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ORIGINAL ARTICLE

Particle swarm optimization trained neural network for structural failure prediction of multistoried RC buildings

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Abstract Faulty structural design may cause multistory reinforced concrete (RC) buildings to collapse suddenly. All attempts are directed to avoid structural failure as it leads to human life danger as well as wasting time and property. Using traditional methods for predicting structural failure of the RC buildings will be time-consuming and complex. Recent research proved the artificial neural network (ANN) potentiality in solving various real-life problems. The traditional learning algorithms suffer from being trapped into local optima with a premature convergence. Thus, it is a challenging task to achieve expected accuracy while using traditional learning algorithms to train ANN. To solve this problem, the present work proposed a particle swarm optimization-based approach to train the NN (NN-PSO). The PSO is employed to find a weight vector with minimum root-mean-square error (RMSE) for the NN. The proposed (NN-PSO) classifier is capable to tackle the problem of predicting structural failure of multistoried reinforced concrete buildings via detecting the failure possibility of the multistoried RC building structure in the future. A database of 150 multistoried buildings' RC structures was employed in the experimental results. The PSO algorithm was involved to select the optimal weights for the NN classifier. Fifteen features have been extracted from the structural design, while nine features have been opted to perform the classification process. Moreover, the NN-PSO model was compared with NN and MLP-FFN (multilayer perceptron feed-forward network) classifier to find its ingenuity. The experimental results established the superiority of the proposed NN-PSO compared to the NN and MLP-FFN classifiers. The NN-PSO achieved 90 % accuracy with 90 % precision, 94.74 % recall and 92.31 % F-Measure.

Keywords Reinforced concrete structures · Structural failure · Artificial neural network · Particle swarm optimization · Multilayer perceptron feed-forward

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network · Scaled conjugate gradient algorithm · Cross-entropy

1 Introduction

Defective building designs, earthquakes and bomb attacks become increasingly frequent in recent times [1]. The main cause of structural failure is the imperfect design that has not established the actual loading conditions on the structural elements. Moreover, the inferior construction materials can be the cause as the loads are considered for materials of precise characteristics. Huge numbers of casualties and property damage rise from overpressure on their reinforced concrete followed by failing of structural elements. For the RC structures, the frequently observed damage is in the form of falling of infill walls and cracking. However, the main prominent failures are the structural failures of modern multistory buildings. The damage is due to intrinsic weakness in the structural system, detailing, design and poor material quality [2].

Consequently, understanding/predicting of the structural failure of multistoried RC buildings has therefore become imperative. This directed the focus of the researchers to extend computational instruments and algorithms to predicate the structural failure. Several techniques are developed to model complex, unknown, nonlinear, or noisy associations, to support engineering solutions by simulating the real applications to realize cost-effective and robust solutions. Structural system modeling can be done to model the structural parameters, structural response and the vibration signatures such as frequencies, damping ratios and mode shapes. Such techniques that can be used for modeling the building structures are machine learning, genetic algorithms (GA) and fuzzy logic to detect damage in structural elements including concrete beams, steel and concrete columns. These models have vital concern in monitoring the civil infrastructure such as in buildings [3], bridges [4] and railways [5].

Neural networks (NN) are progressively taking over from simpler machine learning methods. Various researches have been performed to analyze several topics related to reinforced concrete buildings using ANN. The NN was employed mainly in the study of the postseismic effect on RC buildings. The main stage in the NN it to train the input operates based on the information generated from selected design feature vectors to execute both deterministic/probabilistic constraints investigations during the optimization process. Afterwards, the output of the trained NN is used to predict the structure response in terms of the available constraints due to different design parameters, such as the fundamental periods, shear force and the buildings' top-floor displacement in two directions [6]. Classification process [7] can be used to classify the structures failure, where it can reveal hidden patterns of large datasets so providing better understanding of many real-life datasets. It has extreme use in decision-making to determine a classifier that can distinguish between different data classes and further can put an entity with unknown class label into correct class. Classification process is one of the processes that can be performed using the NN. Thus, classification-based NN can be used to predict and study the different parameters that affect the buildings' structure.

Typically, the NN models' accuracy depends on the training phase to solve new problems, since the ANN is an information processing paradigm that learns from its environment to adjust its weights through an iterative process. Due to the limit of their learning algorithms, they are often getting trapped in local minima. To overcome this shortcoming, evolutionary algorithms are to be used to adopt the search algorithm to evolve the ANN connection weights, learning rules, architectures or the input features. Pierce et al. [8] presented the NN models' reliability for damage detection. Several researchers have employed biologically inspired schemes to enhance the model-based methods as an effort to reduce the shortcomings of the conventional model-based approach. Chen et al. [9] revealed that ANN trained with traditional learning algorithms suffers from the problem of getting trapped into local optima while optimizing the objective function. Consequently, meta-heuristics algorithms can be employed with the ANN to overcome this problem. Such nature-inspired meta-heuristic algorithms [10] are the bacterial foraging optimization algorithm (BFOA), particle swarm optimization (PSO), artificial bee colony (ABC), ant colony optimization (ACO), cuckoo search (CS) and firefly algorithms (FA). One significant characteristic of all these algorithms is their population-based search strategy, where individuals in a population compete and exchange information with each other in order to perform certain tasks [11].

