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Structural failure classification for reinforced concrete buildings using trained neural network based multi-objective genetic algorithm

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Abstract. Structural design has an imperative role in deciding the failure possibility of a Reinforced Concrete (RC) structure. Recent research works achieved the goal of predicting the structural failure of the RC structure with the assistance of machine learning techniques. Previously, the Artificial Neural Network (ANN) has been trained supported by Particle Swarm Optimization (PSO) to classify RC structures with reasonable accuracy. Though, keeping in mind the sensitivity in predicting the structural failure, more accurate models are still absent in the context of Machine Learning. Since the efficiency of multi-objective optimization over single objective optimization techniques is well established. Thus, the motivation of the current work is to employ a Multi-objective Genetic Algorithm (MOGA) to train the Neural Network (NN) based model. In the present work, the NN has been trained with MOGA to minimize the Root Mean Squared Error (RMSE) and Maximum Error (ME) toward optimizing the weight vector of the NN. The model has been tested by using a dataset consisting of 150 RC structure buildings. The proposed NN-MOGA based model has been compared with Multi-layer perceptron-feed-forward network (MLP-FFN) and NN-PSO based models in terms of several performance metrics. Experimental results suggested that the NN-MOGA has outperformed other existing well known classifiers with a reasonable improvement over them. Meanwhile, the proposed NN-MOGA achieved the superior accuracy of 93.33% and F-measure of 94.44%, which is superior to the other classifiers in the present study.

Keywords: genetic algorithm; classification; neural network; reinforced concrete

1. Introduction

In civil engineering industry, reinforced concrete (RC) is one of the most used construction materials that have a significant role in the building structure. However, reinforcement corrosion is a main problem, which requires inspection techniques to evaluate steel corrosion in concrete to protect RC structures. Recently, structural failure due to defective building designs has become a potential threat. One of the main causes of structural failure is the inaccurate assignment of loading conditions, which can cause imperfect design. Low quality construction material may have similar effect as the inaccurate loading conditions. Suddenly, applied load on RC buildings beyond its design load results in failure of the beam and column, which ultimately directs to failure of the RC buildings. Cracking and falling of walls have been the major structural damages observed in reinforced concrete structures. These types of damages are highly expected due to structural failures in multi storied buildings (Fayyadh and Razak 2011). Thus, keeping in mind the sensitivity regarding structural failures, it has become imperative to predict the structural failure of RC buildings with reasonable accuracy.

Machine learning has been proved to be an effective and reliable source of solutions of real life engineering problems seeking cost effective and fast solution. Typically, machine learning, fuzzy logic and optimization algorithms such as genetic algorithms (GAs) methods depicted their efficiency in monitoring railways (Stratman *et al*. 2011), bridges (Chen and Liu 2010) and buildings (Jiang and Adeli 2007) to detect damages in beams, steel and concrete columns. Among several machine learning techniques which have applied to tackle real life problems, Artificial Neural Networks (ANN) (or simply Neural Networks (NN)) (Knezevic *et al*. 2014, Socha and Blum 2007, Dehuri and Cho 2010). Moreover, ANN has been extensively used in analyzing several issues related to RC buildings (Arslan 2010, Arslan *et al*. 2012, Kia and Sensoy 2014, Arslan *et al*. 2015). Furthermore, classification of structural failures can be accomplished by employing ANNs. A trained ANN can be used to predict the class label of a data whose class label

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is unknown (Han *et al*. 2011).

Consequently, various aspects regarding structural failure can be predicted and studied using ANN (Awan *et al*. 2014, Siddiquee and Hossain 2015, Cao *et al*. 2015), where a learning algorithm can be employed to train the network. In this stage the weight vectors of neural network is optimized to achieve maximum accuracy. This is accomplished by optimizing an objective function (*Generally Minimizing Error*). However, researches have revealed that traditional learning algorithms may lead to a premature convergence to local optima specially when dealing with real life problems. Thus, achieving expected accuracy is challenging. Since, the ANN based back-propagation of error strategy is generally trained with learning algorithms which are devised on the scheme of local optimization (Gao *et al*. 2015, Ciancio *et al*. 2015, Mirjalili *et al*. 2015). Thus, it is highly probable that the optimization process may converge to local optima instead of better global optima value thereby, deteriorating the ANN performance to predict/classify the intended target. Such drawback can be efficiently resolved by applying meta-heuristic optimization algorithms to train the Neural Network. Artificial neural networks supported by meta-heuristic optimization techniques achieved better accuracy (Chen *et al*. 2015) compared to the traditional ones.

