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THE USE OF ARTIFICIAL NEURAL NETWORKS (ANN) FOR PRELIMINARY DESIGN OF HIGH-RISE BUILDINGS

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Abstract. *The need for high-rise buildings is increasing in order to meet the challenges posed by rapid urbanization and the exponential growth in population. With recent advancements in computing technologies, innovative materials and new structural systems, the need of prior knowledge about proportioning the geometry and configuration of structural members is also increasing. A relatively quicker and reliable estimation of approximate sizes of members can greatly facilitate the preliminary design and feasibility of the project. This study uses an Artificial Neural Network (ANN) based approach to directly determine some key design parameters based on experience gained from previously designed buildings. It uses a heuristic tool using ANN that can provide fast and reliable results based on two algorithms (i.e. Multi-layer Perceptron with Back Propagation using Levenberg-Marquardt algorithm MLP-BP, and PCA-Sparse-Extreme Learning Machine with online Sequential learning). The ANN models are trained to determine structural design indicators from architectural parameters. The proposed approach can not only provide means for quick estimation of design output, but can also for crosschecking of code based & performance based design very quickly. The objective is to provide means of assisting the design team and clients to make key design decisions based on cumulative experience rather than relying on judgment of individual designers. The approach is demonstrated through the sample networks trained on various case study high-rise buildings for which the required architectural and structural design results have been generated through detailed design.*

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1. INTRODUCTION

A rapid increase in urbanization, limited land for increasing population and the developments in field of construction technology are some of the factors resulting in improved popularity of tall buildings. The convenience of having all of the services in a single building is now becoming a reality with tall buildings even known as mixed-use buildings; some of these buildings may also bring the prospect of being able to live and work without leaving the building [1]. The construction of taller structures becomes more challenging with increasing height [2]. Serviceability, strength and sustainability of a tall building are most important parameters to be considered during building construction which can be obtained by detailed Analysis and design processes. These processes are divided into many phases such as the conceptual designing, preliminary designing, modelling, analysis, final design and detail designing.

The preliminary design of tall buildings involves detailed mathematical justifications and expert knowledge. It is a tedious and time consuming work. Hence to overcome such issues, and to utilize experience obtained from available data, we introduce heuristic tools of Machine Learning. Machine learning is solely focused on developing an algorithm that can learn from past experiences. Artificial Neural Network (ANN), Support Vector Machines (SVM), Genetic algorithm, Decision tree, Fuzzy Logic are few popular Machine learning techniques used for the regression and classification problems. Artificial Neural Network (ANN) is a type of Machine learning tool which consists of massive parallel computational model that imitates the function of a brain. It uses learning algorithm to model and save the knowledge in weighted connections [3]. ANN have been used in many structural engineering related works in past such as Structure Control using Neural Network [4], Predicting drying shrinkage of concrete using Neural Network [5], Neural Network approach for cost estimation of structural systems of building [6]. Trained network can be used to simulate structural data as output for set of new architectural data.

In this study, we use ANN to perform preliminary design of tall buildings by obtaining structural data of buildings as output while feeding in the architectural data as input. The algorithms used are Multi-Layer Perceptron with Back propagation which is the most commonly used procedure and Online Sequential Extreme Learning Machine which is one of the fastest and accurate algorithm. Among various computational tools, Neural Networks have gained lot of popularity due to their ability to identify and learn highly complex and non-linear relationships by employing a black box approach [7]. After years of works and research in ANN, MLP Neural network with back propagation as training algorithm have been the most used and successful computational tool. It consists of number of hidden layers with various number of neurons that traces non-linear relationship between input and output data. Gradient decent is considered to be the most popular back propagation learning method but second order method such as Levenberg-Marquardt algorithm prove to be more accurate. The general concept of Back Propagation in training of network is to find a value of weights to minimize the error between obtained output and target output. ELM are simple learning algorithm for single layer Feed Forward Networks whose learning speed can be thousands of times faster than traditional algorithms such as MLP-ANN, SVM etc. with comparable prediction capability [8]. The basic concept of an ELM is to generate a fixed set of random input weight matrix and compute the best output weight matrix such that the error between target and obtained output is zero. The number of neurons in hidden layer of ELM plays vital role in its performance.

Principal Component Analysis (PCA) are linear dimensionality reduction tools used to shrink multi-dimensional correlated data set into smaller dimensional set of uncorrelated variables. PCA is used for dimensional reduction of data set as well as determining the number of neuron in hidden layer as proposed in [9]. The computed hidden layer architecture is cross validated using concept of Sparse-ELM as proposed in [10]. The network is then regularized using regularization tools and further extended to online sequential learning.

2. METHODOLOGY

Figure 1 below shows the overall methodology adopted in this study. Each part of this methodology will be discussed separately.

