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Neural-based prediction of structural failure of multistoried RC buildings

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Abstract. Various vague and unstructured problems encountered the civil engineering/ designers that persuaded by their experiences. One of these problems is the structural failure of the reinforced concrete (RC) building determination. Typically, using the traditional Limit state method is time consuming and complex in designing structures that are optimized in terms of one/many parameters. Recent research has revealed the Artificial Neural Networks potentiality in solving various real life problems. Thus, the current work employed the Multilayer Perceptron Feed-Forward Network (MLP-FFN) classifier 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. In order to evaluate the proposed method performance, a database of 257 multistoried buildings RC structures has been constructed by professional engineers, from which 150 RC structures were used. From the structural design, fifteen features have been extracted, where nine features of them have been selected to perform the classification process. Various performance measures have been calculated to evaluate the proposed model. The experimental results established satisfactory performance of the proposed model.

Keywords: Reinforced Concrete (RC) structures; structural failure; Artificial Neural Network (ANN); Multilayer Perceptron Feed-Forward Network (MLP-FFN); scaled conjugate gradient algorithm; cross-entropy

1. Introduction

Civil Engineering is an expanded domain concerned mainly with the structures design and analysis. Numerous complex/ heuristic problems encountered the civil engineer there by requires his/her intervention and experience. These challenges oblige the researchers to develop

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computational tools to save time and resources. Hence, Neural Networks (NN), Genetic Algorithms (GA) and Fuzzy Logic either autonomous/integrated (hybrid) are used to support the engineering activities via simulating the human mind to achieve robust and cost effective solutions. These techniques are able to model unknown or complex relationships which are either nonlinear or noisy.

Artificial Neural Network (ANN) can be considered an engineering equivalent of a biological neuron. The ANNs is inspired by the human brain functioning by modeling complex/ unknown functional relationships with interconnected processing units (artificial neurons) that replicate the biological neurons function. Unlike conventional methods that based on predefined relations, ANNs can handle in distinct functional relationships during its learning (training) stage. The ANN model is arranged interconnected computational neurons used to execute a mathematical mapping during a process of learning. The learning facility of neural networks is attributed to the adjustment in the synaptic weight value. Compliance to changing the input-output data, non-linear 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 of Civil Engineering domain.

Numerous studies have been done to analyze different aspects related to RC buildings using ANNs. They have mainly focused on the post-seismic effect on RC buildings. A trained ANN operates the information generated from a number of features selected design vectors to perform both deterministic and probabilistic constraint tests during the optimization process. The trained NN is then applied to predict the structure response in terms of probabilistic and deterministic constraint test due to different design parameters. These parameters are due to several effects, such as fundamental periods, base bending moments, base shear force and top-floor displacement of buildings in two directions. Thus, these parameters are required to be predicted (Caglar *et al*. 2008).

Throughout the last decade, numerous studies have been performed in the Data mining domain to fetch meaningful information from the large amount of available data. The extracted knowledge has successfully been utilized in market survey, production control, customer retention, scientific explorations and evolutionary analysis (Agrawal *et al*. 1993, Chen *et al*. 1996). In data mining, Classification (Pujari 2001, Han and Kamber 2005) is one of the most important tools that aim to reveal hidden patterns of large data sets thereby giving a better understanding of many real life data sets. Classification has utmost utilization in decision making that primarily depends on the accuracy and effectiveness of the classification method being used. Technically, classification is a method to create a classifier that can discriminate between different data classes and further can put an entity with an unknown class label into the correct class.