Neural networks have been established to be a good model for detecting damages in RC structures (Pierce *et al*. 2006). Recently, the authors have proposed a particle swarm optimization (PSO) based NN system to predict the structural failure of the RC buildings, which achieved superior performance (Chatterjee *et al*. 2016). However, due to highly expected accuracy of such predictions which is highly associated with human lives and infrastructure industries, more attempts to realize trustworthy models are proposed in the current study, due to the successful application of the Multi-Objective Optimization (MOO) algorithms in training the NNs. Among several variations of the MOOs (Zitzler and Thiele 1998, Coello 1999, Zitzler *et al*. 2001), non-dominating sorting Genetic algorithm-II (NSGA-II) (Deb 2001) has been proved to be efficient than others.

Earlier, Chatterjee *et al*. (2016) reported the challenges of the traditional methods in determining the structural failure related to a multistory RC building. It has been proved that sufficient improvement is required in order to establish a more trustworthy prediction model. Consequently, the main contribution of the current work is to devise an efficient method that predicts the structural failure based on machine learning and optimization techniques. The proposed method employed the MOGA trained NN (NN-MOGA) to predict the structural failure of the multistoried RC buildings. It is used to optimize the weight vector of neural network in terms of optimizing two different objective functions. The proposed model is compared to a well-known NN model known as the Multilayer Perceptron Feed-forward Network (MLP-FFN) which is based upon the idea of back-propagating the error and adjusting the weight vectors accordingly. The MLP-FFN can have multiple hidden layers, though two hidden layers are sufficient to estimate complex functions efficiently (MacIntyre 2013, Azar *et al.* 2013). The NN performance can further be enhanced by employing PSO to optimize the input weight vector. Thus, in the present work the proposed model is compared with both MLP-FFN (trained with scaled conjugate gradient descent algorithm (Møller 1993)) and NN-PSO in terms of several performance measuring matrices such as accuracy, precision, recall and F-measure.

The rest of the work is organized as follows: Section 2 introduced various related work that conducted NN and optimization algorithms in several RC and civil engineering applications. Afterward, the methodology, the proposed system and the design constraints are explained in Sections 3 through 6; respectively. Finally, the experimental results and discussion followed by the work conclusion are included in Sections 6 and 7; respectively.

2. Related studies

Civil engineering is an expanded domain ranging from water resources to analysis and design of structures. Additionally, the ANNs are extremely parallel distributed processors, which have an expected propensity for storing experimental knowledge to be available for use. Thus, NN applications in RC structures and other civil engineering problems attract the focus of the researchers. Jeng *et al*. introduced a survey for the NN applications in civil engineering problems. The authors reported that the NN has the ability to solve difficult problems, which cannot be solved using conventional engineering techniques (Jeng *et al*. 2003). Such problems involve wave-induced seabed instability, tide forecasting and earthquake-induced liquefaction. It was established that the ANN model can present rational accuracy for civil engineering problems.

One of the most significant applications of the ANN is to study the post seismic effects on RC buildings. Caglar *et al.* initially trained the NN using feature vectors of corresponding buildings used in the study; hence the trained network was employed to detect structural responses for different designs which are mainly differed in terms of sheer force, fundamental periods and buildings' top floor displacement (Caglar *et al*. 2008). Güneyisi *et al*. designed an empirical model using ANN for the prediction of chloride permeability of concretes. The suggested model achieved high capability of estimation of permeability (Güneyisi *et al*. 2009). Sadowski concluded that the ANN approach has a theoretical impact in the prophecy of steel's corrosion current rate in concrete using corrosion current density without connecting to the steel reinforcement (Sadowski 2013). Vanluchene and Sun (1990) discussed the use of NN based back-propagation algorithm to solve three structural engineering problems related to decision making, pattern recognition, and complex numerical engineering problem. In (Hajela and Berke 1991), the authors investigated the neural computing role in structural engineering applications by obtaining the optimum weight of a truss. For structures with large degree of freedom, Rogers proved that NN was computationally less expensive compared to conventional structural analysis methods

(Rogers 1994).