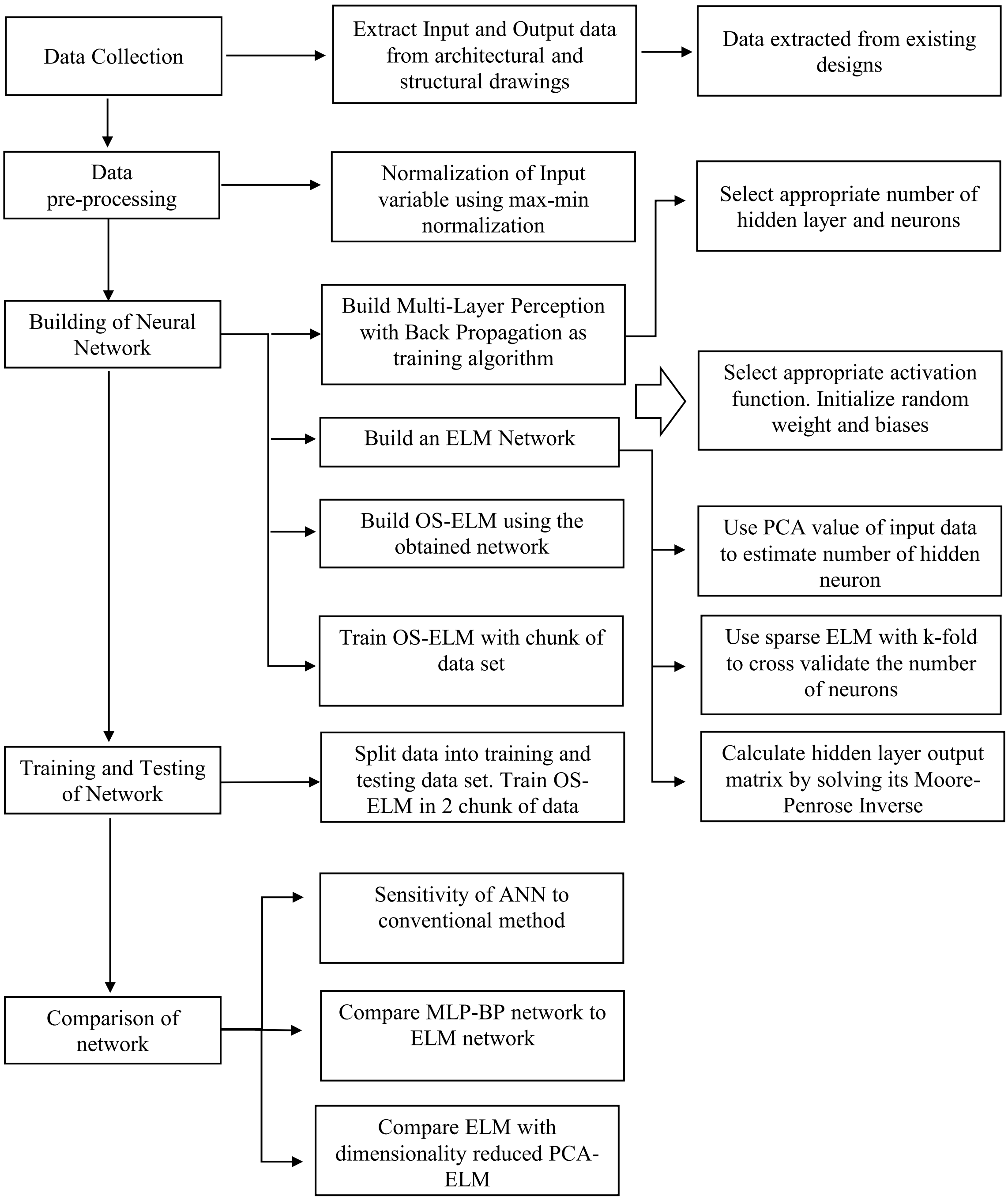


Figure 1: The overall methodology

2.1 Input-output parameters selection

Set of architectural data and structural data were used as input and output data respectively. 14 input parameters such as Number of story, Height of building, cumulative floor area of tower, Floor area of tower, Length of building in X and Y direction, Height per Length in X and Y directions, ratio of length of building in X directions to total length, Height to Length ratio in X and Y directions were provided from the architectural data. Fundamental structural data such as Natural period, Ratio of area of column to total area of tower, Ratio of core Area to Area of tower, Ratio of Weight of building to Floor Area Ratio and Volume of tower, Shear wall thickness, Maximum percentage story drift ratio and Ratio of maximum base shear to total weight of building were taken as output parameters. The data were normalized in range of [0 to 1] using max min normalization. Convergence of network output is usually faster if the average of each training set of data is close to zero [11]. The final output obtained from the models were DE normalized back to the initial scale.