Thus, in the present study, the proposed system employed the PSO trained ANN (NN-PSO) classifier to overcome the NN being trapped in a local optima while predicting the RC structures' failure. Two hundred and fifty-seven RC structures of multistoried buildings dataset were designed by professional engineers. Out of these dataset, only one hundred and fifty RC structures are employed in the current study. The Indian Standard code 'IS 456-2000' is used to establish the limit state design procedure and to determine the structural use of the plain and reinforced concrete.

In the NN training phase, the root-mean-square error (RMSE) has been minimized by the PSO to obtain the optimal input weight vector to the input layer of the ANN. Then, several measuring performance metrics such as the accuracy, precision, recall, Fp-rate and F-Measure have been calculated to evaluate the proposed method. Since, the ANNs can be categorized based on the neuron arrangement and the layer connection pattern into (i) feed-forward NN, (ii) feedback NN and (iii) self-organizing maps. The FFN is a standard NN type that used in various applications. Multilayer perceptron (MLP) is a FFN network model that transforms sets of inputs into sets of outputs via hidden layer. The network is trained in supervised learning scheme with error back-propagation algorithm. Thus, the proposed model has been compared with this well-known MLP-FFN (multilayer perceptron feed-forward neural network) classifier. The latter is trained with scaled conjugate gradient algorithm [12] as learning algorithm.

The remaining work structure is organized as follows: Sect. 2 represented the related work followed by Sect. 3 that represented the proposed system methodology based on a theoretical background of civil engineering aspects, while proposed model is discussed in Sect. 4, which included the PSO algorithm that supported the NN. Section 5 focused on the experimental results, and finally, Sect. 6 included the conclusion.

2 Related work

In 1991, Hajela and Berke [13] determined the optimum weight of a truss to investigate the neural computing role in structural engineering. By the year 1995, Adeli and Park [14] proposed a neural dynamics model for optimal structure design. The authors used the Lyapunov function to improve the neural dynamics structural optimization model, which established its stability. To formulate an objective function for the general constrained structural optimization problem, an exterior penalty function scheme was adopted in the form of the Lyapunov function. By the same year in [15], the NN was used for the preliminary design on the reinforced-concrete rectangular single-span beams by determining the beam depth/width, tensile reinforcement required, and the moment capacity for certain set of input.

Adeli and Karim [16] formulated a general mathematical/computational model for the optimization of cold-formed steel beams. Park and Adeli [17] proposed a distributed nonlinear neural dynamics algorithms for discrete optimization of large steel structures. The convergence, stability and efficiency of the algorithms were examined for an 8904-member structure. The experimental results proved a high parallel processing efficiency of 94 % using a 32-processor configuration.

Elazouni et al. [18] employed the neural network to approximately determine the resource requirements in the design conceptual stage. The experimental results proved the accurate performance of the neural network. In [19], the NN was conducted for optimal concrete beams and reinforced fibrous concrete beams' design. The NN achieved high efficiency compared to the conventional design procedures. Caglar et al. [6] predicted some effects of a building under earthquake conditions by generating data using finite element analysis, while the dynamic response of buildings was obtained by employing a training phase in the NN with 150 data instances along with 15 data instances for validation phase. The authors depicted that multilayer perceptron trained with back-propagation (BP) algorithm can predict these effects effectively. Gupta et al. [20] proposed the ANN for precise prediction of the concrete strength based on parameters such as the specimen's size/shape, concrete mix design and the environmental conditions.

Graf et al. [21] suggested a scheme that facilitated the numerical prediction of future structural responses in dependency of uncertain load processes and environmental influences. This scheme was based on training recurrent neural networks by time-dependent measurement results. Thus, the measurement results' uncertainty is modeled as fuzzy processes that were considered within the recurrent NN scheme. The results proved the ability of this scheme to predict long-term structural behavior of a reinforced concrete plate strengthened by a textile reinforced concrete layer.

Erdem [22] investigated the crucial moment capacity prediction of the RC slabs in fire with the use of the neural network. In [23], the moment–curvature relationship of the RC governed by several variables and nonlinear material performance using ANN was examined. Jakubek [24] calculated the load capacity for loaded reinforced concrete columns based on the neural network. In [25], a nonlinear behavior of three-dimensional structures was predicted. The ANN-based adaptive scheme was investigated to predict the nonlinear behavior of the structure under severe earthquake actions. The experimental results proved that the performance-based design (PBD) can be successfully equipped by ANNs to reduce the computational complexity. In 2013, Maizir and Kassimin [26] employed an ANN for axial capacity prediction of a driven pile by implementing data collected from Indonesia and Malaysia. The proposed system was improved by a computerized intelligent system for predicting the total pile capacity for several pile characteristics and hammer energy. The experimental results established that the NN network models provided a good prediction by considering both stress wave data and properties of both driven pile and driving system in the input data. By the year 2015, Uddin et al. [27] provided a review on using the ANN for fixed offshore structures. The authors concluded that the ANN had advantages over the conventional methods; however, there is no structured method to identify network structure that provided the best solution. The results established that the ANN can be considered as a competent for predicting long-term decay by seawater and corrosion in fixed jacket structures.