For initial design of RC rectangular single-span beams, Mukherjee and Deshpande developed NN system to predict a good initial design including the beam depth/width, the tensile reinforcement required, the moment capacity, and the cost per meter. This design was applied for known input parameters set such as live load, dead load, span, steel type, and the concrete grade (Mukherjee and Deshpande 1995). Sanad and Saka applied ANN for the prediction of the ultimate shear strength of RC deep beams (Sanad and Saka 2001). The obtained result was compared to different empirical relationships. It was proved that the ANN provided superior prediction of shear strength. Hadi demonstrated the ANNs efficiency compared to conventional design methods for optimum design of reinforced fibrous concrete beams and supported concrete beams (Hadi 2003). For circular concrete columns, Oreta and Kawashima explored the ANN for predicting the compressive strength and analogous strain (Oreta and Kawashima 2003).

Nowadays, the innovative techniques develop the ANN model based on optimization procedures become widely used in the engineering domain (Veeramachaneni *et al*. 2003). Generally, nature inspired meta-heuristic have several algorithms such as particle swarm optimization (PSO), bacterial foraging optimization algorithm (BFOA), artificial bee colony (ABC), cuckoo search (CS), ant colony optimization (ACO) and firefly algorithms (FA), which are effective in different engineering applications (Nanda and Panda 2014, Rahmanian *et al*. 2012). Chatterjee *et al*. proposed a PSO trained neural network based model to efficiently predict the structural failure of multistoried RC buildings. Greedy forward selection algorithm has been applied to eliminate redundant features and next PSO was employed to minimize the root mean squared error related with neural network in training stage (Chatterjee *et al*. 2016). Abbass reported multi-objective evolutionary algorithm based approach to optimize the ANN architecture, where the training phase of the ANN requires the determination of reasonable number of architecture to find the best possible one (Abbass 2003). Thus, the multi-objective evolutionary algorithm was employed to tackle this problem. Moreover, the algorithm simultaneously optimized the error related with the network. Multi objective optimization has been employed to train MLP-FFN to maintain a complex trade-off between over-fitting and under-fitting of ANNs (Costa *et al*. 2003). Training set error and norm of weight vectors were used as objectives. The model was compared to the standard back-propagation, support vector machines (SVM), and weight decay based models which employed a single objective while finding the optimal weight vectors. The former one has been claimed to be better than the single objective versions. A novel sliding mode control algorithm (Teixeira *et al*. 2000) has been proposed to guide the trajectory of a MLP-FFN. Two objective functions, namely the training set error and norm of weight vectors were used as objectives which were optimized. The model was found to have a better performance than traditional models. The penalty functions are critical for an effective and efficient search. If the penalties are too harsh, the optimization could quickly converge to the local optimum and be stuck, while, if the penalties are too soft, the search could be very time consuming. Thus, tuning the penalty function parameters is a significant issue, where reported in (Chatterjee *et al.* 2016, Hore *et al.* 2017).

From the preceding extensive survey, the NN proved its efficiency with versatile applications, however it requires significant improvement. Therefore, in the present work, a multi-objective optimization technique is used to support the NN training to solve the problem of structural failure prediction of multistoried buildings. Since, the NSGA-II is a very successful multi-objective optimization technique. Thus, the NN is trained by the NSGA-II. In the current work, the variation of MOGA is known as Non-dominated Sorting Genetic Algorithm-II (NSGA-II) (Deb 2001).

3. Methodology

Studies have revealed that building width/ depth and cross-section dimensions are required to be optimized for optimal design of the RC structures. Moreover, there is several factors influence the reinforcements including the material property, loads on beam, and the beam's cross-sectional dimensions. In the present work, a multistory buildings dataset of one hundred fifty RC structures is designed by specialized civil engineers and used in the existing study. For structural failure prediction of RC buildings, the classification of the RC structures into 'Structure Failure' and 'No Structure Failure' is required. The ANN is involved for the classification process; furthermore the MOGA is used to optimize the weights of the NN for outstanding classification. In the current work, NSGA-II is employed to train the ANN, thereby ensuring a more stable ANN model to predict structural failure.