Output Parameters | Input parameters

Architectural parameters

- Number of stories
- Total height of tower H
- Cumulative floor area (CFA)
- Length of tower along x direction
- Length of tower along y direction
- Area of floor at top of podium level
- Length of core wall along x direction
- Width of core wall along y direction
- Ratio of total tower height to length of tower along x direction
- Ratio of total tower height to length of tower along y direction
- Ratio of dimension of tower along x to along y direction.
- Ratio of total tower height to length of core wall along x direction.
- Ratio of total tower height to length of core wall along y direction.
- Ratio of dimension of core wall along x to along y

Structural design parameters

- Natural period of building
- Ratio of area of column to total area of tower
- Ratio of core Area to Area of tower
- Ratio of Weight of building to Floor Area Ratio
- Ratio of Weight of building to volume of tower
- Shear wall thickness
- Maximum percentage story drift ratio
- Ratio of maximum base shear to total weight of building

Figure 2: Input and Output parameters Extracted from Architectural drawings and Structural drawings respectively

2.2 Data processing

The total input-output data set of 38 buildings were divided into 30 training data and 8 testing data sets. 14 input parameters were taken as input from the architectural data and 8 output parameters were taken as output from the structural data. Same data sets were trained and tested using both the MLP-BP and OS-ELM models respectively and compared in terms of speed and accuracy. In MLP-BP algorithm, all input parameters were used to predict each output parameter individually. Each model was designed with different architecture, i.e. the number of hidden layers and their neurons for prediction of different set of outputs. There is no direct difference in the ultimate separation capabilities of networks with various number of layers; they might, however, differ in other aspects like the separation performance with a limited number of neurons, or the generalization made or training speed [12]. The OS-ELM model were first tested for general ELM algorithm and then Online Sequential (OS) process was added later onto the model. The OS refers to sequential learning procedure where the network is trained using chunk by chunk of data [13]. 14 input parameters were used to map single outputs and multiple set of outputs. Several important parameters that control the network model include the max-min data normalization, nonlinear transfer function (Sigmoid), bias and weights, hidden layers and their neurons, learning rate, and the number of epochs in MLP and Moore Penrose inverse in ELM.

In MLP-BP network, the weight parameters and biases between all the layers were randomly generated. The output of previous layer acts as input for next layer. The weights, bias and input were calculated and passed through the activation function. The output of last layer was compared to the target output and error was calculated. The error was back propagated using second order Levenberg-Marquardt algorithm and weights were updated at each epoch. The weights were updated with a learning rate which improves the convergence capacity of the model [14]. The architecture of network depends upon nature of data set, learning parameter, number of iterations, transfer function and the characteristics of the data used [15]. Different networks with various architecture were tried and the best performing networks were selected. Stopping criteria was introduced to stop the training process once the error tend to zero. The final updated weights were saved for the training purpose. Although the MLP-BP shows good generalization, it has few drawbacks such as the local minima, overfitting of data, difficulties in defining the structure, and repetitive iteration or Epoch. The overfitting of model cause network to lose its generalization ability [16].

In OS-ELM network, the single hidden layer (with neurons equal to or less than the number of sample) is initialized and the input weights and bias are generated in random [17]. The ELM uses non-differentiable or even discontinuous functions as an activation functions. For example, the Sigmoid, hyperbolic tan, and Gaussian functions can be used to map the non-linear relations [18]. The output weights are calculated using Least Mean Square Error equation such that the error between target and obtained output is zero. Basically, the ELM trains a Single Layer Feed Forward in two main stages: (1) random feature mapping and (2) linear parameter solving [19]. The output weights were saved and used for testing of data. The ELM shows extremely fast training speed, good generalization, and universal approximation capability [20]. The data was reduced to 2 dimensional set from 14 using PCA.

The network architecture of ELM was specified using PCA method in which 98% of variance was taken into consideration. The obtained number of hidden neuron were cross validated using the concept of Sparse-ELM. The input data were divided into cross validation data set using the k-fold, where the input data were divided into equal number of data sets. The networks with specific hidden node were trained using three-fourth of data set and tested on remaining one-fourth. The best network architecture was selected based on its mean accuracy. The OS ELM was introduced on selected networks. In OS-ELM, the network is added using chunk by chunk of data. The weights connecting hidden layer to output weight is updated with addition of each chunk of data. The weight between input layer to hidden layer and its bias are again randomly generated and lumped below the existing weight matrix array for initial data set. The process is carried out in two stages, (a) the initialization phase where the initial set of data is trained, and (b) the sequential learning phase where the network is updated for additional chunk of data.

The simulated output values of network were reported and compared with the actual values obtained from the results of detailed analysis and structural design. The model with least error was saved in each case. The accuracy of developed networks was evaluated with a view to use them in future as a helpful tool to perform the preliminary design of tall buildings.

2.3 Computer Software

The Python based IDE called PyCharm was used for modelling of both MLP and ELM. Software selection was based on ability of the software to perform the computation required, its availability and most importantly the platform it provides to develop a user interface package. Neural Network requires solving of various mathematical calculations which can be performed using tool such as 'numpy' in Python. It is one of the most used programing languages for solving various classification, regression, pattern recognition, curve fitting problems as it contains one of the best toolboxes for construction of a Neural network.

