to produce a final solution. Another is the dynamic structure that has

employed scalar coefficients so-called gating networks for a non-linear fusion of the outputs of the single expert. In the current study, the second type is employed for combining and assigning the contribution of each model in the final predictions. Extracting the best weights of each model motivates researchers to include an optimization algorithm in the formulation of CM. The following equation is embedded in the optimization algorithm for finding the optimal contribution of each model in the overall estimation:

$$Overall\ \ output = \alpha_1 \times ONN^{\beta_1} + \alpha_2 \times OFIS^{\beta_2} + \alpha_3 \times OSVR^{\beta_3} \tag{4}$$

where α_i and β_i are constant coefficients which are defined by BA as an optimization method. The previous results show that BA as an optimization technique is more reliable and efficient than the trial–and–error tuning method [18].

2.5. Bat-inspired algorithm

BA developed by Yang is a meta-heuristic algorithm, which has recently become an apt tool for implementing complex optimization problems [30]. This novel optimization method was designed by inspiring the echolocation behavior of bats in order to look for food and prey. In nature, the bats use their ears for identifying the size and location of surrounding objects. Indeed, they used the frequency of the echo reaching from loud sound impulses that emitted by themselves to determine the size and location of their prey [31]. This searching and finding strategy of a bat is the basis of developing BA technique for optimization implementation. In this method bats randomly fly with velocity (v) and their positions (x_i) are proposed as probable solutions of an optimization problem. The bats release sound with a loudness (A) and wavelength (λ) to discover

their prey. Different numbers are taken from a uniform distribution in the range of $[f_{\min}, f_{\max}]$ and they are assigned as frequencies (f) as the following form:

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta \quad (5)$$

$\beta \in [0,1]$ is a random number that is found by the uniform distribution. Velocities are updated by the following equation:

$$v_i^t = v_i^{t-1} + (x_i^t - x_{gbest})f_i \quad (6)$$

x_{gbest} is the global best solution at time t. Positions are updated with the random walk method as follows:

$$x_{new} = x_{old} + \rho A^t, \qquad \rho \in [-1,1] \quad (7)$$

Where A^t is the average loudness of all bats at time t and ρ is a random coefficient. When a bat gets closer to the position of its prey (new solution), the loudness (A) decreases and the pulse emission rate (r) increases as follows:

$$A_i^{t+1} = \alpha A_i^t, \qquad \alpha \in [0,1] \quad (8)$$

$$r_i^{t+1} = r_i^0[1 - \exp(-\gamma t)] \quad (9)$$

α and $\gamma > 0$ is a constant parameter similar to the cooling scale factor of a cooling schedule in the simulated annealing.

These parameters including velocities, frequencies, and positions are updated during algorithm repetitions until a stop condition is achieved. This was a brief introduction to the BA. Complementary details can be found in [31]. Previous studies proved that this methodology is more accurate, reliable, efficient, and less time-consuming than the other optimization algorithm

for extracting the optimal parameters of intelligent models [18]. As a new meta-heuristic algorithm model, BA is employed in this study for extracting proper values of weight and bias of NN, tuning of membership function of FIS, determining the precise value of free parameters of SVR, and finding optimal contribution of OMs in CM. In the current research, the following fitness function is employed in the BA algorithm.

$$Fitness\ function = \frac{1}{n}\sum_{i=1}^{n}(output_i - target_i)^2 \quad (10)$$

Here $output_i$ is a prediction value that is drawn with an optimized intelligence model (NN, FIS, SVR, and CM) and $target_i$ is the real measured value.

3. Data input/output space

The main aim of this paper is to develop a predictive model, based on integrating three OMs, in order to estimate the value of CSMS. It should be noted that, regarding previous studies, CSMS can be determined as a function of CS of material (mortar and break) that contributed in form of it. Hence, these parameters (CS of mortar and break) are considered as inputs for the quantitative estimation of CSMS. Owing to the dependency of constructing models on data, 96 records were extracted from the open-source literature, 70 percent of those are used to construct models and select those parameters and 30 percent are adopted to assess the proficiency (generalization) of the trained network [4, 6, 9, 10, 32-47]. Descriptive statistics including minimum value, maximum value, mean value, mode, standard deviation (SD), skewness, kurtosis, coefficient of variation (CV) of used data for constructing and evaluating CM models are given in table 1.

4. Results and discussion

In this research, three OMs are first established and then the CM is proposed for combining the outputs of OMs. The integration of OMs by CM provides opportunities to reap benefits of the

OMs, and leads to the development of more accurate models that reflect the underlying relationship between the input parameters and target values. Prior to applying BA for optimization of intelligent models as well as extracting the optimal weights of each OMs in the final prediction, the BA regulation parameters must be adjusted. These regulation parameters are given in table 2. Moreover, four types of accuracy evaluation indices namely coefficient of determination (R^2), mean percent of absolute error (SMAPE), average absolute relative error (AARE), and mean square error (MSE) are employed to quantitatively analyze the predictive results of the different models. Their expressions are given Eqs. 11-14 as follows:

