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Preliminary Design of Tall Buildings Using an Artificial Neural Network

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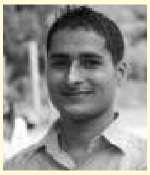

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Abstract

With the rapid increase in the need for tall buildings to accommodate exponentially growing urban populations, quick and reliable estimations of approximate sizes of shear walls and columns by knowing typical response parameters and primary structural component indicators can greatly facilitate preliminary design and feasibility of the project. This research presents the outcome of an Artificial Neural Network based approach to directly determine design parameters based on the experience gained from previously designed buildings. Artificial Neural Network models are trained to determine structural design indicators from architectural parameters. The objective is to provide the means of assisting the design team and clients to make key design decisions based on cumulative experience rather than relying on the judgment of individual designers. The approach is demonstrated through the sample networks trained on about thirty eight tall buildings for which required architectural and structural design results have been generated through detailed designs.

Keywords: Artificial Neural Network, Performance-based design, preliminary design, tall buildings

Introduction

Tall buildings prevalent today around the world are a result of increasing research, development and innovation in the field of Civil Engineering. They are subjected to not only gravity loads, but may also experience significant amounts of lateral loads caused by severe ground motions, strong winds and other environmental loading. Efficient structural systems are being designed to transfer all of these loads safely to the ground (Ali and Moon, 2007). Since the effects of earthquake and wind loads increase with the height of the building, a significant consideration of lateral loads is more important for taller structures (Halder and Dutta, 2010). Preliminary design of tall buildings is the initial step during the design process. While designing tall buildings, conceptual design, preliminary design, preliminary analysis of structure, details design, final design and detailing of structures are all conducted to complete the total design process (Lützkendorf and Lorenz, 2006). Preliminary building design is defined as the selection and proportioning of the most suitable and appropriate structural components such as beams, columns, slabs, foundations, and bracing systems (Taranath, 2011). In the initial design stage, the known value of some key building design and response parameters are very useful pieces of information to select the most appropriate size of structural components.

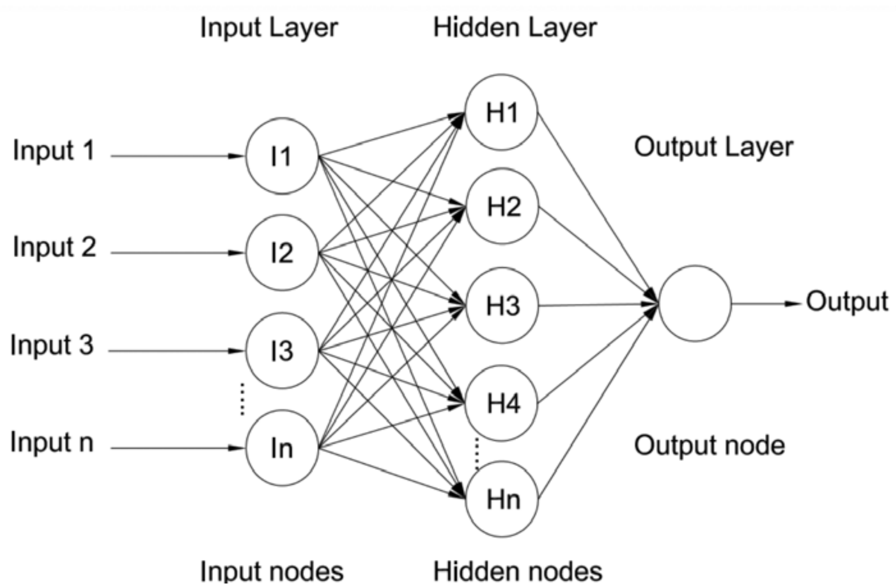

Figure 1. Schematic Diagram of an Artificial Neural Network (ANN) (Source: AIT-Consulting)

An Artificial Neural Network, Fuzzy Logic, Rich Picture Approach, Analytical Hierarchy Process, or Hybrid Mixed Approach are some emerging techniques and applications of artificial intelligence used for preliminary tall building design and the optimization of structural components and the selection of proper structural systems (Adeli, 2001). Proportioning structural systems on knowledge-based expert systems, which are usually implemented by complex computer programs, are trained to use a knowledge base to solve real-life problems. It is a very useful technique to increase accuracy during the preliminary design phase (Poon, 2000).