These mentioned studies proved the efficiency of using the ANN to predict and study the different parameter effects on the buildings. Consequently, in the present study a prediction of RC structures' failure has been handled by employing the MLP-FFN with scaled conjugate gradient algorithm as learning algorithm in (Møller 1993). A dataset of 257 RC structures of multi-storied buildings was designed by professional engineers. 150 out of these datasets have been used. In the training phase, a Cross-Entropy error function has been used. Then, several performance measuring parameters such as the accuracy, precision, recall, Fp-rate and F-Measure has been calculated to evaluate the proposed method. The proposed model is capable of identifying if a given RC structure will fail in future or not. Hakim and Razak (2014) presented a review which included technical literature for previous two decades related to the structural damage detection using ANNs with modal parameters including natural frequencies and mode shapes as inputs.

The remaining of this work is organized as follows: Section 2 represents the related work followed by section 3 to introduce the methodology based on a theoretical background on Civil engineering aspects. While, proposed model is discussed in section 4 followed by Section 5 focuses on the experimental results are depicted and, finally section 6 includes the conclusion.

2. Related work

Hajela and Berke (1991) tested the neural computing role in structural engineering to obtain the optimum weight of a truss. Mukherjee and Deshpande (1995) proposed neural network for preliminary reinforced-concrete rectangular single-span beams design. The network calculated a good preliminary design via determining the beam depth, the beam width, tensile reinforcement required, and the moment capacity for certain set of input parameters such as the live load, dead load, steel type and concrete grade. At the design conceptual stage, the authors in (Elazouni *et al*. 1997) presented the use of the neural network to estimate the resource requirements. The results demonstrated that accurate performance of the neural network as adaptable tool. Hadi (2003) suggested neural network for optimum simply supported concrete beams and reinforced fibrous concrete beams design. The results verified the ANNs effectiveness compared to conventional design techniques. Jakubek (2012) employed the neural network to calculate the load capacity for loaded reinforced concrete columns. Gupta *et al.* (2006) suggested the ANN for precise prediction of the concrete strength based on different parameters such as the specimen's size and shape, concrete mix design, and the environmental conditions.

Caglar *et al*. (2008) employed Multilayer perceptron trained with back-propagation (BP) algorithm to predict several effects of a building under earthquake by generating data using Finite Element Analysis. The authors claimed that NN based approach can determine these effects successfully. Dynamic response of buildings has been obtained by employing a training phase with 150 data instances along with 15 data instances for validation phase. Joghataie and Farrokh (2008) proposed a new activation function based on Prandtl-Ishlinskii operator in the Feed-Forward neural networks to analyze Non-linear frame structures. The authors used the GA to train the network in order to analyze two shear frames for a single degree of freedom (SDOF) and a 3DOF (both subjected to earthquake excitations). The authors have claimed a high precision of the proposed models in solving hysteretic problems.

Erdem (2010) investigated the application the neural network was employed for the ultimate moment capacity prediction of the RC slabs in fire. Bagci (2010) examined the moment-curvature relationship of the RC governed by many variables and non-linear material performance using ANN.

Kameli *et al*. (2011) predicted a seismic response of RC frames having masonry in-filled walls using ANN. Using Finite Element Method (FEM), a total of 855 data instances has been used to train the ANN to predict the roof displacement and base shear displacement. A multi-layer perceptron (MLP) has been trained with Levenberg-Marquardt (LM) BP algorithms and a Radial Basis function (RBF). Then, the authors used the Mean square error (MSE) and correlation coefficient to evaluate the ANN performance. The results proved that the ANN trained with RBF is fast and accurate in determining the objective. Jasim and Mohammed (2011) deployed the neural network for the ultimate spandrel beams torsional strength prediction. The results of the resilient BP algorithm were compared to a steepest descent algorithm.

Lagaros and Papadrakakis (2012) proposed a prediction of nonlinear behavior of 3-dimensional structures. A new ANN based adaptive scheme was proposed in order to nonlinear behavior under severe earthquake actions. The results proved that the Performance-based design (PBD) can be successfully tackled by ANNs and can considerably reduce the computational complexity.

From the previous survey, it is clear that the ANN has an essential role for the structures design under different conditions and parameters. Therefore, this proposed work adds a contribution by employing the ANN not for the design, but in order to classify the structural failure of multistoried reinforced concrete buildings via detecting the failure possibility of the multistoried RC building structure in the future or not.