1. Coefficient of determination (R^2)

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (Y_{i\ pred} - Y_{i\ obs})^2}{\sum_{i=1}^{n} (Y_{i\ pred} - \overline{Y}_{obs})^2} \tag{11}$$

2. Mean square error (MSE)

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (Y_{i\ obs} - Y_{i\ pred})^2 \tag{12}$$

3. Average absolute relative error (AARE)

$$AARE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{Y_{i\ obs} - Y_{i\ pred}}{Y_{i\ obs}} \right| \tag{13}$$

4. Symmetric mean absolute percentage error (SMAPE)

$$SMAPE = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{Y_{i\ obs} - Y_{i\ pred}}{Y_{i\ obs} + Y_{i\ pred}} \right| \tag{14}$$

where $Y_{i\ obs}$ is the measured value of the sample i, $Y_{i\ pred}$ is the predicted value of the sample i, $\hat{Y}_{obs}$ is the average of the measured value, and n is the number of samples. When the values of AARE,

SMAPE, and MSE are close to zero as well as the value of R^2 is close to 1, a model with superb performance is achieved.

4.1. ONN results

In the first step, NN optimized by BA is developed for the estimation of CSMS. Fig. 3 (a) shows the run of BA for the optimization of NN. For finding the optimum number of neurons in the hidden layer, the effectiveness of models based on statistical criteria in a different number of neurons is evaluated. As shown in Fig. 4, a model with 3 neurons in the hidden layer has the best performance (highest R^2 and lowest MSE). The optimal values of weights and bias of ONN that are adjusted by BA are given in table 3. Fig. 5 (a) shows the regression plot of CSMS that is obvious, ONN provides a good estimate. The comparison of the measured values with the predicted values versus the sample numbers is demonstrated in Fig. 6. When the point is close to the line, the model has a brilliant performance at the aforementioned point. As shown in this figure, in most of the sample points, the aforementioned intersection takes place and therefore ONN has an acceptable accuracy in the prediction of CSMS. Moreover, for each division of the data set (training and testing subdivision), statistical parameters, namely R^2, MSE, SMAPE, AARE are calculated. Based on these evaluation indexes, ONN is a good option for the modeling of CSMS.

4.2. OFIS results

In the second stage, FIS optimized by BA is applied for the modeling of CSMS. Fig. 3 (b) displays the fitness curves of the BA in the parameter optimization process which leads to the determination of the membership function that are in the FIS model. The membership function parameters of OFIS that are extracted by BA are given in table 5. Fig. 5 (b) reveals the cross plot of the predicted values versus the measured values of CSMS. As seen in this figure, an excellent agreement exists between the predicted values and the real values. A similar conclusion can be drawn when a

comparison of the measured values with the predicted values versus the sample numbers is investigated in Fig. 7. In addition, table 4 listed the values of R^2, MSE, SMAPE, and AARE for the training and testing datasets. Consequently, this part reveals that the OFIS approach has an acceptable accuracy in the estimating of CSMS.

4.3. OSVR results

In the third stage, the SVR model in which optimum values of penalty parameters are determined by BA is employed for relating CSMS to CS of break and mortar. Fig. 3 (c) shows the MSE versus the iteration during SVR free parameters tuning in the training set. Table 6 gives the correct values of free parameters of SVR. Fig. 5 (c) depicted the crossplot of predicted values versus measured values of CSMS. As shown in Fig. 5, the predicted values of CSMS have an acceptable match with its target values. Moreover, Fig. 8 demonstrates a close correspondence between the calculated and the desired results that substantiated the high ability of OSVR in the prediction of CSMS. To validate the accuracy of OSVR, its results are furthermore evaluated with statistical indexes (table 4). As the OSVR can generate results with the highest R^2 and lowest MSE, SMAPE, and AARE, it can therefore conclude that this improved model is significantly better than the other two OMs in the quantitative estimation of CSMS.

4.4. CM results

In the final stage, the CM is employed to use the outputs of OMs and obtain a unified model which reaps the benefits of OMs. With the aid of BA, the weights which indicate the optimal contribution of each of the models in the final prediction are calculated. The process of searching for optimal weights of OMs by virtue of BA is shown in Fig. 3 (d). The values of determining weights are listed in table 7. Fig. 5 (d) illustrates the scatter diagram between the laboratory CSMS values and the predicted values. Furthermore, Fig. 9 demonstrates how much the estimated CSMS matches

with the observed value. In table 4, the achieved results are assessed based on the statistical parameters in training and testing allocations. Regarding table 4, Figs. 5 (d) and 9, the CM model has a good capability in the estimation of CSMS.

4.5. Comparative study

The modeling accuracy and generalization performances of the constructed models (ONN, OFIS, OSVR, CM) as well as the linear and nonlinear models which are available in the literature are tabulated in table 8 thereby their performance is analyzed in terms of statistical criteria defined in section 4. As seen in this table, compared to OMs which use as elements of the CM and empirical correlations developed in previous studies, the CM model has results with smaller values of AARE, SMAPE, and MSE and a higher value of R^2 that is an indication of its superiority in the estimation of CSMS. The aforementioned statistical assessment of the results of the current study demonstrated that the CM approach, which combines the results of OMs by BA, has magnificent performance and, also is more effective than its elements (OMs) and the conventional empirical correlations as well.