Recently, the optimization algorithms were used to support the neural network for various structural applications. Joghataie and Farrokh [28] suggested an activation function based on the Prandtl–Ishlinskii operator in the feed-forward NN to evaluate the nonlinear frame structures. The genetic algorithm (GA) for optimization was employed to train the network in order to study two shear frames for a single degree of freedom (SDOF) and a 3DOF. The results claimed a high precision of the suggested models to solve the hysteretic problems. Plevris and Papadrakakis [29] handled the structural optimization problems by implementing the enhanced PSO algorithm along with a gradient-based quasi-Newton sequential quadratic programming (SQP) technique. The proposed PSO explored the design space detected the neighborhood of the global optimum. Afterwards, a nonlinear weight update rule for the PSO and a constraint handling technique for structural optimization were proposed. The efficiency of the proposed technique was discussed in some benchmark structural optimization problems. The numerical results confirmed the capability of the suggested methodology to get better optimal solutions for structural optimization problems than other optimization algorithms.

The above-mentioned extensive literatures claimed that ANN has a fundamental role for the structure design under diverse parameters and constraints. Jointly with, the new trend to involve the optimization algorithms supported the NN performance. Therefore, the current work added a contribution by employing the ANN to classify the structural failure of multistoried reinforced concrete buildings instead of concerning the structure design. This contribution is performed via detecting the failure possibility of the multistoried RC building structure in the future or not. In addition, the novelty of the work can be indicated by employing the PSO to enhance the performance of ANN to achieve aforesaid objective.

3 Methodology

It is required to design the reinforced concrete beams to support any structure with external loads as well as for flexure and shear forces along the length of the beam based on structural analysis. For optimal structure design, several parameters should be optimized. Such parameters are the cross-sectional dimensions and the building width/depth. Classically, any structure design can be executed in different ways, where numerous parameters affect the reinforcements such as the loads on beam, material property, and the cross-sectional dimensions of beam. Afterwards, the designed beam is verified for the limit state of serviceability and safety against collapse.

3.1 Structure design assumptions

The Indian Standard code ‘IS 456-2000’ [30] is applied in the current study on the structural use of the plain and reinforced concrete as well as it determined the limit state design procedure. In addition, all the following used clauses are applied from [30]. Several parameters are considered, such as the loads on the outer walls of intermediate floors, loads of parapet walls on top floor or on the internal walls of internal floors, the beams’ cross section, number of beams, the building area, the columns’ section, and number of columns.

In the present study, the assumption that the beams are parallel to the x-axis and parallel to the z-axis is applied based on ‘STAAD. Pro.’ Thus, every single node to node connection is considered as one beam. Meanwhile, the columns are represented by beams parallel to the y-axis. To plot different plans of the ‘STAAD. Pro v8i’ structure, line diagram is exploited by the system. Additionally, the concrete volume and the reinforcement area values are acquired from the STAAD output file. In the proposed structure, the used beams of one meter size are assumed. Accordingly, only beams and columns are designed, while the slab design is not included, but their loads are imposed on the beams. Additionally, in the stair case, the loads are computed and imposed on the adjacent beams. Based on the IS 456:2000, the cross-sectional dimensions of the reinforced concrete beams are chosen. The limit state method of serviceability is employed to calculate the effective overall depth of the beam. As per assumptions, the overall depth to width should be in the range of 1.5 to 2, while the effective beam depth is given in the ‘Clause 23.0.’ The beam depth is designed to validate that the percentage of the required steel is around 75 % of the particular sectional area. Generally, the beam design procedure is according to the clause that available in the IS 456:2000 in ‘Clause 23.0’ (Compliance with Law Licenses). The bending moment and the shear coefficients are calculated based on clause number 22.5.1 and 22.5.2, respectively, of the IS 456:2000 [30]. Furthermore, for the redistribution of moment, the clause number 22.7 followed by ‘37.1.1’ is used. The clause number 37.1.1 is described the redistribution of moments in continuous beams and frames. In case, elastic maximum moment diagram is greater than the moment capacity after redistribution, and the subsequent expression will be achieved:

$$\frac{x_u}{d} + \frac{\partial M}{100} \leq 0.6 \tag{1}$$

Here, x_u is the neutral axis depth, d is the effective depth and ∂M is the percentage reduction in moment.