3. Methodology

Generally, a RC beams are designed to support any structure with external loads such as walls, slabs of roofs and floor systems. Thus, there are different parameters that should be considered for optimal structures design. For example, the cross-section dimensions are generally assumed based on the service ability requirements. In order to control deflections within safe permissible limits, both the building width and depth are fixed and selected based on the wall thickness and the housing reinforcements.

In addition, the reinforcements in the beam are designed for flexure and shear forces along the length of the beam based on structural analysis. The designed beam is checked for the limit state of serviceability and safety against collapse.

Typically, the design of any structure is not unique as it can be performed in different ways as several parameters affect the reinforcements such as material property, loads on the beam, cross-sectional dimensions of beam, etc.

3.1 Structure design assumptions

In the current study, the 'IS 456-2000' (Indian Standard 2000) plain and reinforced concrete is followed. The 'IS 456-2000' is an Indian standard code of practice for common structural use of plain and reinforced concrete, jointly with the limit state design procedure. Various parameters are considered, such as the loads of parapet walls on the top floor, loads on the outer walls of intermediate floors, loads on the internal walls of internal floors, the building area, the beams cross section, the columns section, number of beams, number of columns.

Here, the 'STAAD. Pro' is applied, which refers to the beams parallel to the *x*-axis and parallel to the *z*-axis. While, the beams parallel to the y-axis are considered as the columns. Every single node to node connection is considered one beam. Thus, line diagram is used by the system to plot 10 different plans of 'STAAD. Prov8i' structure. The 'STAAD.Pro V8i' is an integrated finite element analysis (FEA) that used to analyze and design any structure exposed to different load types. From the STAAD output file, the values of the concrete's volume as well as the area of the reinforcement are obtained. In this structure, only beams and columns are designed. A slab design is not done, as it assumes the number of beams of one meter size to be used. While, the loads on the slabs are taken in the accounts and it is imposed on the beams. Besides in stair case, the loads are calculated then it is imposed on the adjacent beams.

The cross sectional dimensions of the RC beams are selected based on some criteria of the IS 456:2000. The effective depth and overall depth of the beam is calculated by the limit state method of serviceability. Also, it is assumed that the overall depth to width should be in the range of 1.5 to

2. The depth of the beam should be such that the percentage of steel required should be around 75% of that particular sectional area. In the IS 456:2000 in ‘Clause 23.0’ (Compliance with Law - Licenses), the procedure of beam design is given. Thus, the beam design is according to the clause. In ‘Clause 23.0’, the effective depth of the beam is given. Even as, the clause number 22.5 of IS 456:2000 is followed for the continuous beams moment and shear coefficients. The bending moment and the shear coefficients are calculated based on clause no. 22.5.1 and 22.5.1, 22.5.2; respectively (Indian Standard 2000).

Moreover, ‘Clause 22.7’followed by ‘37.1.1’ are to be used for the redistribution of moments, where the latter describes the redistribution of moments in continuous beams and frames. If the moment capacity after redistribution is less than that from the elastic maximum moment diagram, the following relationship will be satisfied

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

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

Furthermore, the Span/depth ratio of the continuous beam is given by the IS 456:2000, where the span is the length from a support centre to and the depth is the average depth from the top of the beam to the bottom. Therefore, the span-to-depth ration is the span divided by depth. There is a recommendation for basic span/depth ratio that can be modified by using factors k_C, k_t, k_f. Where, the modification factor for compression reinforcement is k_C, the modification factor for tension reinforcement is k_t, while the reduction factor for flanged beam is k_f. Normally heavy dead loads and live loads are carried by continuous beams. The span/depth ratio is between 15 and 20 in the practical cases. However, sometimes span/depth ratio is taken as 26 if the depth is shallow or high reinforcement is required.