3.1 Multi-objective optimization

In real life applications, the optimization problems involve multiple objectives to be optimized simultaneously while obtaining a solution. Multi-objective optimization can formally be framed as follows (Teixeira *et al*. 2000):

1. Find the vector $\bar{x}_p = [x_1 \; x_2, \ldots, x_n]^T$ of n decision variables such that $\bar{f}(\bar{x}_p) = \left[f_1(\vec{x}), f_2(\vec{x}), \ldots, f_n(\vec{x}) \right]^T$ satisfies some constraints.
2. The vector $\bar{x}_p$ is said to be Pareto optimal if and only if there exist no $\vec{x}$ such that $\forall i \in \{1,2,\ldots n\}$, $f_i(\vec{x}) \le f_i(\vec{x}_p)$ and there exist at least one i such that $f_i(\vec{x}) < f_i(\vec{x}_p)$.
3. The set of solutions which is generated due to Pareto optimality are generally addressed as non-dominated solutions.

In the present work, the MOGA is employed to train the ANN.

3.1.1 The GA chromosome representation

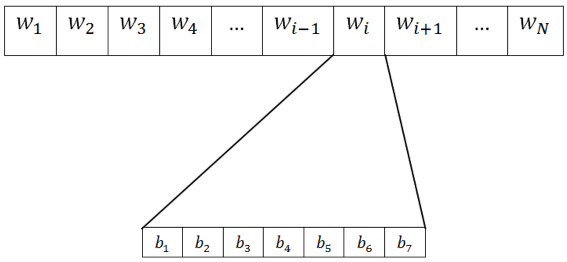

Fig. 1 A typical candidate solution in form of a chromosome

Each candidate solution in any kind of the GAs variation is considered as a chromosome. Thus, initial set of solutions and forth is actually encoded in form of chromosomes. Each chromosome is typically a binary string. In the case of training NN each chromosome admits for a point in the N dimensional space, where N is the total number of connections between the artificial neurons in the corresponding NN. Representation of a typical candidate solution in form of a chromosome is depicted in Fig. 1.

Where, w_i denotes the ith weight which is further described as a binary string of seven bits. The value of N as well as the number of bits to represent each weight can vary based on the problem under concern.

3.1.2 The NSGA-II fitness functions

In the proposed NSGA-II based method, two objective functions are optimized, namely the root mean squared error (RMSE) and the Maximum Error (ME). The RMSE is used as one fitness (*Objective*) function. 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 as follows

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

where, v_{d_k} denotes the originally observed value of k^{th} data instance and v_{c_k} denotes the predicted value by the classifier. Apart from the RMSE, the NSGA-II is used simultaneously to optimize the ME which can be defined as

$$ME = Z_{\alpha/2}\frac{\sigma}{\sqrt{n}} \tag{2}$$

where, $Z_{\alpha/2}$ denotes the z-score having confidence level $(1-\alpha)$ and σ denotes standard deviation of n many samples. The objective of the NSGA-II is to find the Pareto optimal front from which no further improvement is possible without sacrificing one of the objectives.

3.1.3 Multi-objective genetic algorithm

Both the MOGA and the GA principles are similar in almost all the processes except in the optimization process and the selection processes of members to the next generation. In the optimization process, the MOGA tries to optimize multiple objectives which are sometimes contradictory to each other. A general MOGA algorithm has been depicted in Algorithm 1 as follows.

Algorithm 1. Multi-Objective Genetic Algorithm

Begin
  Initialize the population;
  If (Termination condition not satisfied?)
    Crossover;
    Mutation;
      Calculate multiple object functions for each member of population;
    Select members for next generation;
  Endif
End

Algorithm 1 illustrates that the selection process comes after a ranking of the current population. In the present work, it is achieved by a Non-dominated sorting (Deb, 2001) which has been used in the NSGA-II algorithm. The Non-dominated sorting process in NSGA-II is faster than the previous version. In addition, it also assures elitism of next generation which is a key factor of successful and efficient convergence of the algorithm.