2.4 Improvement of generalization capability of network

The performance of networks with different architecture was checked. The performance of networks were evaluated in terms of mean square error between actual output and target of data set. Errors may be calculated using other measure such as the sum square error, the root of mean square error, correlation coefficient between actual and simulated value. The least value of mean square error for train and test set shows the actual performance of the network. The data were divided into training and testing set. Generally network works well with training data set but its prediction capability to the test data may be poor due to overfitting. Hence, early stopping criteria comes in handy to overcome overfitting problems [21]. Random weight generation can affect the generalization capability of network as well [8]. Nguyen & Widrow method was introduced such that the random initialized weights were controlled and it improved the generalization of the network. The selection of learning rate affects the network hence, momentum can be added to improve the prediction ability of the network [11]. Bias and its weight added to the network aligns the irregularities in the transfer function. All these functions were added to the network as to improve its performance.

2.5 Implementation of network

The Neural network developed in this research work can be used by structural engineers to perform preliminary design of buildings in a non-conventional fashion. They can feed in set of input and output data, train the network and then use it to predict output for further unknown input data set. The input parameters can be taken from the architectural data of the building to predict the structural design of the building. The designer can select data set from either performance based design or code based design to predict building design of new buildings. This research moreover helps in evaluation of the appropriate network out of the two algorithms used i.e. MLP-BP and OSELM.

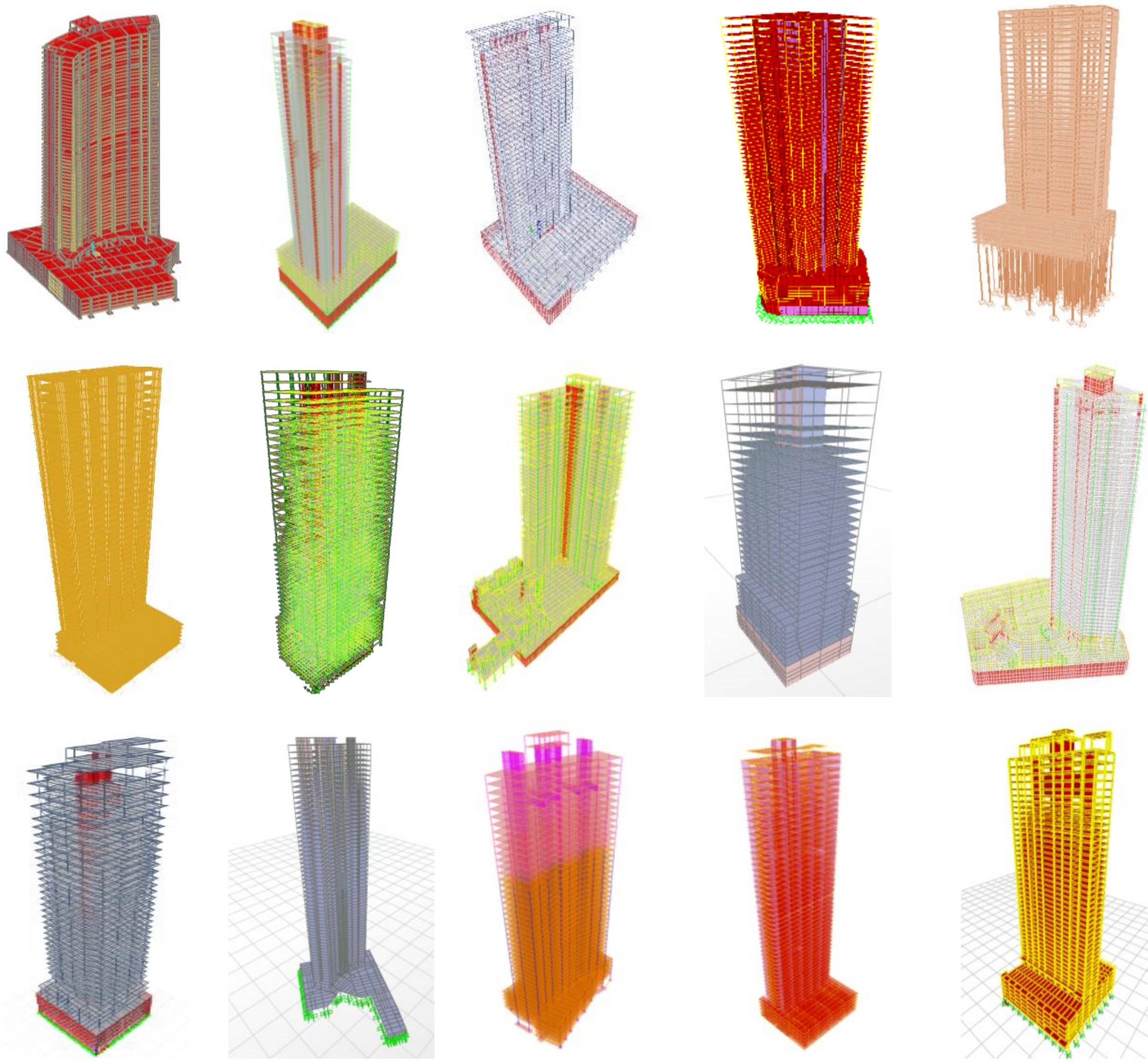


Figure 3: Full 3D nonlinear models of some of the tall buildings used in this study

3. ANALYSIS, RESULTS AND DISCUSSION

Model I: Model for prediction of natural period of building (sec) using MLP-BP

The architecture of network was changed and the network with least MSE was selected as best network. The network was selected for minimum MSE between computed output and actual output of natural period of the building. For Model I, The architecture was selected in 14:20:1 ratio as it showed least MSE in training. The network was used to test the test data set. Its performance for test data set is as per Figure 4.