Since the deflection is defined as the degree to which a structural element is displaced under a load. Therefore, in this study, the deflection check is done as per Clause 23.2, where the control of deflection is given. Modification factor for tension reinforcement is achieved from the graph of modification factor versus the percentage tension reinforcement. Modification factor for compression reinforcement is achieved the graph of modification factor versus the percentage compression reinforcement (Indian Standard 2000). Slenderness limits for the beams to ensure the lateral stability is specified by Clause 23.3. The cantilever beams are used generally to support Chazza slabs or Canopy of largest span at the entry area of the building. The cantilever beams are generally designed for maximum moments and shear forces develops at support section; this is normally a reinforced concrete column.

The column design has followed the procedure of the compression member as per Clause 25.1.1. As the definition of the compression member of the column or strut is the effective length that exceeds three times the least lateral dimension. Clause number 25.1.2 describes the type of compression member. From Clause 25.1.2 Short and Slender Compression Members is defined. A compression member may be considered as short when both the slenderness ratios $\frac{l_{ex}}{D}$ and $\frac{l_{ey}}{b}$ are less than 12, where: l_{ex} is the effective length with respect to the major axis, D is the depth with respect of the major axis, l_{ey} is the effective length with respect to the minor axis, and b with width of the member. Otherwise, it shall consider as a slender compression member. From Clause 25.1.3, the Unsupported Length of any compression member is calculated. The effective Length of the compression members is given in Clause number 25.2. In the absence of the more exact analysis, the effective length of the columns is obtained as described in (Indian Standard 2000). If a column is sway or no sway that can be calculated by stability index Q that given by

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

Where, Σp_u is the sum of axial loads on all columns in the storey, Δ_u is the elastically computed first order lateral deflection, H_u is the total lateral force acting within the storey, and h_s is the height of the storey.

The effective length ratios for a column in a frame with no sway are calculated from the graph of β_1 versus β_2, where β_1 and β_2 are equal to $\frac{\sum k_C}{\sum k_C + \sum k_b}$. The summation is to be done for the members framing into a joint at top and bottom; respectively. Also, k_C and k_b are the flexural stiffness for column and beam; respectively. The effective length of the compression member is determined in (Indian Standard 2000). The slenderness limits for the columns are determined from Clause 25.3. The minimum eccentricity of the columns is determined from Clause 25.4. In the limit state of collapse: compression Clause 39 is followed. In case of the limit state of collapse: flexure Clause number 39 is specified. For the short axially loaded members in compression the axial load on the member is given in Clause 39.3. It can be determined by

$$p_u = 0.4 f_{Ck}.A_C + 0.67 f_y.A_{sc} \tag{3}$$

Where, the axial load on the member is p_u, the concrete area is A_C, while the longitudinal reinforcement for the columns area is A_{sC}, f_{ck} is the concrete characteristic compressive strength and f_y is the characteristic strength of compression reinforcement.

In the case of compression member that are subjected to combined axial load and biaxial bending, following equation is used at the design time as (Indian Standard 2000)

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

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}. Where

$$p_{uz} = 0.45 f_{Ck}.A_C + 0.75 f_y.A_{sc} \tag{5}$$

For limit state of collapse: shear Clause 40 is followed. At the time of the loads calculation on the stair and during the design of stairs, Clause 33 is followed.

Therefore, the pervious parameters are used to achieve the main contribution of the proposed study by predicting/ classifying the RC structures' failure based on the MLP-FFN with the scaled conjugate gradient algorithm as learning algorithm.