5. Conclusions

Because the masonry walls are fundamental components in the masonry buildings, proposing a reliable model for the determination of CSMS is essential. In this paper, three optimized intelligent based models, including ONN, OFIS, and OSVR integrated with CM are applied for making quantitative formulation between the CSMS commingled of CB and MC with CS of the mortar and that of the bricks. This strategy has the advantage of reaping the benefits of OMs by calculating those optimal contributions through the BA method. For the purpose of evaluation, the results of CM are investigated based on statistical criteria, including R^2, AARE, SMAPE, and MSE. Moreover, in order to demonstrate such superiority, the CM is compared with those elements

(ONN, OFIS, and OSVR) as well as the previous empirical approaches. Investigation of the results that are obtained from the current paper lead to the following conclusions:

1. All OMs (ONN, OFIS, and OSVR) excel in the estimation of the CSMS commingled CB and MC with good accuracy.
2. Among three OMs, the OSVR has the best results according to statistical measurement.
3. Judging based on the performance indicators concludes that CM reflects a higher accuracy than individual OMs as well as existing empirical equations.
4. This study concluded that CM with optimized elements is a state-of-the-art method for modeling the CSMS commingled CB and MC as a function of the CS of the mortar and that of the bricks.

Declarations of interest:

Authors Contributions:

Mahsa Gholami contributed to the study's conception, design, and revisions. Conceptualization and coding: Mahsa Gholami and Amin Gholami. Data and methods: Amin Gholami. Writing—original draft preparation: Mahsa Gholami and Amin Gholami.

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The authors declare that they have no conflict of interest.

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The data and the generated code in the study are available by request from the corresponding author.

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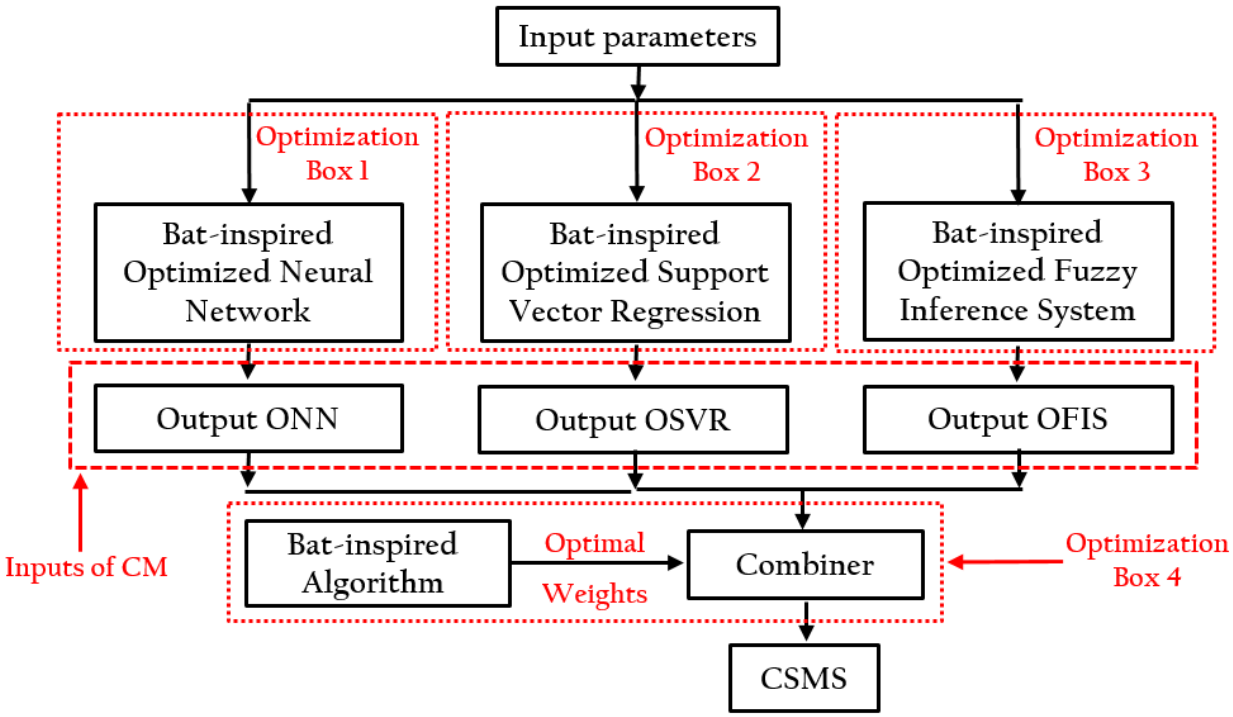

Fig. 1 How CM integrates OMs for obtaining CSMS.