3.2 Neural network for classification

The ANN is one of the most used modeling approaches (Maren *et al.* 2014, Baughman and Liu 2014). It achieves accurate classification even with very small dataset. It can handle imprecise relationships during its training stage. The ANN structure is consists of interconnected computational neurons, which involved in the mahematical mapping through the learning process, which attempt to adjust the weight value. Initially, the training phase is started by a part of the dataset to classify its inputs along with its class label to create the classification model. Afterward, the validation phase is performed to confirm the effectiveness of the trained model using another dataset. Finally, the evaluation phase is used to test the classification model accuracy using another set of test data. In general, the artificial neuron uses the input signal (x) and their equivalent weights (w) to form the input (N_j). This input is then surpassed to a linear threshold filter till it exceeds the output signal (y) to another neuron. If N_j exceeds the threshold of that neuron, the neuron is inspired. The net input (N_j) is calculated by the following equation

$$N_j = \sum_{i=1}^{n} w_{ij} x_i \tag{3}$$

where, n is the number of the input signals, w is the weight and x is the strength of each signal. Consequently, the output (y) is computed as follows

$$y = \begin{cases} 1, & if \ N_j \geq \theta_j \\ 0, & if \ N_j < \theta_j \end{cases} \tag{4}$$

Here, (θ_j) is the bias. The sigmoid and logistic functions can be used as an activation functions. The perceptron learning rule is employed to attain the optimal weight vector in finite number of iterations (Rojas 2013). For the MLP-FFN experiments, two-layer perceptron feed-forward network can be conducted (Dash *et al.* 2010). A multi-step procedure based on NN is used to accomplish the classification of the RC structures' failure as follows.

4. Proposed method

In the current study, the proposed system employed the MOGA optimization algorithm to tune the trained ANN classifier's weight to overcome being trapped in local optima while the RC structures' failure classification. Thus, the data instances are classified into two classes, namely '*Structure Failure*' and '*No Structure Failure*', which used in advance to predict the failure of RC structures. The ANN using MLP-FFN is trained with the support of the MOGA optimization algorithms as illustrated in Algorithm 2.

For structural failure prediction of the RC buildings, algorithm 2 depicted that the proposed system is initiated by a per-processing phase, which performed before the classification of the dataset. The pre-processing phase included feature extraction of the significant attributes, followed by data cleaning and normalization to remove the noise and to reduce the distance between attribute values; respectively. Prior to the classification phase, the dataset is divided into training dataset (80%), validation dataset and the testing dataset (20%). During the training phase, different algorithms are applied to the training dataset, where the weight of the ANN is optimized using the MOGA with the RMSE and ME defined in equations (1) and (2); respectively being the fitness (*Objective*) functions. Afterward, the optimized weight vector is used for training, validation and test phases.

Algorithm 2. ANN training by MOGA

```
Begin
    Pre-processing of data;
    Define Neural Network;
    Initialize weights randomly;
    If (Convergence?)
      Feed input data;
      ANN;
      Compute tranfer function;
      Compute activation;
      Calculate multiple object functions for each member of
       population;
      Select members for next generation;
      Apply MOGA to adjust weight vector;
    Else
      Use ANN with optimized weight vector for training;
    Endif
End
```

5. Design constrains

It has been previously discussed that the proposed system classifies the data instances into two main classes, namely: 'No Structure Failure' that denotes the stable condition and 'Structure Failure' that denotes 'structural failure'. If any of the components fails in the structure that is denoted as the failed structure. If any of the structure does not fail, then it is classified as the 'no structural failure'. Though the structure could be failed due to different failure causes, but here for this case 15 different components have been considered for the experiment purpose, where after the training 9 features has been extracted. Load cases with various combinations are used during the design time following the IS 456: 2000 code prohibition. Main cause of the failure of any structure is the load coming from different components. In order to transfer the load, adequate number of beams and columns are required. However, due to the aesthetic purpose, the number of beams and columns has to be decreased that may lead to structure failure. Thus, the number of columns (NOC) and number of beams (NOB) play a vital role in designing any RC structure. It is easy to distribute the loads to ground if the total area of the structure is large. So, it is always preferable to have a large area (A) of structure. Thickness of the side walls of interior floors (TSIF) and thickness of inner walls of interior floors (TIIF) are another important design factors. Though, economy is a factor while designing as unnecessarily over thickness of TSIF and TIIF leads to higher expenses of structure. However, in terms of the structural purpose, these two are always kept as minimum as possible to prevent further increment of the self-weight of the RC structure. In addition, the Depth of beam (D) and width of beam (W_b) play a pivotal role to distribute the load to the adjacent column. With the increase of the depth and width of the beam, load carrying capacity also increases. Nonetheless, the depth and width keep minimal as much depth decreases the inner space of the building. Sometimes, it obstructs the aesthetic view. In this case, in order to keep the reinforcement percentage intact, width of the building is increased up to certain limit. Like depth of beam and width of beam, breadth of column (BC) and width of column (WC) are also important to transfer the load to the soil. Here variation in the breadth and width of the column is done in different models to check the failure.