3.1 Classification based on Neural Network

A multistep procedure is followed to accomplish the classification of the RC structures' failure. The general classification steps for any application are as follows: i) The training phase, where a set of training data (part of the dataset that consists of attribute values) is used to identify an entity along with its class label to construct the classification model. The model tries to acquire sufficient knowledge to understand how the entities are classified into giving classes. ii) The Evaluation (testing) phase, where the constructed model accuracy tests with a set of test data. This phase is used to find the class of each entity and evaluate the classification accuracy. For more accurate results, sometime data cleaning, data selection and transformation are performed. Generally, there are different data modeling tools, while the ANN (Haykin 1998) is considered the most popular one. It assures high precision and accurate classification even if very little data are available. These ANN advantages are due to its following characteristics: is a self-adaptive data driven method, has the capability to approximate any function with random accuracy (Hornik 1991), has the facility to model real life problems as it has nonlinear models, and is able to find posterior probabilities that provide a way to statistical analysis (Richard and Lippmann 1991).

ANNs can formally be defined as structures comprised of highly interconnected adaptive simple processing units known as artificial neurons or nodes that are capable of performing parallel computation at a large scale of data processing and knowledge representation (Jain *et al.* 1996, Schalkoff 1997). Mostly, nonlinearity, high parallelism, robustness, fault and failure tolerance, learning, ability to handle imprecise and fuzzy information, and their capability to generalize have been successfully embedded in an ANN (Jain *et al*. 1996).

The principle idea behind the mechanics of a single artificial neuron and 'Perceptron' are devised by Rosenblatt in 1958. An artificial neuron receives inputs as stimuli from the environment, combines them using the input signal (x) and their corresponding weights (w) to form 'net' input (net_j). The 'net' input is then passed through a linear threshold filter and finally passes the signal (output, y) to another neuron. The neuron is activated if and only if net_j exceeds the threshold (or bias 'ϑ_j') of that neuron. The net input (net_j) is calculated by the following linear equation

$$net_j = \sum_{i=1}^{n} w_{ij} x_i \tag{6}$$

It is computed for 'n' input signals by adding the dot products of weight (w) and strength (x) of each signal. Thus, the output (y) which is the activation function is calculated as follows

$$y = \begin{cases} 1, \; if \; net_j \geq \vartheta_j \\ 0, \; if \; net_j < \vartheta_j \end{cases} \tag{7}$$

Fig. 1 depicted a typical artificial neuron having an activation function, which used as step

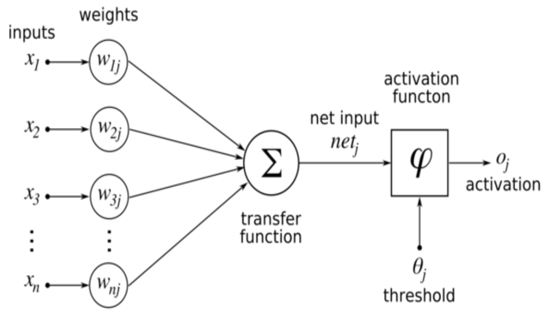

Fig. 1 A typical Artificial Neuron having 'n' inputs

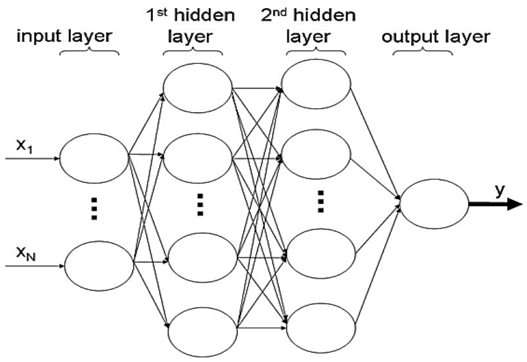

Fig. 2 A typical 2-layer perceptron feed-forward network

function (Maren *et al*. 2014, Ghannouchi *et al*. 2015). The weighted sum of the inputs is used as transfer function. Though, several other functions such as sigmoid and logistic can be used.

Several learning algorithms are available to train a NN. The perceptron learning rule is one of the basic learning algorithms that have been derived to get optimal weight vector infinite number of iterations, regardless of the initial weight vector. This rule has been found to be usable only for linearly separable classes. To improve the performance of NN several network architectures have been proposed. Fig. 2 depicts one typical 2-layer perceptron feed-forward network that is also used for the MLP-FFN experiments.