Considering the span as the length from a support center, while the depth is the average depth from the top of the beam to the bottom, thus the span/depth ratio for the continuous beam is specified by the IS 456:2000. It is recommended to modify the span/depth ratio using the factors K_c, K_t and k_f, where K_c is the modification factor of compression reinforcement, K_t is the modification factor of tension reinforcement and k_f is the reduction factor of flanged beam. Since the heavy dead loads and live loads are carried by continuous beams, thus in practical cases the span/depth ratio is between 15 and 20, even though sometimes the span/depth ratio is considered to be 26 in the case of shallow depth or if required high reinforcement. In addition, the deflection (degree of the structural element displacement occurs under a load) is done as per Clause 23.2, where the deflection control is specified.

In the present study, the modification factor of tension/compression reinforcement is accomplished from the modification factor graph versus the percentage tension/compression reinforcement, respectively [30]. Clause 23.3 is assigned to specify the slenderness limits for the beams that achieved the lateral, since the cantilever beams are used commonly to support the Chazza slabs or canopy of the larger span at the building entry area. Therefore, the cantilever beams are usually proposed for maximum moments and shear forces developed at support section, and this is normally a reinforced concrete columns. Clauses number 25.1.1 and 25.1.2 are followed to describe the column design and the type of compression member, respectively. Also, Clause 25.1.2 is used to define the Short and Slender Compression Members.

With the definition that l_{ex} is the effective length with respect to the major axis, D is the depth with respect to the major axis, l_{ey} is the effective length with respect to the minor axis, and b with width of the member. Thus, a compression member can be considered as short when the slenderness ratios $\frac{l_{ex}}{D}$ and $\frac{l_{ey}}{b}$ are less than 12; otherwise, it will be considered as a slender compression member. The unsupported length of any compression member is calculated based on Clause 25.1.3. The compression members' effective length is specified in Clause number 25.2. The stability index Q can be calculated as follows in the case of sway/no sway column.

$$Q = \frac{\sum P_u \Delta_u}{H_u h_s} \tag{2}$$

where $\sum P_u$ is the sum of the axial loads on all columns in the story, Δ_u is the elastically computed first-order lateral deflection, H_u is the total lateral force acting within the story and h_s is the height of the story.

From the graph of β_1 versus β_2, the effective length ratios for a column in a frame with no sway or without restraint against sway is calculated. β_1 and β_2 are equal to $\frac{\sum k_c}{\sum k_c + \sum k_b}$ where the summation is to be done for the members framing into a joint at top and bottom, respectively, and k_c and k_b being the flexural stiffness for column and beam, respectively. From [30], the effective length of the compression member is established.

From Clause 25.3, the slenderness limits for the columns are given. The minimum eccentricity of the columns is available from Clause 25.4. For the collapse limit state, the compression/flexure Clause 39 is applied. For the short axially loaded members in compression, the axial load on the member is available in Clause 39.3 that can be determined by:

$$P_u = 0.4 f_{ck} \cdot A_c + 0.67 f_y \cdot A_{sc} \tag{3}$$

where P_u is the axial load on the member, f_{ck} is the characteristic compressive strength of the concrete, f_y is the characteristic strength of compression reinforcement, A_c is the area of concrete and A_{sc} is the area of longitudinal reinforcement for columns.

For the compression member that subjected to combined biaxial bending and axial load, following equation is applied for design [30]:

$$\left[\frac{M_{ux}}{M_{ux1}}\right]^{\alpha_n} + \left[\frac{M_{uy}}{M_{uy1}}\right]^{\alpha_n} \leq 1.0 \tag{4}$$

where M_{ux} and M_{uy} are the moments about x and y axes due to design loads, M_{ux1} and M_{uy1} are the maximum uniaxial moment capacity for an axial load of P_u, bending about x and y axes, respectively, and α_n is related to P_u/P_{uz} as:

$$P_{uz} = 0.45 f_{ck} \cdot A_c + 0.75 f_y \cdot A_{sc} \tag{5}$$

For limit state of collapse, shear Clause 40 is applied. At the time of the load calculation on the stair and during the stair design, Clause 33 is used.

Consequently, the exceeding mentioned parameters are applied to realize the major contribution of the current study by predicting/classifying the RC structures' failure based on the MLP-FFN with scaled conjugate gradient learning algorithm supported by the PSO optimization algorithm.

3.2 Classification-based neural network

The artificial neural network (ANN) [31, 32] is considered the most popular one modeling tool. It guarantees accurate classification even with very little available data. The ANN is an engineering equivalent of the biological neuron as it is inspired by the human brain functioning. ANNs can handle indistinct functional relationships during its learning (training) stage, unlike the conventional methods that based on predefined relations. The ANN model is arranged interconnected computational neurons employed to execute a mathematical mapping during a process of learning. The NN learning facility is attributed to the adjustment in the synaptic weight value. Compliance to changing the input–

output data, nonlinear function mapping and the capability to capture indefinite relationships provides the ANNs a flexibility to model the real-world problems, such as applications in the civil engineering domain. To accomplish the classification of the RC structures' failure, a multistep procedure based on NN is followed.