In the RC structure, the steel bars are used as reinforcement to prevent the tension as concrete is weak in tension. So, the grade of steel (f_y) is important as higher grade of steel resists higher amount tension. Like grade of steel different grade of concrete (f_{ck}) is used for the resistance of the compression. Different grade of concrete costs different and resistance to compression is also different. That is why it is varied to see the structure failure in different cases. The bearing capacity of soil (q) is maximum average contact pressure between soil and foundation, which should not create shear failure in soil. Bearing capacity of soil is utmost important in case of geotechnical engineering as it is the capacity of soil to support loads that is applied to the ground. Consequently, as the soil mass is changed, the bearing capacity of the ground is also changed. With the change of the bearing capacity, the chance of structure failure is also changes. The concrete volume (V_c) and the reinforcement area (A_r) is also calculated at the time of design as it directly affects the cost of the structure.

Table 1 Initial dataset features

Sl.	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

Table 2 Dataset features after feature extraction

Sl.	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	wb	Width of beam
6	BC	Breadth of column
7	WC	Width of column
8	Vc	Concrete volume
9	Ar	Reinforcement area

6. Results and discussion

The proposed system classifies the data instances into two main classes: ‘No Structure Failure’ that denotes the stable condition and ‘Structure Failure’ that denotes structural failure. Since, the prediction computational cost increases immensely with the increased number of the extracted features. Additionally, the inappropriate features may direct to over-fitting. Therefore, the Greedy forward selection algorithm (Zhang 2009) is extensively used to improve the computational efficiency with superior accuracy. The forward feature selection method is initiated by evaluating all feature subsets that involve only one input attribute. Subsequently, forward selection establishes the best subset consisting of two components. Afterward, the input subsets are evaluated with three and more features. The advantage of the used Greedy forward selection algorithm is that it works with a sparse solution explicitly, which leads to efficient computation. The proposed procedure conducted the initial dataset features given in Table 1.

However, for proficient computational procedure, the features are selected as tabulated in Table 2 using the greedy forward selection method as depicted in (Guyon and Elisseeff 2003).

Since, in the NN training phase, the MOGA is used to minimize the RMSE and optimize the EM to attain the optimal input weight vector to the ANN’s input layer. Furthermore, the proposed method is compared to the same ANN based PSO optimization algorithm. Thus, to measure the system performance several metrics (Karayiannis and Venetsanopoulos 2013) such as the accuracy, recall, precision, and F-Measure are calculated to assess the proposed system compared to the PSO based system, where:

- Accuracy is referred to the ratio of the sum of data instances classified properly to the total instances’ number, which given by

$$Accuracy = \frac{(tp+tn)}{(tp+fp+fn+tn)} \tag{5}$$

- Recall (tp -rate) is the ratio of the true positive (tp) to the total number of data instances classified under positive class, given by

$$Recall = \frac{tp}{(tp+fn)} \tag{6}$$

- Precision is the ratio of correctly classified data instances in positive class to the total number of data instances classified to be in positive class, given by

$$Precision = \frac{tp}{(tp+fp)} \tag{7}$$

- F-Measure is a combined depiction of the recall and precision, which defined as

$$F-measure = 2\times\frac{Recall?\ \ recision}{Recall+Precision} \tag{8}$$

where, *tp* (true positive) is the number of ‘positive’ data that classified as ‘positive’, *fp* (false positive) is the number of ‘negative’ data that classified as ‘positive’, (iii) *fn* (false negative) is the number of ‘positive’ data classified as ‘negative’ and *tn* (true negative) is the number of ‘negative’ data, which classified as ‘negative’.