Model II: Model assessment for prediction of natural period of building (sec) using ELM

The model trained can be used to predict the natural period of building response using 14 architectural parameters. The model was trained using fix set of input weights generated using Nguyen method. The network architecture consisted of 2 neurons in hidden layer. The network showed fast training speed with good generalization capability comparable to MLP-BP network. The network was tested for the training set and its prediction capability is shown in Figure 4.

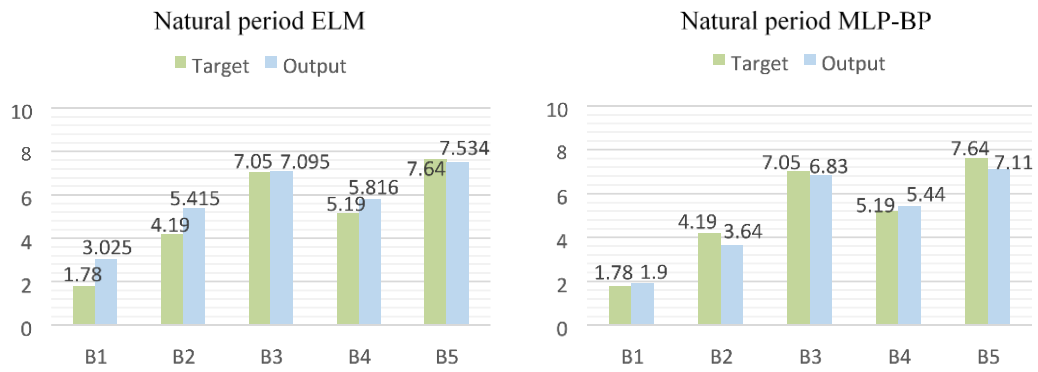


Figure 4: Comparison of natural period of test buildings with simulated natural periods from artificial neural network using ELM and MLP-BP.

Model III: Model assessment for ratio of weight per unit floor area of tower (KN/m²) using MLP-BP

ANN model III was trained to predict weight of building per unit floor area of tower. The data set were taken from code based design of buildings. The network architecture was changed and network with least MSE between obtained output and target output was selected as the best network. For Network model II, network architecture of (14:15:1) showed higher correlation to training and testing set. The prediction ability of network is shown in Figure 5.

Model IV: Models assessment for ratio of weight of building per unit area of tower (KN/m²) Using ELM

ELM was used to train a network that predicts ratio of weight of building per unit area of tower using architectural data set. The input output parameters were passed through the network and best fit output weight is generated. Hidden layer with 2 neurons showed the best prediction performance. The weights were saved and used for testing. The training speed of network was really fast with good generalization capability. The prediction capability on testing data set is shown in Figure 5.

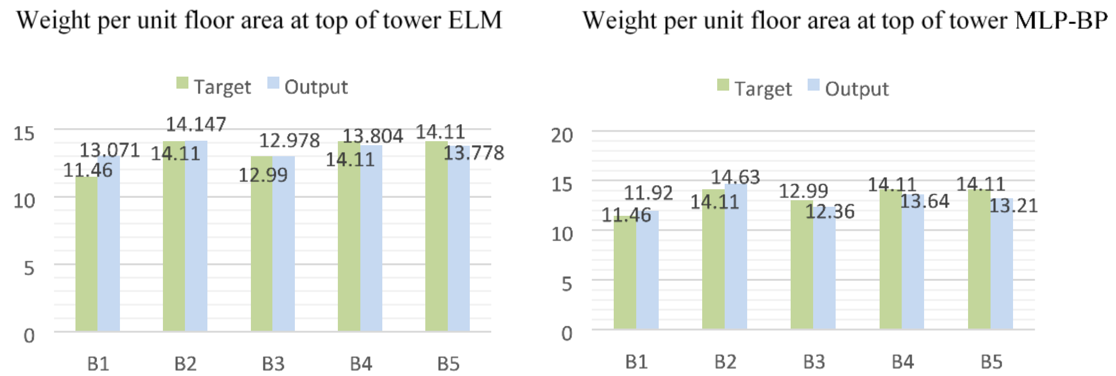


Figure 5: Comparison of weight per unit area of tower of test buildings with simulated weight per unit area of tower from artificial neural network using ELM and MLP-BP.