Typically, for any application, the classification steps are as follows: (i) the training phase, where part of the dataset that consists of attribute values (a set of training data) is engaged to identify its entity along with its class label to construct the classification model. The model attempts to obtain sufficient knowledge to understand the entities way for classification into given classes, (ii) the validation phase is used to validate the effectiveness of the model using another dataset, which was not used in the training phase, and (iii) the evaluation (test) phase, where the constructed model accuracy is tested with another set of test data. This phase is used to find the class of each entity and evaluate the classification accuracy. Generally, the artificial neuron forms input (N_j), using the input signal (x) and their analogous weights (w). This input is then exceeded to a linear threshold filter till it finally passes the output signal (y) to another neuron. The neuron is stimulated if N_j exceeds the threshold of that neuron. The net input (N_j) is computed by a linear equation given by:

$$N_j = \sum_{i=1}^{m} w_{ij} x_i \tag{6}$$

where m is the number of the input signals, w is the weight and x is the strength of each signal. Consequently, using the bias (θ_j), the output (y) is calculated as follows:

$$y = \begin{cases} 1, & \text{if} \quad N_j \geq \theta_j \\ 0, & \text{if} \quad N_j < \theta_j \end{cases} \tag{7}$$

Several activation functions such as sigmoid and logistic can be used. To obtain the optimal weight vector in finite number of iterations regardless of the initial weight vector, the perceptron learning rule is to be used [33]. Numerous network architectures have been proposed to improve the NN performance. Typical two-layer perceptron feed-forward network can be used for the MLP-FFN experiments [34]. Consequently, the MLP-FFN is employed for the classification step in the proposed system. Moreover, using optimization algorithms can be used to support the MLP-FFN.

3.3 Particle swarm optimization

Typically, the particle swarm optimization (PSO) method is employed mainly to solve global optimization problems. The PSO-based algorithm is well suited to handle nonlinear, nonconvex design spaces with discontinuities, has fast convergence characteristics and is robust. Therefore, compared to other evolutionary algorithms, PSO is considered a prospective candidate for optimum structural design.

Particle swarm optimization is one of the most popular population-based optimization techniques as it considers a population of particles (candidate solutions) in D-dimensional search space [35]. Each particle is associated with a fitness value that estimates the particle's ability to achieve the objective. Initially, the particles are placed randomly in the search space and the swarm moves inside the search space to reach the optimal fitness. Particles are associated with a 'pbest' which is accounted for the best solution in the hyperspace ever visited by a particle. The best value achieved by any particle of the swarm is denoted by 'gbest' (or the global best). Each particle's position and velocity are initialized randomly. After every iteration, the fitness values of the particles are calculated and necessary adjustments are made to the position/velocity of each particle to move them to optimal fitness. This adjustment is performed depending on the following equations.

$$\begin{aligned} v_i(t+1) = v_i(t) + a_1 * r_1 * (\text{pbest}_i(t) - x_i(t)) \\ + a_2 * r_2 * (\text{gbest}_i(t) - x_i(t)) \end{aligned} \tag{8}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{9}$$

A general algorithm of PSO is described in the following algorithm

Algorithm: General algorithm for Particle Swarm Optimization

Start
The particles of the Swarm is placed at random positions with zero velocity
For n : 1 : Swarm-size **do**
Compute fitness
end for
for i : 1 : Number-of-iterations **do**
for j : 1 : Swarm-size do
Update *pbest*
  Update *gbest*
Adjust position and velocity
  Calculate fitness for the new population
end for
End for
End

Unlike local search-based optimization techniques, the PSO does not suffer from premature convergence to local optimal solutions. Consequently, the PSO optimization algorithm is used to support the MLP-FFN.

4 Proposed method

In the current study, the PSO algorithm is involved to support the artificial neural network training. The ANN classifier trained with PSO (NN-PSO) is employed to handle the predicting structural failure problem of multi-storied reinforced concrete buildings.

The network architecture MLP-FFN used is [36], where the learning algorithm is benchmarked against traditional back-propagation and other algorithms. The flow of the current experiment using MLP-FFN has been depicted by a flow diagram in Fig. 1. The MLP-FFN steps are as follows. Step 1 is the preprocessing which is performed before the classification step on the dataset and is included: (i) feature selection, which extracted the most important attributes and has effective features to classify the dataset precisely into two or more classes, (ii) data cleaning noise removal and filling up empty entries by suitable data using means of statistical analysis, and (iii) data normalization which is required before classification to reduce the distance between attribute values. The second step is to divide the dataset into training dataset and the testing dataset, where in the present work 90 % of the data are assigned as training data and rest (10 %) as validation and testing data. Then, step 3 is the training phase to train the dataset using different algorithms to build the required classification model. Finally, step 4 which included the testing phase where the classification models obtained from the training phase is employed to test the accuracy of the model.

In the present work, the PSO algorithm is used to support the previously mentioned MLP-FFN classifier. The particles of the PSO algorithm are initialized with a random position in D-dimensional hyperspace with zero velocity. The value D depends on the dataset attribute number to be used for training and testing the NN. The values corresponding to each of the dimensions are within range 0 to 1. This is achieved by normalizing the dataset values within the expected range. The position of each particle is actually a D-dimensional vector, which can be used as the input weight vector of the input layer of the NN.