Consequently, the MLP-FFN is to be used for the classification step in the proposed system.

4. Proposed system

The experiments are performed using real coded MLP-FFN. Scaled conjugate gradient algorithm (Møller 1993) has been used as the learning algorithm and Cross-entropy has been used as error function. The learning algorithm is well known and benchmarked against traditional BP and other algorithms. The network architecture MLP- FFN used was introduced in (Han and Kamber 2005). The basic flow of experiment opted in the present work is discussed below:

i) Preprocessing: it is performed before the classification step on the dataset as follows:

a) Feature Extraction: This step involves the task of extracting those attributes that are most important and have effective features to classify the dataset accurately into two or more classes. The selected, extracted features of the proposed system are mentioned clearly in the results section.

Meanwhile, the classes' separation depends on the class distributions and the used classifier. Therefore, for optimum feature set with the Bayes classifier; the minimum error for the given distributions will be achieved. Then, classes' separation becomes equivalent to the probability of misclassification due to the Bayes classifier. Theoretically, the Bayes error is the optimum measure of feature effectiveness as it is calculated experimentally. That is, having selected a set of features intuitively from giving data; estimate the Bayes error in the feature space. A major disadvantage of the Bayes error is due to its explicit mathematical expression is not available except for a very few special cases. Even for normal distributions, the calculation of the Bayes error involves a numerical integration, except for the equal covariance case.

b) Data Cleaning: The data might contain missing values or noise. It is important to remove noise and fill up empty entries by suitable data by means of statistical analysis.

c) Data Normalization: is required before classification to reduce the distance between attribute values. It is generally achieved by keeping the value range in between -1 to +1.

ii) Dividing the dataset into two parts, namely the training data set and the testing dataset. In the present work 90% of the data is used as training data and rest (10%) as validation & testing data. Since, the selection of test training and validation percentage is itself an optimization problem. Thus, a future scope is to select the optimal test training and validation percentage setting.

iii) Training phase: the training dataset is supplied to different algorithms respectively to build the required classification model.

iv) Testing phase: where the classification models obtained from the training phase is employed to test the accuracy of the model.

The flow of the experiment has been depicted by the block diagram in Fig. 3.

Fig. 3 demonstrated the proposed NN model consisting of the following processes: i) pre-processing the RC dataset to extract the significant features such as the height of parapet wall, thickness of side/ inner walls of interior floors, depth/ width of the beam, breadth/ width of the column, concrete volume and the reinforcement area. This is followed by feature extraction, cleaning and normalization, performed to attain clean data with reduced distance between the attributes. ii) classification of RC structure data is a two class problem namely: ‘Structure Failure’ and ‘No Structure Failure’. 90% of the overall experimental data is used to train the neural network to classify the RC structure data instances. iii) Finally, test/ validation phases are performed followed by performance metrics generation. Classification output helps to predict the status of the RC structural failure.

5. Results and discussion

The experiments are carried out by following the previous proposed model. The initial dataset description has been depicted in Table 1. After ‘Feature Extraction’ the features selected are tabulated in Table 2 by employing the greedy forward selection method as described in (Guyon and Elisseeff 2003). The experiments are then performed upon the dataset considering the features of Table 3.