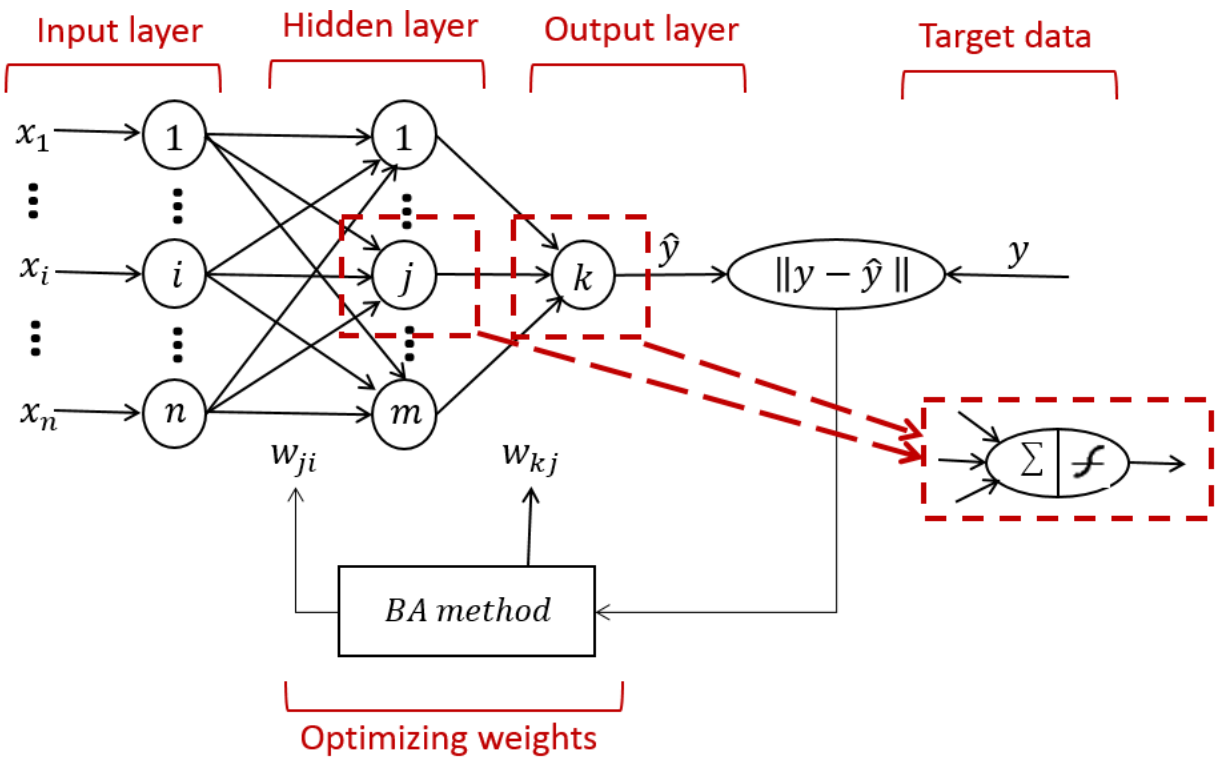

Fig. 2 Embedding of the BA in NN formulation for optimizing of its parameters.