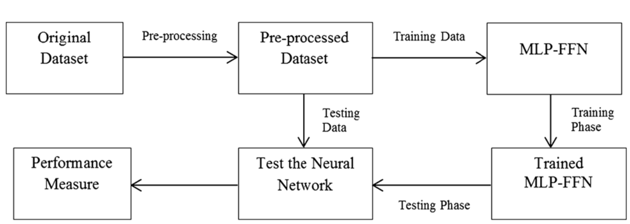

Fig. 1 Flow diagram for MLP-FFN classifier

The root-mean-square error (RMSE) is used as the fitness (objective) function; thus, the PSO has been engaged to minimize the RMSE during the training phase of the NN. It is calculated as the difference between the values anticipated by a classifier and the values actually discovered from the surroundings of the system being modeled. The RMSE of a classifier prediction with respect to the computed variable v_{c_k} is determined as the square root of the mean-squared error and is given by:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{k=1}^{n}\left(v_{d_k} - v_{c_k}\right)^2}{n}}, \tag{10}$$

where v_{d_k} denotes the originally observed value of kth data instance and v_{c_k} denotes the predicted value by the classifier. The objective of the PSO is to find a weight vector (a position in the hyperspace) that can result in minimum RMSE from the neural network. Figure 2 summarizes the pervious procedure steps for the proposed system to classify the RC buildings' failure classes.

Figure 2 illustrates that a preprocessing step is applied for feature selection and data cleaning. Afterwards, the proposed PSO trained ANN (NN-PSO) classifier is employed to overcome the NN trapping in a local optima while predicting the RC structures' failure. The RMSE has been used as an objective function for the PSO that used to determine the optimal input weight vector for ANN input layer. To attain the optimal ANN weights, the computed hidden layer weight values were used with the PSO objective function till convergence achieved. Once the convergence of the PSO algorithm occurred, the obtained ANN weights are the optimal values that used for the classification process. The main target of the proposed method using the NN-PSO is to classify the data instances into two classes 'Structure Failure' and 'No Structure Failure,' which used further to predict the RC structural failure.

5 Experimental results and discussion

One hundred and fifty RC structures of multistoried buildings dataset that designed by professional engineers are employed in the current study. Based on the previous proposed model, the experiments are carried out using real-coded ANN, MLP-FFN and NN-PSO. Scaled conjugate gradient algorithm [12] has been opted as the learning algorithm, and cross-entropy [37] has been employed as error function for the ANN and MLP-FFN. The description of the initial dataset features is depicted in Table 1.

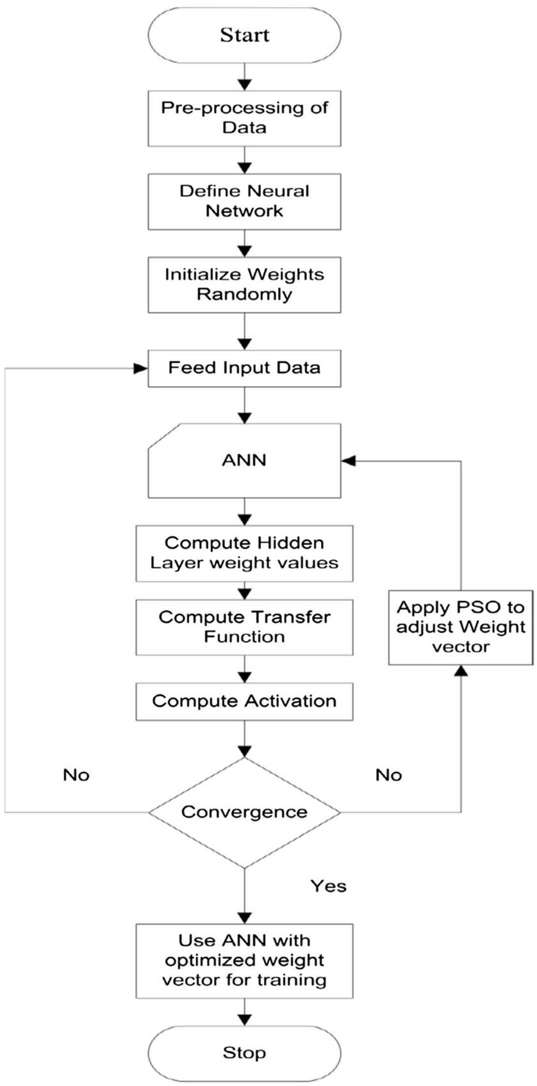

Fig. 2 Flowchart of artificial neural network training using PSO

Typically, during the classification process, as the number of employed features increased, the computational cost for predictions will increase immensely. Additionally, the irrelevant input features may lead to over-fitting. Greedy forward selection algorithm [38] has been extensively used in various applications to improve the computational efficiency with good accuracy. The forward feature selection procedure starts by evaluating all feature subsets that comprise only one input attribute. Subsequently, forward selection determines the best subset consisting of two components. Later, the input subsets with three, four, and more features are evaluated. It provided most significant progress at each step in order to achieve sparsity. The forward greedy algorithm strength is due to the fact that it works with a sparse solution explicitly and thus computationally efficient.