Different branches of artificial intelligence, such as knowledge-based expert systems, linear optimization, genetic algorithms, and artificial neural network tools, can be used for the preliminary design of tall buildings (Cohn and Dinovitzer, 1994). An Artificial Neural Network is an information processing system consisting of massively large parallel connections. It is a mathematical model designed for input-output mapping, which achieves perceptual tasks, recognition tasks, and mimics the behaviour of the human brain (Al Shamisi, Assi et al., 2011).

An Artificial Neural Network (ANN) with a supervised learning has a process that is divided into two stages: an ANN model, developed and trained to learn the relationships between inputs-outputs and adjusting the error by modifying the weight of each neuron is the first stage, and the second is the use of a network model to predict the output for new input data (Zhang, Eddy Patuwo et al., 1998). ANN can be used in the structural engineering field. Trained networks can be used to simulate outputs from similar types of new problems. Gershenson (2003) suggested that ANN is a very useful tool to generalize a complex problem using simple linear or nonlinear functions in elementary units to arrive at a proper solution.

Objectives and Methodology

The overall objective of this paper is to estimate basic design and response parameters of tall buildings using architectural information in the preliminary design stage. The known values of design and response results allow engineers to confidently choose the appropriate size of structural components at the beginning of the design process (Group, 2010). The simulated output from the network is compared with the provided target. Feed Forward Networks are commonly used in engineering applications. In multilayer neural networks, hidden layers are arranged between input and output layers, and