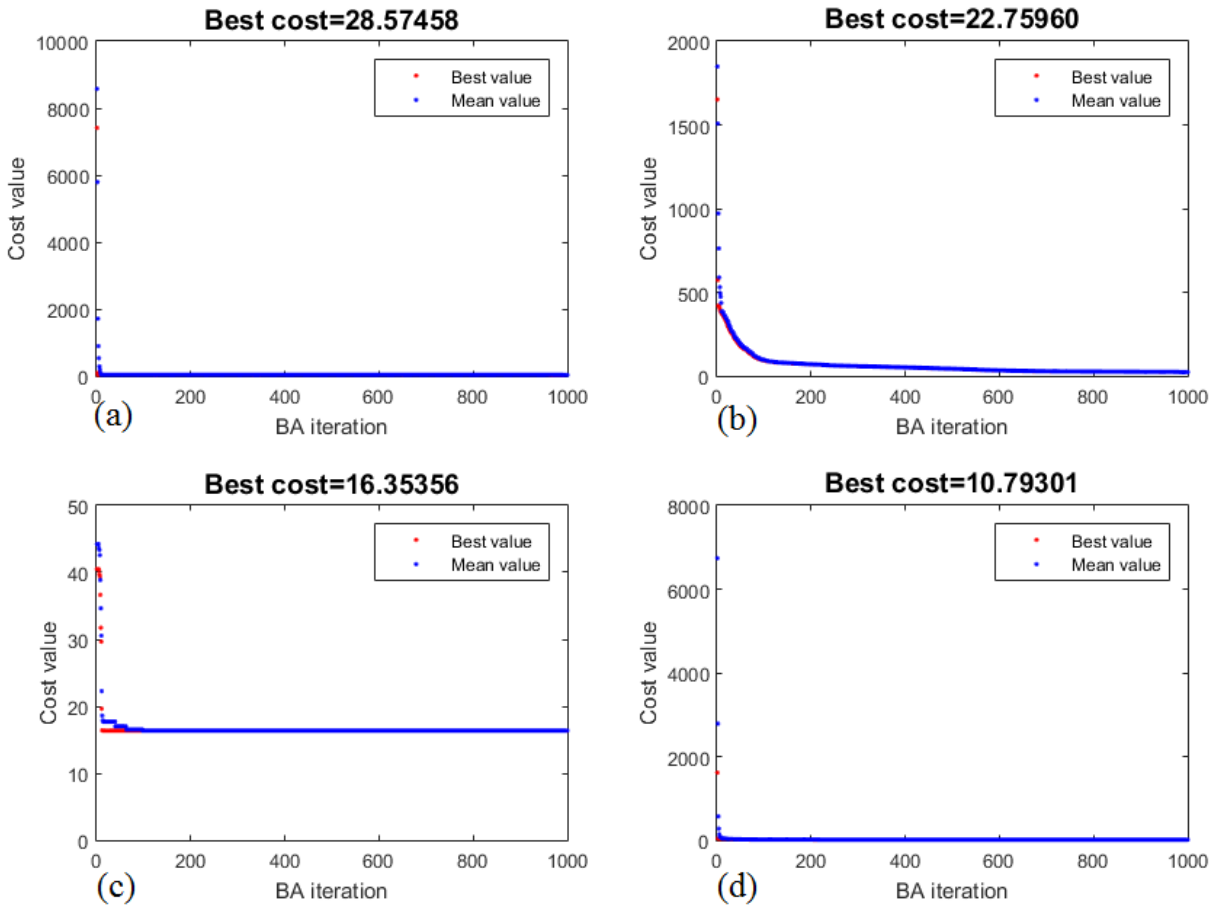

Fig. 3 Mean and best value of cost function in each iteration for (a) ONN, (b) OFIS, (c) OSVR, and (d) CM model.

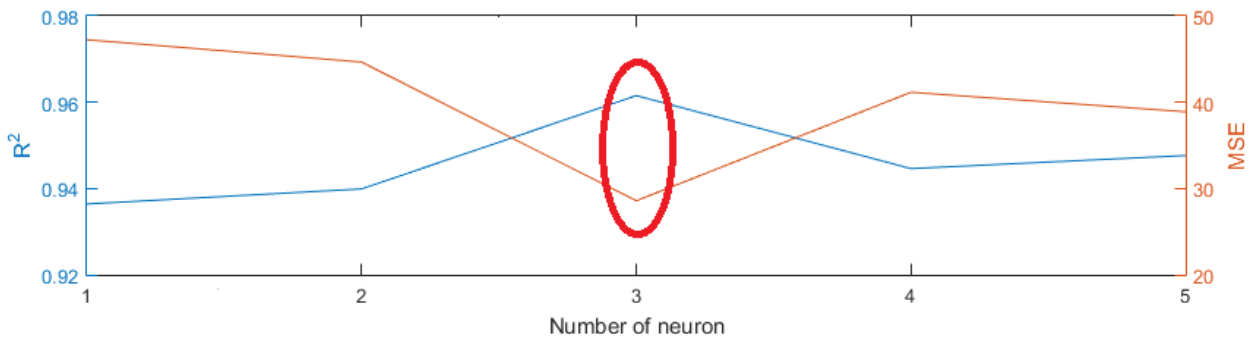

Fig. 4 Statistical assessment for selecting of the best value for numbers of neurons in the hidden layer.