In addition, the confusion matrix for classification performance visualization is included to find out any misclassification due to the classifier. In this matrix each column represents a predicted class, while each row specifies an actual class. In the current study, Table 3 tabulates the confusion matrix for the testing phase of NN-MOGA.

Table 3 depicted that 11 RC structures are classified correctly as structure failure case, while 17 structures are classified correctly as ‘*No structure failure*’. Furthermore, since the ANNs has different types based on the layers connection pattern and the neurons arrangement, including Feed-back NN, Feed-forward NN (FFN), and Self-

Table 3 Confusion matrix of testing phase for NN-MOGA

Predicated Class / Actual Class	Structure Failure	No Structure Filure
Structure Failure	11	1
N Structure Failure	1	17

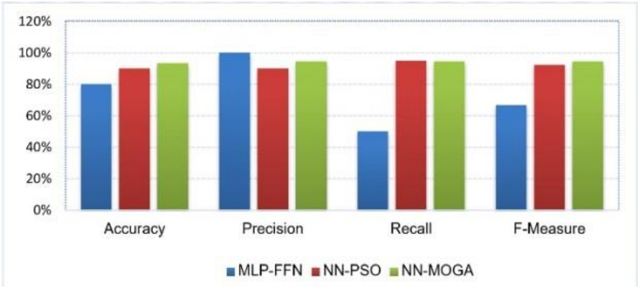

Fig. 2 Performance comparison of the different classifiers in terms of several performance metrics

Table 4 Performance comparison of proposed model for testing phase

	MLP-FFN (%)	NN-PSO (%)	NN-MOGA (%)
Accuracy	80	90	**93**
Precision	100	90	**94**
Recall	50	**95**	94
F-Measure	67	92	**94**

organizing maps. The FFN is a standard NN type that used in various applications, where also the Multilayer Perceptron (MLP) is a FFN network form that transforms sets of inputs into output sets through a hidden layer. The network is trained in supervised learning design with error back propagation algorithm. In the current study, the number of input layer neurons is set to nine as the reduced set of features contains nine features (Table 2). The hidden layer contains 35 neurons and output layer contains two neurons each corresponding to one of the classes. The size of hidden layer is decided by a trial and error method. Consequently, the proposed system is compared to this well-known MLP-FFN classifier. For comparison purpose, the predefined metrics are calculated for the different classifiers as depicted in Figure 4, where a performance comparison of the different classifiers with the proposed NN-MOGA classifier is included.

Fig. 2 establishes that the proposed NN-MOGA outperformed the MLP-FFN and the NN-PSO in the structural failure of multistoried RC buildings' classification, which can be used further for failure prediction. The metric values obtained in Fig. 4 is tabulated in Table IV, which included a comparison between the proposed NN based MOGA and both the NN based PSO and the classic MLP-FFN classifier in the test phase.

Table 4 established the poor accuracy of MLP-FFN compare to the NN based optimization algorithms. Conversely, the proposed NN-MOGA proved its superiority compared to all with achieved accuracy of 93.33%. In the testing phase, the MLP-FFN model provided an accuracy of 80% with 100% precision, 50% recall and F-Measure of 66.67%. The NN-based particle swarm optimization (NN-PSO) achieved 90% accuracy with 90% precision, 94.74% recall and 92.31% F-Measure in the testing phase. Meanwhile, the proposed NN-MOGA achieved the superior accuracy of 93.33% and F-measure of 94.44%, which is the best compared to the other classifiers. Furthermore, Fig. 3 demonstrated the time executed during the training phase of the different models.