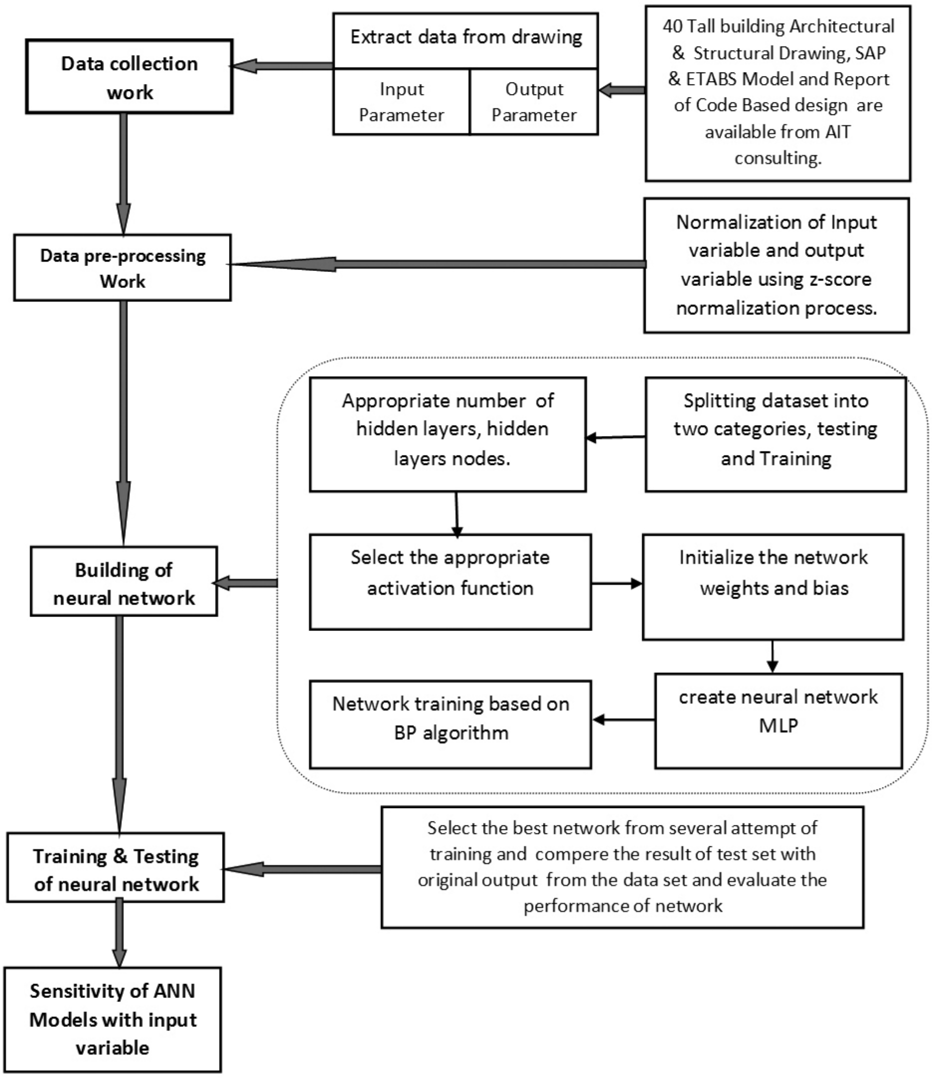

Figure 2a. Total work break down during development of Artificial Neural Network model with supervised learning (Source: AIT-Consulting)

each hidden layer has many neurons (Kavzoglu, 1999). This system can be seen as a group of parallel processing units. Hidden layers and output layers received information from neurons in the preceding layer through links with associated weight. Each neuron performs computations to calculate a weighted sum and the weighted sum is transferred through a transfer function to neurons in the next layer, or even a network output if it is an output layer (Kalman Šipoš, Sigmund et al., 2013; Hasançebi and Dumlupınar, 2013). Figure 1 shows a typical multilayer neural network consisting of a number of neurons arranged in layers. Each neuron is connected with neurons of the following layer. Each of the input parameters is multiplied by their corresponding weight. The product is then added with corresponding biases, called a weighted sum. The weighted sum is then fed in to an activation function which gives the output of one neuron.

For creating a trained network we require an existing data set of inputs and outputs. The same trained network we designed by using the existing data set can be used to simulate outputs for new problems of a similar nature. Figure 2a explains an overview of the methodology adopted to develop this system. Data from 40 already designed tall buildings is collected using their architectural and structural drawings. The extracted data is then divided into two categories based on its intended uses i.e. training of the ANN system and its subsequent testing. The buildings' dimensions taken from architectural drawing were used as input variables for the network to simulate the various responses and structural design parameters of tall buildings. The important fundamental response parameters and design information of buildings, such as the natural period of the building, weight per unit floor area of the building, weight per unit volume of the tower, the maximum thickness of the shear wall, ratio of the total area of core wall to the floor area, and the ratio of the column area to the floor area at the top podium level, were taken from results of structural designs from code based design processes for the training of eight different ANN models. Figure 2b enlists all input and output parameters as well as corresponding