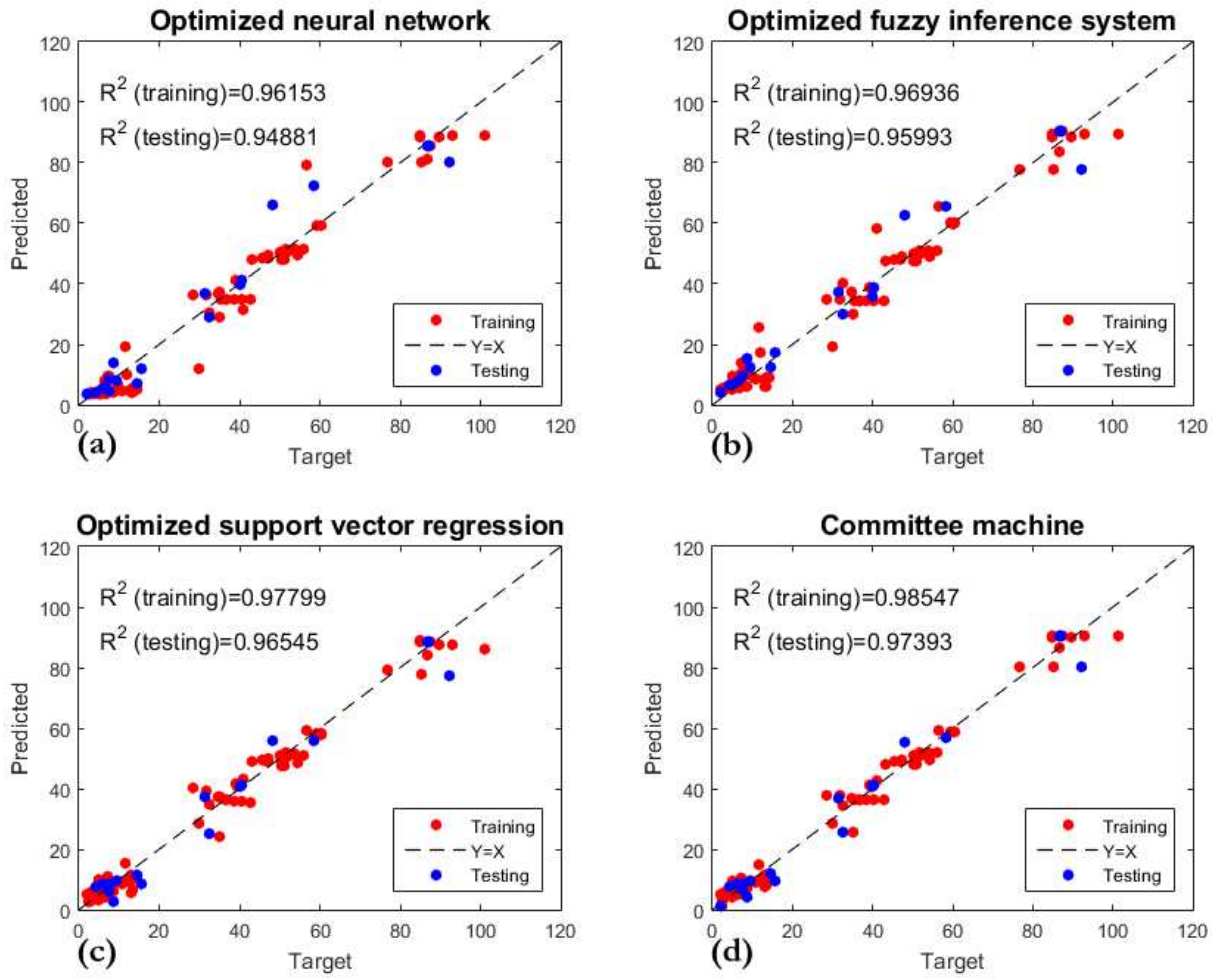

Fig. 5 Predicted versus real value of CSMS for (a) ONN, (b) OFIS, (c) OSVR, and (d) CM model.

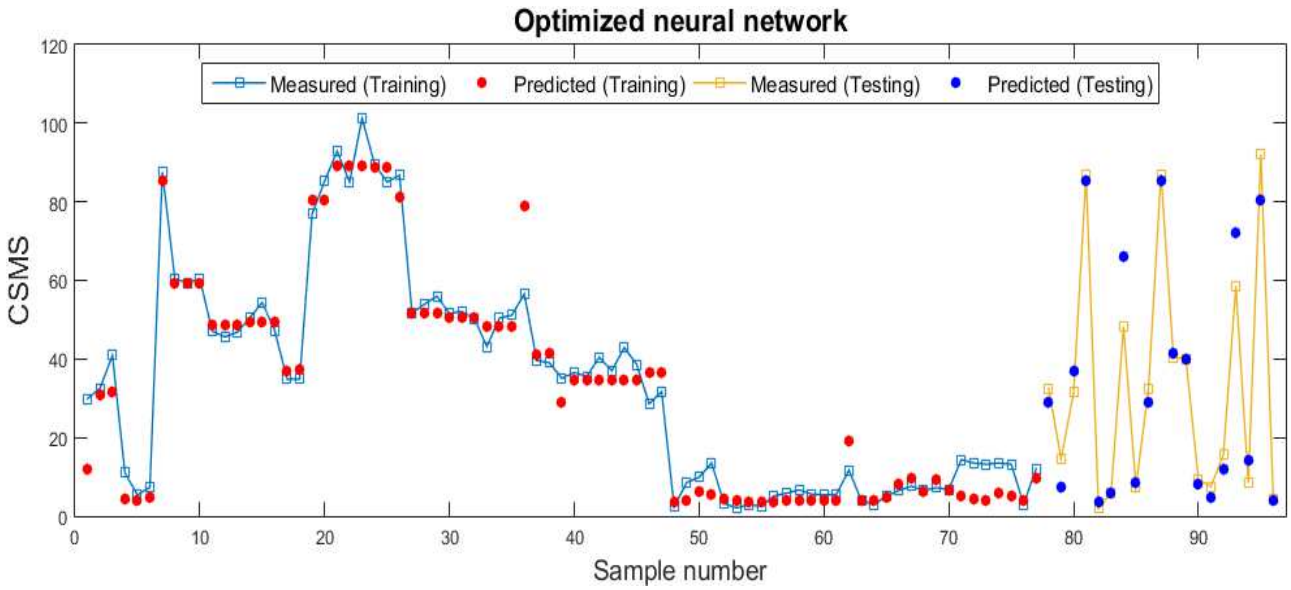

Fig. 6 Measured compared with estimated in each sample number for ONN.