Model V: Models assessment for ratio of weight of building per unit volume of tower (KN/m³) Using MLP-BP

The minimum mean square error for training set was found with an architecture of ratio 14:10:5:1. The network contained two hidden layers with 10 and 5 neurons. The model can be used for calculation of ratio of weight of building per unit volume from architectural data set. The performance of the selected network to test data set is shown in Figure 6.

Model VI: Models assessment for ratio of weight of building per unit volume of tower (KN/m^3) using ELM

The best fit output for training and testing set was found with an architecture of ratio 14:12:1. The network contained hidden layer with 9 neurons. The model can be used for calculation of ratio of weight of building per unit volume from architectural data set. The performance of the selected network to test data set is shown in Figure 6.

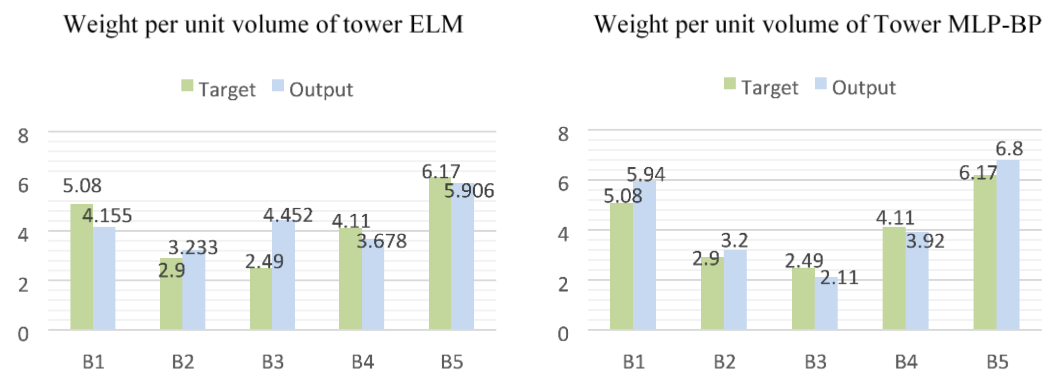


Figure 6: Comparison of weight per unit volume of test buildings with simulated weight per unit volume from artificial neural network using ELM and MLP-BP

Model VII: Models assessment for maximum story drift ratio using MLP-BP

Network model VII is used to predict maximum story drift of the building from given set of architectural data. The network with architecture 14:10:1 was selected as best network due to its low mean square error for the training set. The network was used to test the testing set of data and its ability is shown in Figure 7.

Model VIII: Models assessment for maximum story drift ratio using ELM

This network model is used to predict maximum story drift of the building from given set of architectural data. The network with architecture 14:9:1 was selected as it showed best fit on training and testing data. The network was used to test the testing set of data and its ability is shown in Figure 7. The training time of network was 0.14 sec and testing time was 0.034 sec.

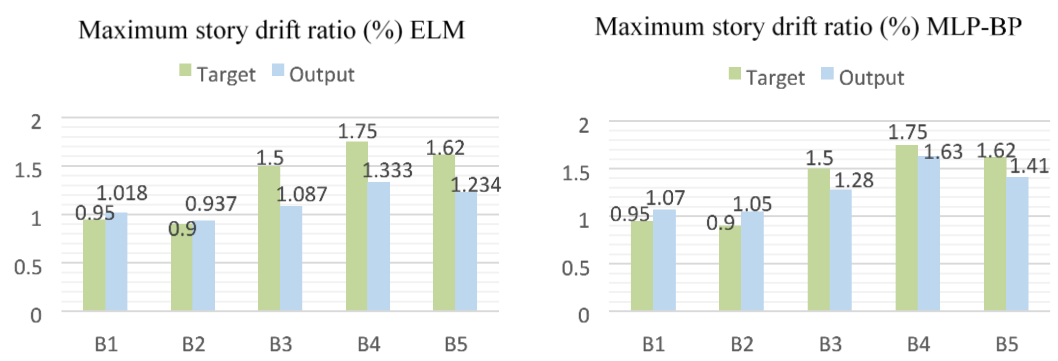


Figure 7: Comparison of Maximum story drift of test buildings with simulated Maximum story drift from artificial neural network using ELM and MLP-BP

Model IX: Model assessment for prediction of 2 output i.e. natural period of building (s) and Maximum story drift using ELM

Two output data were tested using same set of architectural data set. The network showed good generalization capability with two output as well. The Training speed was as fast as 0.084 sec and testing time was 0.015 sec with good accuracy. The network was trained using set of 14 input parameters and 2 output parameters with hidden layer consisting 2 neurons. Its performance is shown in Figure 8.

Figure 8: Comparison between Actual output and simulated output of two output data predicted at once from architectural data using ELM.

Model X: Model assessment for prediction of 3 output i.e. natural period of building (s), ratio of weight of building per unit volume of tower (KN/m^3) and Maximum story drift

The network was trained to predict 3 output at once using the architectural data. The training speed was 0.099 sec and testing time was 0.031 sec. The performance of the network on testing data is shown in Figure 9.