Table 1 Initial dataset features

Si.	Feature	Explanation
1	NOC	No. of columns
2	NOB	No. of beams
3	A	Area
4	HPW	Height of parapet wall
5	TSIF	Thickness of side walls of interior floors
6	TIIF	Thickness of inner walls of interior floors
7	D	Depth of beam
8	w_b	Width of beam
9	BC	Breadth of column
10	WC	Width of column
11	f_y	Grade of steel
12	f_{ck}	Grade of concrete
13	q	Bearing capacity of soil
14	V_c	Concrete volume
15	A_r	Reinforcement area

Subsequently, the features are selected as tabulated in Table 2 by employing greedy forward selection method as described in [39].

Several statistical performance measurement metrics are used to evaluate the proposed system performance. These metrics are calculated from the confusion matrix [40] that illustrated in Table 3. The confusion matrix provides the performance visualization of the classification algorithm. Each column of the matrix denotes the examples in a predicted class, while each row indicates the examples in an actual class. This matrix assists in finding out any type of misclassification due to the classifier. The confusion matrix entries are as follows: (i) True positive (TP) is the number of 'positive' cases that categorized as 'positive,' (ii) false positive (FP) is the number of 'negative' cases that categorized as 'positive,' (iii) false negative (FN) is the number of 'positive' cases categorized as 'negative,' and

Table 2 Dataset features after feature extraction

Si.	Feature	Explanation
1	HPW	Height of parapet wall
2	TSIF	Thickness of side walls of interior floors
3	TIIF	Thickness of inner walls of interior floors
4	D	Depth of beam
5	w_b	Width of beam
6	BC	Breadth of column
7	WC	Width of column
8	V_c	Concrete volume
9	A_r	Reinforcement area

Table 3 Typical example of confusion matrix of binary classification problem

Predicted class	Positive	Negative
Actual class		
Positive	TP	FP
Negative	FN	TN

(iv) true negative (TN) is the number of 'negative' cases categorized as 'negative.'

Theses performance metrics are such as: (i) the accuracy, which is defined as a ratio of sum of the instances classified correctly to the total number of instances, (ii) precision, which is known as the ratio of correctly classified data in positive class to the total number of data classified as to be in positive class, (iii) recall (TP rate), which is defined as the ratio of tp to the total number of instances classified under positive class, and (iv) F-Measure, which is defined as a combined representation of precision and recall. The mathematical expressions for these metrics are given by:

$$\text{Accuracy} = \frac{\text{tp} + \text{tn}}{\text{tp} + \text{fp} + \text{fn} + \text{tn}} \tag{11}$$

$$\text{Precision} = \frac{\text{tp}}{\text{tp} + \text{fp}} \tag{12}$$

$$\text{Recall} = \frac{\text{tp}}{\text{tp} + \text{fn}} \tag{13}$$

$$F - \text{measure} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{14}$$

The proposed method classifies data instances into two classes, namely (i) 'Structure Failure' that denotes structural failure of the current data and (ii) 'No Structure Failure' that denotes the stable condition of the current structure. Table 4 tabulates the confusion matrix for the testing phase of NN-PSO, while Fig. 3 demonstrates the cross-entropy versus the epochs plot for training, validation and testing phases using the NN-PSO approach. The best validation performance of 0.13265 has been achieved in 34th epoch. Figure 4 reports the error histogram with 20 bins for the same.

The experimental results of different classifiers have been tabulated in Table 5. Different performance measures have been calculated by following the metrics Eqs. (11–14). The experimental results of different classifiers have

Table 4 Confusion matrix of testing phase for NN-PSO

Predicted class	Structure failure	No structure failure
Actual class		
Structure failure	18	2
No structure failure	1	9

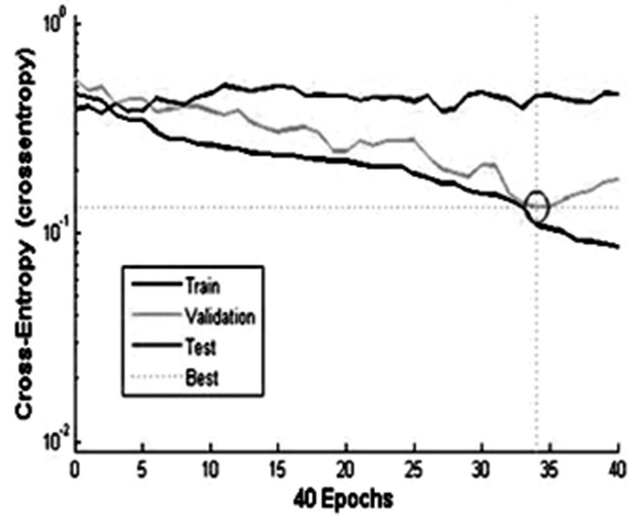

Fig. 3 Plot of the cross-entropy versus the epochs for training, validation and testing phases of the NN-PSO approach