Fig. 3 depicts that the time consumed by different models during the training phase. The MLP-FFN takes 25 s, while the NN-PSO takes 46 s. The proposed method takes 129 s to train the network. Thus, the time consumed by the

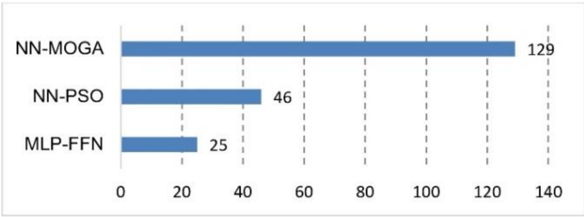

Fig. 3 Time taken in the training phase of different models measured in seconds

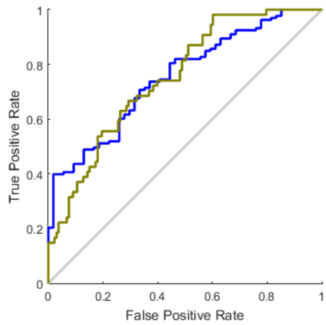

Fig. 4 Receiver Operating Characteristics (ROC) curve of MLP-FFN model

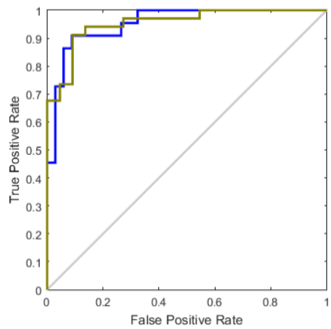

Fig. 5 Receiver Operating Characteristics (ROC) curve of NN-PSO model

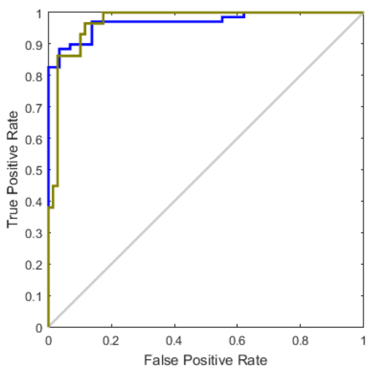

Fig. 6 Receiver Operating Characteristics (ROC) curve of NN-MOGA model

proposed algorithm is obvious as the time consumed by NSGA-II. Thus, the proposed method executed long time compared to the other two optimization algorithms.

Figs. 4 through 6 illustrate the Receiver Operating Characteristics (ROC) curves of the MLP-FFN, NN-PSO and NN-MOGA models; respectively. ROC curves are statistically equivalent to Wilcoxon rank test which is used to check the statistical significance of a model prediction (Hand 1997). The ROC curve of MLP-FFN reveals that the results are not statistically significant, which indicates that the MLP-FFN is not suitable for structural failure prediction task. The ROC curve of the NN-PSO shows a reasonable significance and establishes the fact that the results reported in Table 4 are statistically significant. The ROC curve of NN-MOGA reveals the superiority of the model over other models. The ROC curves for both classes are tending towards the top left corner of ROC plot, indicating highly statistically significant results. This further establishes the superiority of NN-MOGA model.

From the preceding results, it is established that the proposed NN-MOGA is superior to the MLP-FFN and the NN-PSO in terms of the accuracy and the other performance metrics. However, the NN-MOGA suffers from long execution time compared to the other methods. Consequently, it is recommended to compare the proposed method performance with other civil engineering applications that employed other optimization algorithms.

7. Conclusions

Structural failure prediction has a vital role in the building design, maintenance and monitoring, which requires proper analysis of the factors that influences the construction. Several studies have been developed for the prediction and analysis of the RC buildings based on NN (Van *et al.* 2007, He and Xu 2009, Bilgehan and Turgut 2010, Bilgehan 2011, Chou *et al.* 2011, Adriana *et al.* 2013, Martí-Vargas *et al.* 2013, Deshpande *et al.* 2014, Chandwani *et al.* 2015). Thus, accurate classification using meta-heuristic supported ANN is considered in the proposed system to tune the weight vector in the training phase, while minimizing the RMS and ME value. The current work employed a robust multi-objective optimization technique based on GA. The performance of the proposed approach for the problem of predicting structural failure is compared to the NN-PSO trained NN where the PSO and the classic MLP-FFN classifier.

The simulated experimental results established that the NN-MOGA is significantly outperformed the previous models in predicting the structural failure of a multistory RC building based PSO as well as in the case of using the MLP-FFN classifier in terms of the different performance metric values. NN-MOGA achieved an accuracy of 93.33%. The performance of prediction model could further be improved to establish a more trustworthy model to predict the structural failure prediction of RC buildings. Nevertheless, the future scope of the work would be directed to that direction.

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