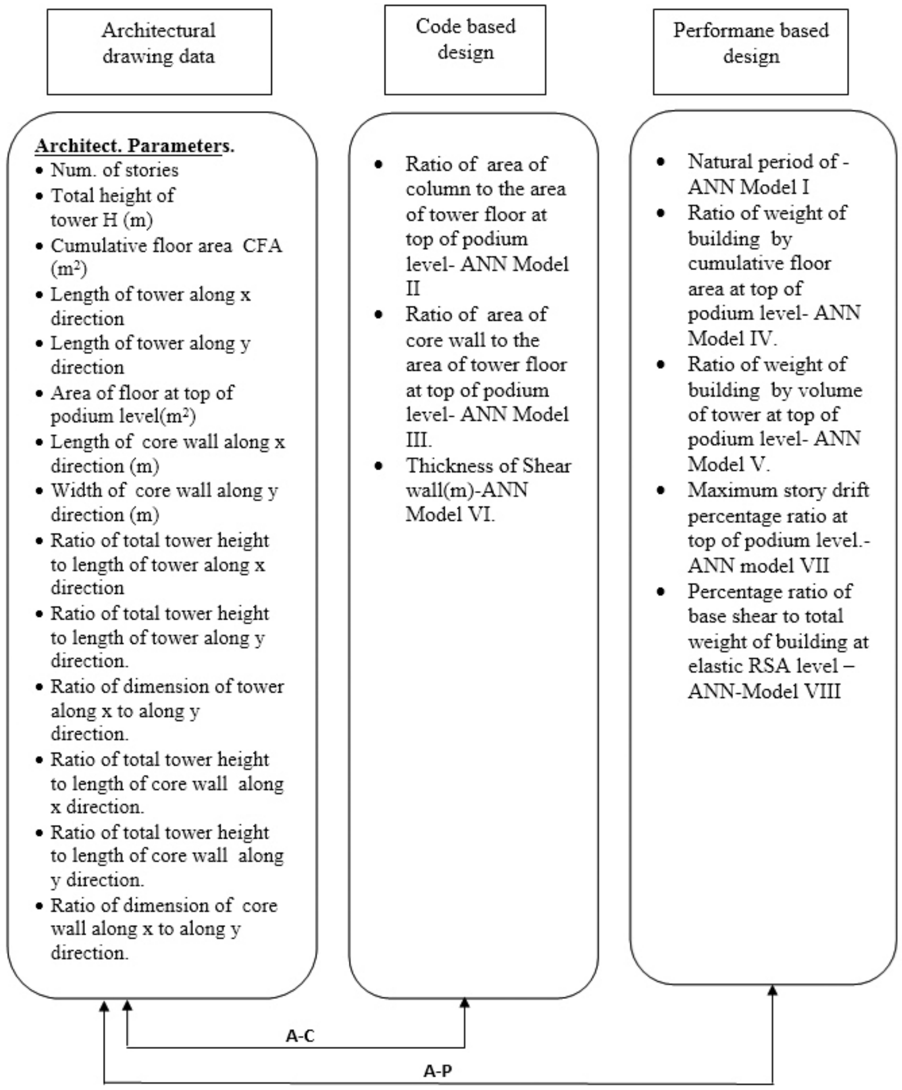

Figure 2b. Input and target variables for artificial neural network model construction (Source: AIT-Consulting)

ANN models for each output prediction.

Models were trained for the mapping of key design and response parameters directly from architectural drawings. Rescaling raw numerical data to specific boundaries of the largest and smallest ranges was done using Z-score data normalization (Sola and Sevilla, 1997). Figure 3 shows full 3D finite element models for some of the case study buildings, created and analysed to extract actual design outputs.

Data Processing

In an ANN black box model with supervised learning, input and target data were fed into input and output layers respectively (Adeli, 2001). The network architecture depends upon the nature of input and output data sets. MATLAB version 7.14 was used because it provides a convenient programming environment and has various built-in functions helping the user to automate the process (Al Shamisi, Assi et al., 2011). The data collected from architectural drawings and structural designs from the code based design process of 38 buildings were used as inputs and targets for each network. The input data was taken from architectural drawings and the target data was taken from structural design results. Fourteen input variables and single target variables were chosen and trained for each network. Controlling parameters defined during the network building and training were: data normalization, number of hidden of layers, number of nodes in hidden layers, transfer functions, mu for L-M algorithm, number epochs, data size partitioning into training, validation and testing sets, minimum gradient of the performance function, and the maximum validation check. Details of all these parameters can be seen in Adeli (2001).

The number of hidden layers and nodes in each hidden layer depends upon the nature of data sets and the transfer function, learning parameter, number of iterations, transfer functions, and the characteristics of the data used (Kavzoglu, 1999). Large numbers of hidden nodes are able to capture better results than fewer hidden nodes. Similarly, large numbers of hidden nodes and hidden layers, although time consuming to train, tend to produce good results during training and validation. However, large errors may occur during testing new data sets due to over-fitting (Rotich, 2014). Network performance was checked with different numbers of hidden nodes and different numbers of hidden layers, and such performance did not follow any particular pattern. Different networks with changing nodes in hidden layers were trained (Nagendra and Khare, 2006) and the best network was selected with the least mean square error in training and testing sets.

Nguyen and Widrow's weight initialization algorithm was used in the MATLAB programming environment during the initialization of the initial weight. The training process was stopped when the error approached zero or as specified in the stopping criteria of the network. The trained neural network model uses the weights which were saved during the stopping of the training process. In a L-M algorithm, there is a better convergence capacity and less of an effect from local minima because of the high converging capacity at the beginning of training (Dai, 2013). The nonlinearity of the input-output was defined by introducing a transfer function in hidden nodes. Generally, hidden layers use nonlinear activation functions, and output layers use pure linear activation functions.