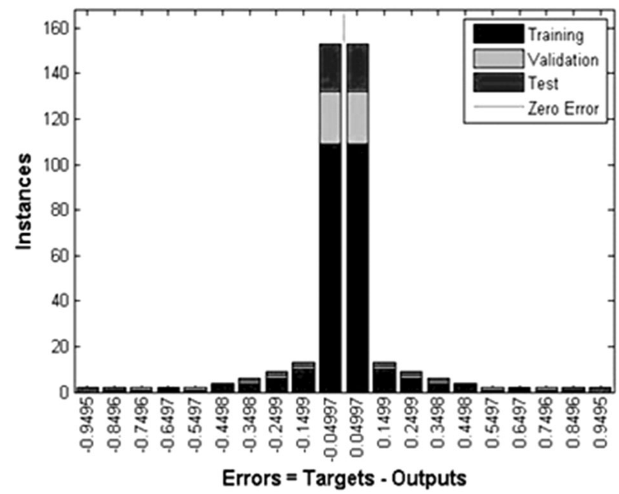

Fig. 4 Error histogram for training, validation and testing phases for the NN-PSO approach

Table 5 Performance comparison of proposed model for testing phase

	NN (%)	MLP-FFN (%)	NN-PSO (%)
Accuracy	66.67	80	90
Precision	76.92	100	90
Recall	58.82	50	94.74
F-Measure	66.66	66.67	92.31

been tabulated in Table 5. This table depicted the poor accuracy of NN, which achieved 66.67 %, while the NN-PSO achieved the superior accuracy of value 90 %. Additionally, it is established that the NN had the worst performance compared to the two other methods as it

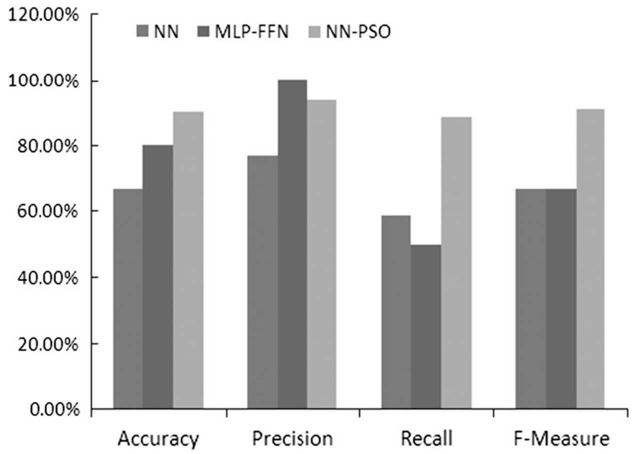

Fig. 5 Performance comparison of the different classifiers in terms of several performance metrics

achieved 76.92 % precision, 58.82 % recall and 66.66 % F-Measure. Meanwhile, the MLP-FFN classifier achieved better performance than the NN. In the testing phase, the MLP-FFN model provided an accuracy of 80 % with 100 % precision, 50 % recall and F-Measure (66.67 %).

Finally, compared to the NN-based particle swarm optimization (NN-PSO), the attained accuracy of the classifier was 90 % with 90 % precision, 94.74 % recall and 92.31 % F-Measure in the testing phase. Figure 5 depicts the performance comparison of the different classifiers with the proposed NN-PSO classifier.

Figure 5 establishes that the proposed NN-PSO outperformed the NN and MLP-FFN in predicting the structural failure of multistoried RC buildings.

Generally, several studies have been conducted based on neural network as well as optimization algorithms in various applications [41–54]. In addition, extensive works have been done to classify as well as to analyze earthquake performances of the RC buildings based on NN and other classifiers [55–58]. In the current study, the neural network supported by PSO optimization algorithm proved its efficiency with 90 % accuracy to classify and thus predict the structural failure of multistoried RC buildings.

The current study established that the ANN-based PSO optimization was efficiently used to classify the structural failure of multistoried RC building structure instead of concerning the structure design. Employing the PSO to enhance the performance of ANN to the required classification adds an innovation to the current study.

6 Conclusion

There are copious causes for structural failure, which necessitates proper analysis of all factors that affects the construction. Additionally, it is important that the designers, builders and owners to be fully conscious of the failure reasons carry out all preventive measures.

The present work has considered a quite challenging in the field of machine learning as the traditionally well-known models based on neural networks fail to achieve the expected performance due to the premature convergence of the NNs while trained with local search-based optimization algorithms

The NN-PSO-based model to predict the structural failure of a multistoried RC building was suggested, where the PSO algorithm was engaged to select the optimal weights for the NN classifier.

The proposed model has been compared with NN and MLP-FFN that is trained with scaled conjugate gradient algorithm which has been found to be benchmarked against traditional back-propagation and other algorithms. Besides, cross-entropy has been used as the error estimator.

The NN-PSO performance has been evaluated by different standard performance measure metrics. The experimental results established the dominance of the proposed model for detecting the structural status of a multistoried RC building structure.

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