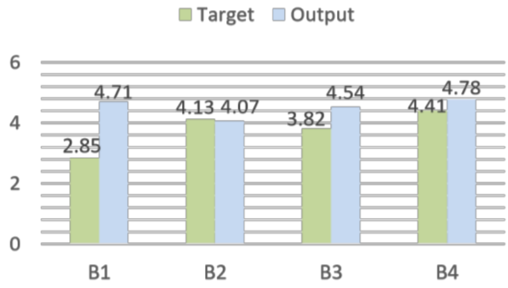
Model XI: Model assessment for estimation of best network

The network model were selected on basis of its accuracy using k-fold ELM. In this model, we display the accuracy to predict natural period of 5 building using architectural data of model with different number of neurons. The number of neurons is obtained using PCA and numbers near that value is tested for better options.

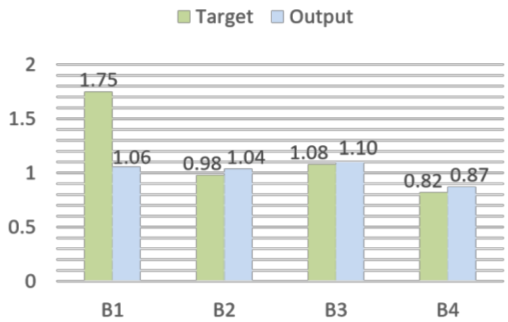
Model XII: Model assessment on network with reduced dimensionality on input data set using PCA

The network model were selected on basis of its accuracy using k-fold ELM. In this model, we display the accuracy to predict natural period of 5 building using architectural data of model with different number of neurons. The number of neurons is obtained using PCA and numbers near that value is tested for better options. The dimension of input data is reduced using PCA. For 98% variance, the PCA value was 2 on our input set. Hence the data with 14 parameters were reduced to 2 parameters. The accuracy of each network model is presented in Figure 11. Figure 12 shows that ELM performs better than PCA-ELM, i.e. higher dimensional data set shows better prediction capability compared to smaller dimension. But PCA-ELM have almost comparable accuracy compared to normal ELM. With increasing data set, dimensionality reduction helps in larger data handling with robustness in prediction ability.

(a) Natural period



(b) Weight of building per unit volume of tower



(c) Maximum story drift

Figure 9: Comparison between actual output and simulated output of three output data predicted at once from architectural data using ELM.

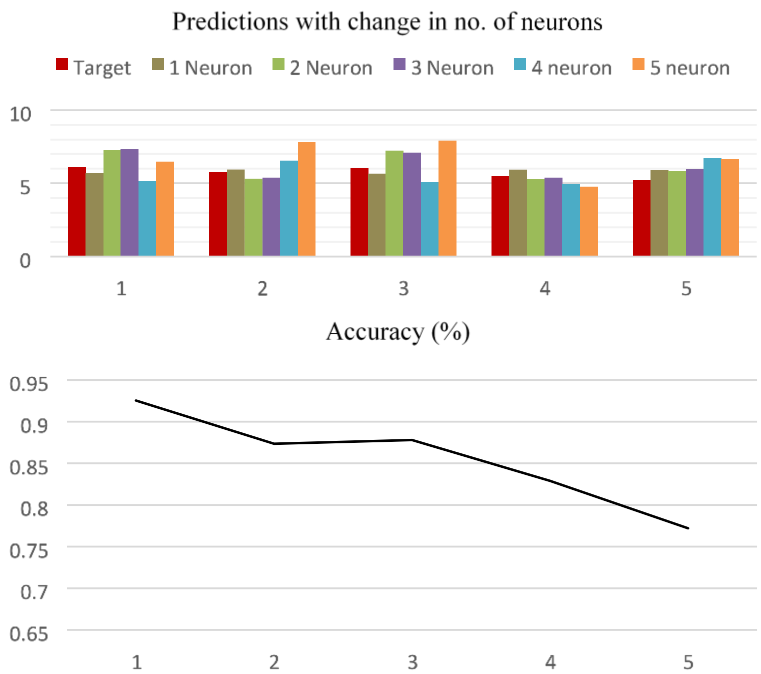


Figure 10: Prediction capability of network with different number of hidden layer neurons on natural period of building using architectural data.