When the trained network reached the minimum error it was tested with new data set. The simulated outputs of networks were compared with the actual values obtained from structural design results. If the error was reduced to a significant range then the model was saved. Network results were used for the preliminary design of tall buildings so the best network would be able to simulate the output for new tall buildings. During the training process, training data was divided into training, testing, and validation sets. The convergence criteria was measured by determining statistical properties i.e. the MSE between the simulated and actual results from the structural design, which were compared and reported for each model.

Improvement of the Generalization Capability of the Network

The networks fit well with training data sets, but the prediction capability of networks to the test data set may be poor due to over fitting or over training of the network. As suggested by Calin and Dumitru et al. (2002) an early stopping approach was used to overcome overtraining and to generalize the network. The first subset is the training set, used for computing the gradient and updating the network weights and biases. The second subset is the validation set (Prechelt, 1998). The error on validation sets is monitored during training processes. The validation error normally decreases in initial phases of training as the training set error. The data division during model construction into training, validation and testing sets were randomly kept with the ratios of 70%, 15% and 15% respectively. The valid networks have to correlate well with training, testing, and validation sets, and with the least MSE value of simulated and actual output for training and test data sets.

The performance of networks with different buildings were evaluated in terms of the mean square error between the actual output and the target of the data set. Errors could be expressed in terms of other statistical measures, such as the mean square error, sum square error, the root of the mean square error, mean absolute error, and the correlation coefficient between the actual and simulated value. The mean square error of the target and ANN-model output of different architecture networks, including one layer, two layers and three layers with different numbers of hidden nodes, were compared to evaluate the performance of the network. MSE is very popular for signal processing because of the simplicity to calculate it and they require less computing memory. The least value of the mean square error for training and testing sets shows the actual performance of the network. The correlation coefficient of actual and simulated values for training and testing sets shows the performance of the network. Some networks performed very well but others did not. The best network was chosen with the least MSE and the highest correlation to the training, testing and validation set. The networks were then used to simulate design and response parameters for the preliminary design purposes of tall buildings and the results are shown in the subsequent section.

Analysis Results and Discussion

Developed neural network models were employed to simulate the key design and response parameters of tall buildings directly from architectural parameters. Input parameters for the models of new buildings can be taken from architectural drawings.

Figure 3. Full 3D nonlinear models of some of the tall buildings used in this study (Source: AIT-Consulting)

The output of the network was expected to be the most accurately simulated output, similar to the structural design values found through code based and performance based design. The networks for different targets can be used for new buildings. In the initial design stage, structural engineers can find the required data for inputs and simulate outputs from trained networks. The performance and simulated outputs from eight different networks will be shown separately in this section.

Model I: Model Assessment for the Natural Period of the Building (seconds)

The most appropriate artificial neural network model among several architecture networks and learning algorithms were chosen based on their MSE and the actual natural period by structural design procedures and simulated outputs by the networks. The network with a minimum MSE in training sets and test sets was selected as the best network among several models. For Model I, network architecture 14:20:1 with an L-M learning algorithm shows the least MSE in training and test data sets among different architecture networks. The performance of the 14-20-1 network for the test building is shown in Figure 4.1. From Figure 4.9, it is clear that Model I is sensitive to the vertical dimension of the building. With increases in the vertical dimensions of buildings, the natural period of the test buildings simulated by Model I was also increased.

Model II: Model Assessment for the Ratio of Column Area by Floor Area at the Top of the Podium Level

The network was trained with the architectural parameters of buildings as input variables. A ratio of column to floor area, and the area at the top of the tower podium level of tall buildings were used as a target variable. The top of the podium in tall buildings is one of the critical sections during design because most of the shear stress concentrates at that section. The most appropriate artificial neural network model among several architecture networks and learning algorithms were chosen based on its mean square error between the target value and output during the training process. For network Model II, a network architecture of (14:15:15:1) with a L-M learning algorithm shows the least mean square error in the testing data sets. Figure 4.2 shows that the ratio of column area to the floor area at the top of the podium level from code based design procedures and the simulated results from the artificial neural network Model II were very close to each other. This demonstrates that the model can follow the pattern of code based design procedures. Figure 4.10 shows that the sensitivity of network models with changing vertical building dimensions keeps all others constant.