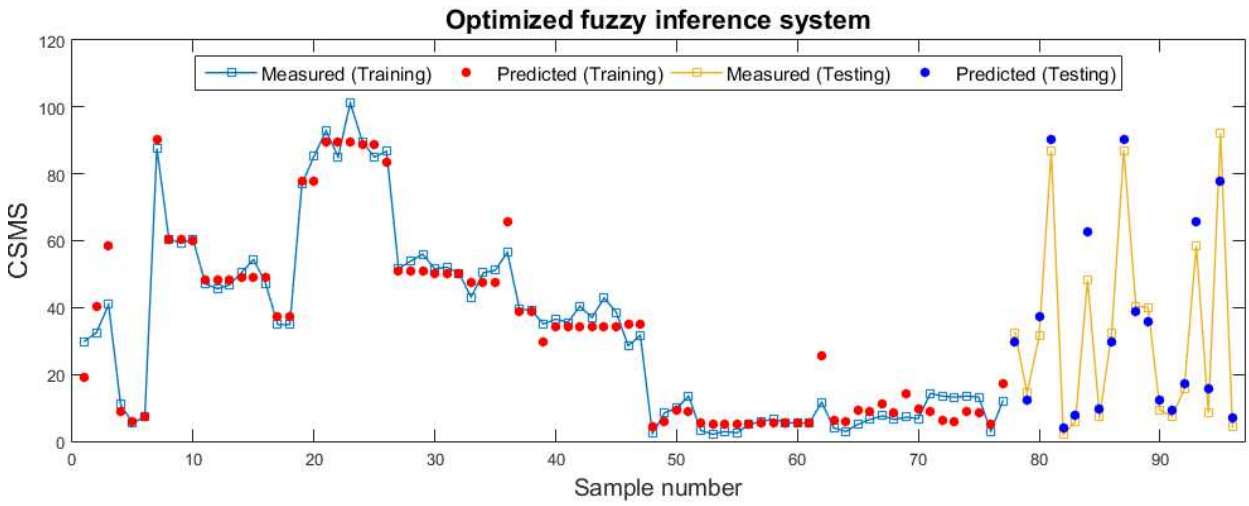

Fig. 7 Measured compared with estimated in each sample number for OFIS.

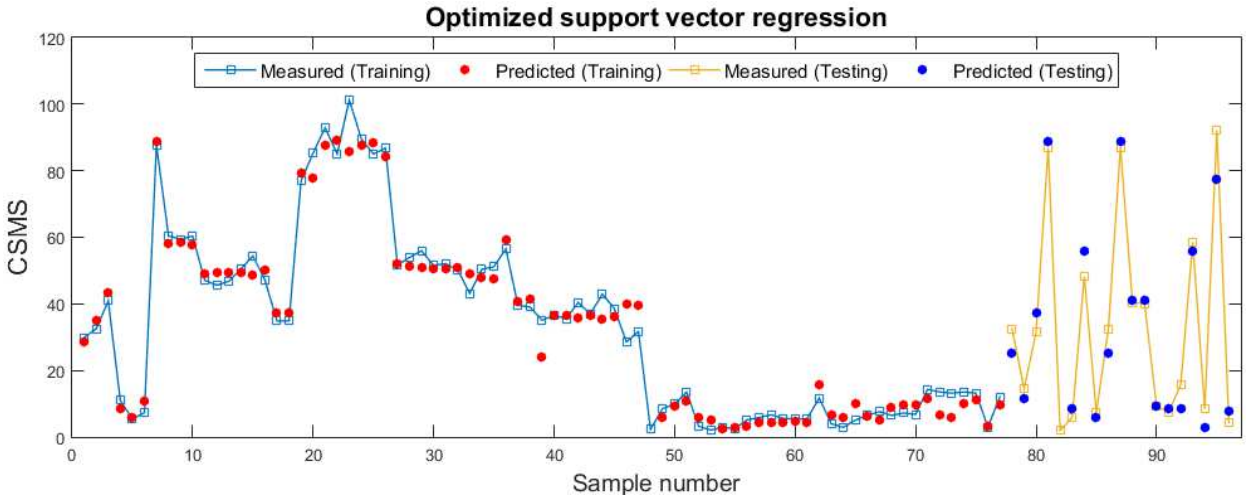

Fig. 8 Measured compared with estimated in each sample number for OSVR.