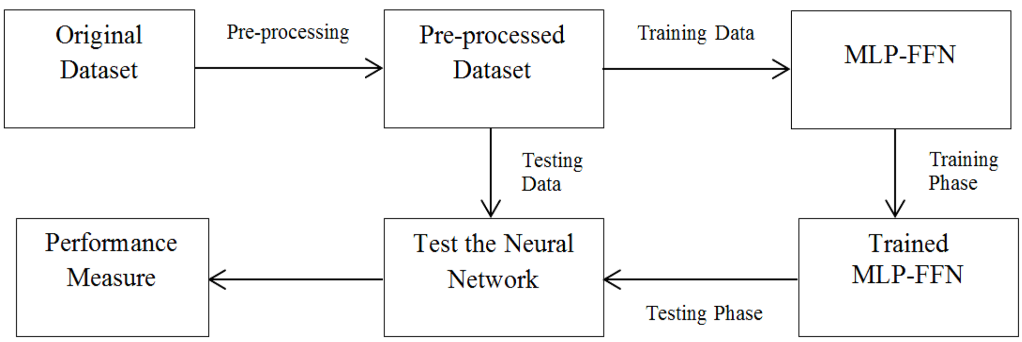

Fig. 3 Block diagram of proposed model

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

	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 a binary classification problem

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

To measure the proposed system performance, several statistical performance measures such as the accuracy, precision, recall, Fp-rate and F-measure are to be calculated as given by (Sokolova and Lapalme 2009, Srivastava and Singh 2015). Measuring the performance parameters which are defined as follows;

- Accuracy: is the ratio of sum of the instances classified correctly to the total number of instances.

$$Accuracy = \frac{tp + tn}{tp + fp + fn + tn} \tag{8}$$

• Precision: is the ratio of correctly classified data in positive class to the total number of data classified as to be in positive class.

$$Precision = \frac{tp}{tp + fp} \tag{9}$$

• Fp-Rate (false-positive rate): is the same as precision except it is measured on negative class.

$$FP\ rate = \frac{fp}{fp + tn} \tag{10}$$

• Recall (TP rate): is the ratio of tp to the total number of instances classified under positive class.

$$Recall = \frac{tp}{tp + fn} \tag{11}$$

• F-measure: is a combined representation of Precision and Recall and is defined as follows.

$$F - measure = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{12}$$

Therefore, a confusion Matrix (Schalkoff 1997) is to be calculated to provide visualization of the performance of a 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 helps to find out any type of misclassification due to the classifier. It provides more detailed analysis than classification accuracy. Classification accuracy is not a reliable metric for assessing the performance of a classifier as it may produce misleading results when the numbers of samples in different classes vary greatly. The confusion matrix entries can be defined as follows;

i) True positive (TP) is the number of ‘positive’ instances categorized as ‘positive’.
ii) False positive (FP) is the number of ‘negative’ instances categorized as ‘positive’.
iii) False negative (FN) is the number of ‘positive’ instances categorized as ‘negative’.
iv) True negative (TN) is the number of ‘negative’ instances categorized as ‘negative’.

Fig. 4 depicted the Confusion matrices of training, validation, testing phases along with an overall confusion matrix for the proposed model. The model has achieved an outstanding performance of in training and validation phases by correctly classifying all data instances. Overall an accuracy of 99% has been achieved.

In Fig. 5 the error histogram has been depicted for all data instances. The histogram has revealed that most of the instances have been found near the minimum error region. Thus, the model is found to be extremely accurate. In Fig. 6 the cross-entropy versus the Epochs plot has been shown.

The plot in Fig. 6 revealed that the best validation performance (0.016) has been achieved at the 50th epoch of validation phase. Fig. 6 reports that the best cross-entropy reaches the 50th epoch for both the training and validation phases. As Matlab NN tool box is extensively used for this

Fig. 4 Confusion matrices of training, validation, testing & overall cases. Class ‘1’ denotes structural failure and ‘2’ denotes the building is structurally stable