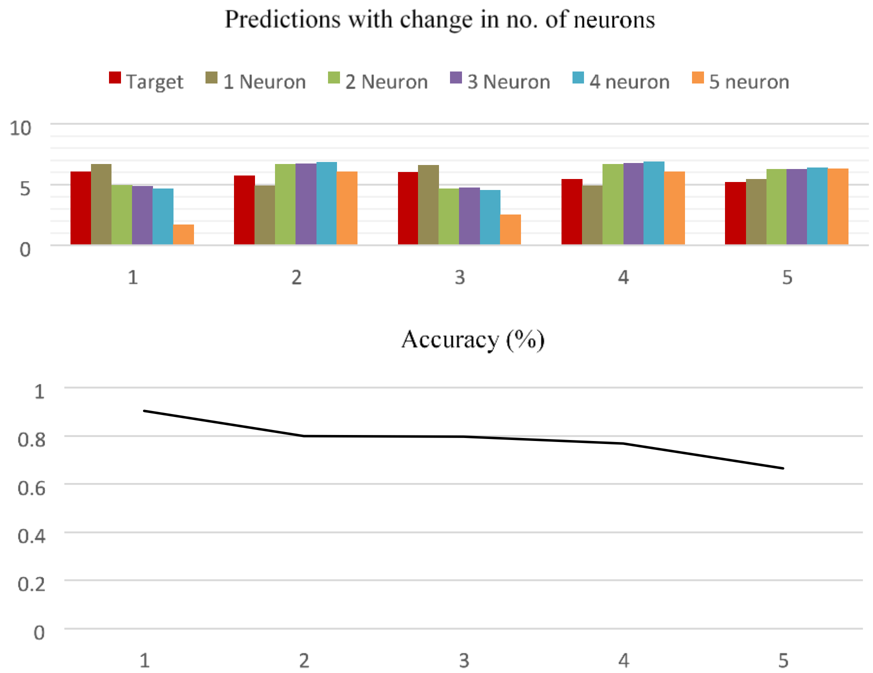


Figure 11: Prediction capability of network with different number of hidden layer neurons on natural period of building using dimensional reduced architectural data.

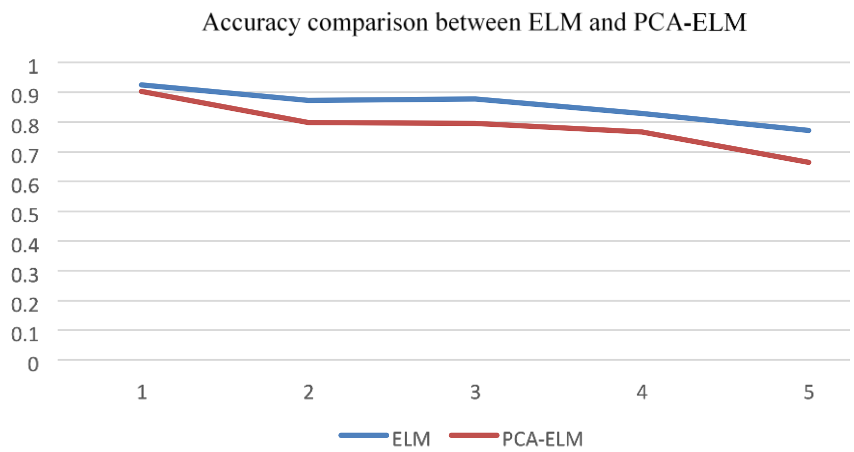


Figure 12: comparison of accuracy of ELM and PCA-ELM in prediction of natural period of building using architectural data.

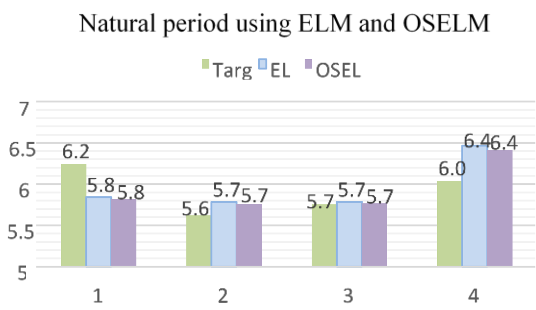


Figure 13: Comparison between target natural period and simulated natural period using ELM and OSELM network

Model XIII: Model assessment for prediction of target natural period of test building to simulated natural period using ELM and OSELM

Natural period was computed using extreme learning machine where set of 20 data were trained. The network was tested for 4 building. Online sequential algorithm was implemented and 2 data set were trained again. Then the network was tested for same set of test data. The result is shown in Figure 13. The network architecture used was hidden layer with 2 neurons. The OSELM network i.e. network with additional training data added shows slightly better predicting capability.

4. CONCLUSION

- Various key structural parameters can be determined from architectural data using the ANN approach. The selected models can be used in preliminary design of tall buildings. Well-trained ANNs can reliably predict the key structural parameters from architectural drawings. These networks map the nonlinear relationship between input and output.
- The MLP with Back Propagation as learning algorithm have good generalization capability but requires large training time. For new building set, the Pearson correlation coefficient was found to be over 80% for MLP-BP.
- The ELM algorithm shows fast training speed with comparable generalization capability. The training and testing time of network was less than a second for each model. Online sequential learning in ELM helps the model to be used in online platform where additional training data can be used to fine tune the network.
- The accuracy obtained using ELM is up to 93% for the best fit network. The network is selected using PCA value and cross validation concept of Sparse-ELM.
- The dimensionality reduction of input data using PCA shows comparable generalization capability and its concept can be brought in use when the parameter and sample of data increases.
- The performance of networks can be improved by adding more data and using regularization functions or bootstrapping. The network performance of MLP-BP can be improved by using optimization tools such as genetic algorithm.
- Wind design parameters can be added for higher accuracy and wider applicability in future studies.

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