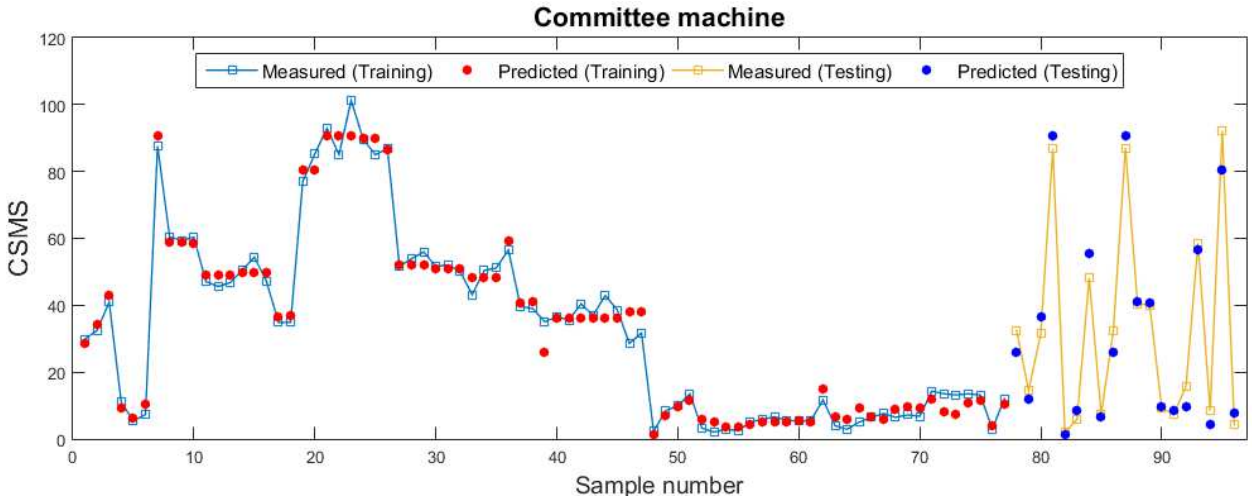

Fig. 9 Measured compared with estimated in each sample number for CM

Table 1 Statistics measure of the dataset that used in the current study for constructing of models [4, 6, 9, 10, 32-47].

Parameter	Unit	Maximum	Minimum	Mean	Mode	SD	Skewness	Kurtosis	CV
CS of brick	Mpa	52.60	0.45	14.16	14.20	12.77	1.32	0.84	90.19
CS of mortar	Mpa	101.70	8.20	57.79	94.25	35.12	-0.14	-1.76	60.77
CSMS	Mpa	101.27	2.00	33.60	13.50	27.75	0.69	-0.49	82.59

Table 2 Regulation parameters of BA for a run in ONN, OFL, OSVR, and CM model.

Parameter	Value			
	ONN	OFL	OSVR	CM
Number of variables for optimization	12	28	3	6
Population size	100	100	10	20
Maximum iteration	1000	1000	100	1000
A_0	0.5	0.5	0.5	0.5
r_0	0.5	0.5	0.5	0.5
$f_{\min}$	0	0	0	0
$f_{\max}$	2	2	2	2

Table 3 Optimum values of weights and biases for building the ONN.

Layer	Node	Weights			Biases
		IW1		IW2	
Hidden	Node 1	-0.8232		-2.2809	-2.0759
	Node 2	2.2259		0.9619	-0.8749
	Node 3	-1.0999		2.1610	0.8433
Output		Node1	Node2	Node3	
	Node 1	0.7961	-0.2874	1.1340	-0.2515

Table 4 Statistical analysis of CM and its optimized elements (OMs).

Model	Allocation	R^2	MSE	AARE	SMAPE
ONN	Training	0.96153	28.57458	0.21640	12.28031
	Testing	0.94881	42.93184	0.21415	10.29001
	Total	0.95877	31.41612	0.21595	11.88640
OFIS	Training	0.96936	22.75960	0.24632	10.53420
	Testing	0.95993	33.60601	0.26121	10.74610
	Total	0.96731	24.90629	0.24926	10.57614
OSVR	Training	0.97799	16.35356	0.20922	10.70395
	Testing	0.96545	28.97980	0.26571	17.52078
	Total	0.97526	18.85250	0.22040	12.05311
CM	Training	0.98547	10.79301	0.17706	7.88424
	Testing	0.97393	21.86863	0.20547	10.49501
	Total	0.98296	12.98506	0.18268	8.40096

Table 5 MF parameters of OFIS that calculated through run of BA

Layer	Variable name	MF parameters							
		MF1		MF2		MF3		MF4	
		σ	Mean	σ	Mean	σ	Mean	σ	Mean
Inputs	CS of MC	0.1218	-0.6882	0.1812	-0.8984	0.1218	-0.4727	0.1018	-0.5801
	CS of CB	0.1414	0.8406	0.1201	-0.7968	0.1141	0.1298	0.1042	0.7497
Output	CSMS	-0.1350		0.1350		1.0678		-0.0892	
		0.1077		0.2669		-0.5368		0.8048	
		-0.7634		-0.6012		0.2556		-0.2044	

Table 6 Values that are achieved by BA for generation of the OSVR.

Parameter	Value
Gamma	2.1914
C	9.3636
epsilon	0.001

Table 7 Determined Weights via BA which indicate optimal contributions of OMs in CM.

Parameter	Value
α_1	0.7253
α_2	0.4622
α_3	0.7719
β_1	0.0149
β_2	0.1143
β_3	1.0591

Table 8 Comparison between CM and OMs as well as empirical correlations.

Model	R^2	MSE	AARE	SMAPE
Mann [7]	0.75192	189.02769	0.48266	19.07000
MLR [15]	0.88174	90.10720	0.45510	12.21081
Dayaratnam [8]	0.40447	453.76572	0.37410	22.24458
OSVR	0.97526	18.85250	0.22040	12.05311
ONN	0.95877	31.41612	0.21595	11.88640
OFIS	0.96731	24.90629	0.24926	10.57614
CM	0.98296	12.98506	0.18268	8.40096