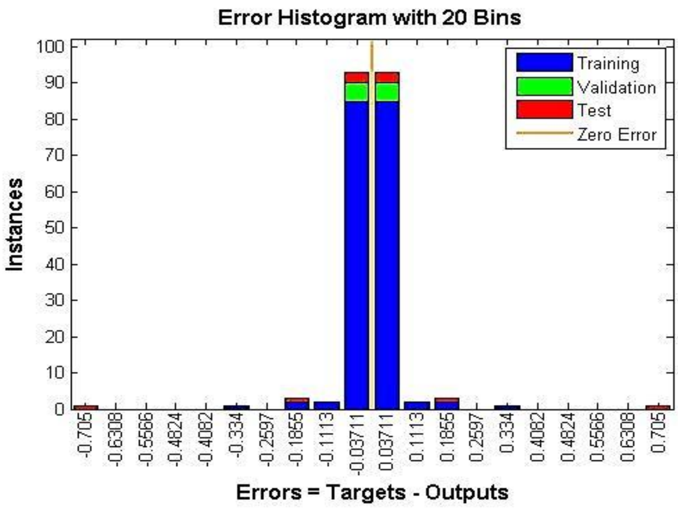

Fig. 5 Error histogram of the different phases. Maximum instances have been found near minimum error region

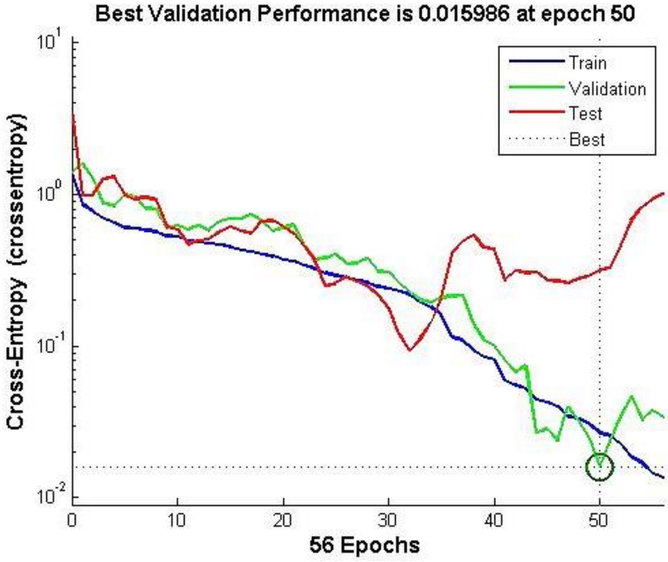

Fig. 6 Cross-entropy versus epochs plot depicting the performance of the model in different phases

Table 4 Performance measures of the proposed model for different phases

	Training	Validation	Testing	Overall
Accuracy	100	100	80	99
Precision	100	100	100	100
Recall	100	100	50	98.04
Fp-rate	0	0	0	0
F-Measure	100	100	66.67	99.01

study, available tr.best_epoch built-in function of the said tool box is used to evaluate the performance of network after training phase termination. Function output indicates the iteration at which the validation performance reached minima. Significant increase of test curve before the increase of validation curve indicates the possibility of test data over fitting. In the present work, 90% of the data is used as training data and rest (10%) as validation & testing data. Selection of training, test and validation (in %) is in itself an optimization problem. It is believed that, more study is required to investigate the behavior of proposed classified model with larger data pool and size varying optimal partition selection of training, test and validation data.

Since, the accuracy may not be a good performance parameter, hence the couple of other parameters that are obtained from the confusion matrix, has been used and are found to be promising. Table 4 illustrated different performance metrics for training, validation and testing phases along with the overall performance.

Table 4 established that 100% precision has been achieved in the 'Testing' phase, while the overall recall has a value of 98.04% for the proposed model. Therefore, the proposed system is promising and efficient for determining the status of the multistoried RC building structure.

6. Conclusions

The present work has proposed an MLP-FFN based model to predict the structural failure of a multistoried RC building. The proposed model has been trained with a scaled conjugate gradient algorithm which has been found to be benchmarked against the traditional back-propagation and other algorithms. Besides, Cross-Entropy has been used as the error estimator. The performance of the model has been evaluated by using several standard performance measurement metrics. The experimental results have suggested that the proposed model is extremely successful in determining the structural status of a multistoried RC building structure.

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