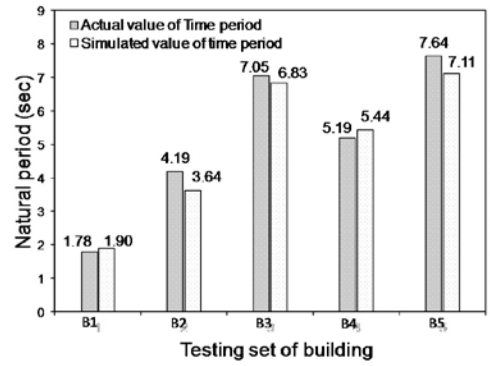

Figure 4.1 Comparison of natural period of test buildings with simulated natural periods from artificial neural network.

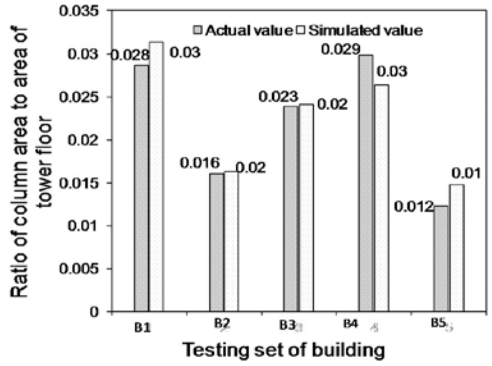

Figure 4.2 Comparison of actual ratio of total area of column to total area of tower of test building with simulated from artificial neural network.

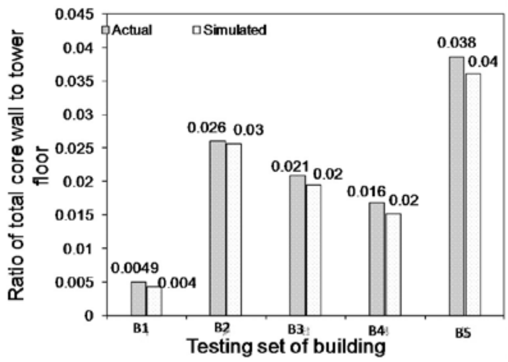

Figure 4.3 Comparison of actual ratio of total area of core wall to total area of tower of test building with simulated from artificial neural network.

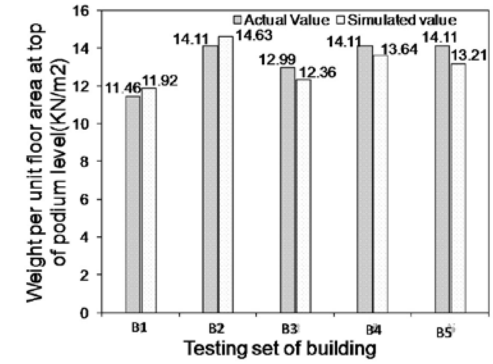

Figure 4.4 Comparison of actual weight per unit floor area of tower of test building with simulated from artificial neural network.

Figure 4.1-4. Comparison of actual and simulated output values from ANN models (Source: AIT-Consulting)

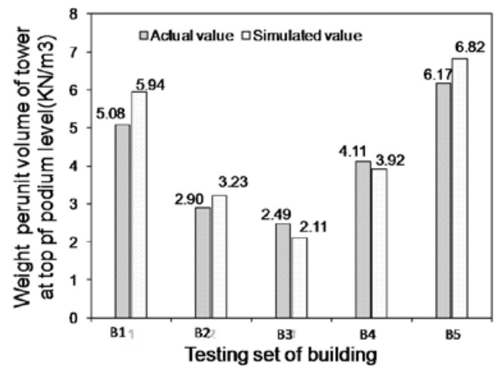

Figure 4.5 Comparison of actual weight per unit volume of tower of test building with simulated from artificial neural network.

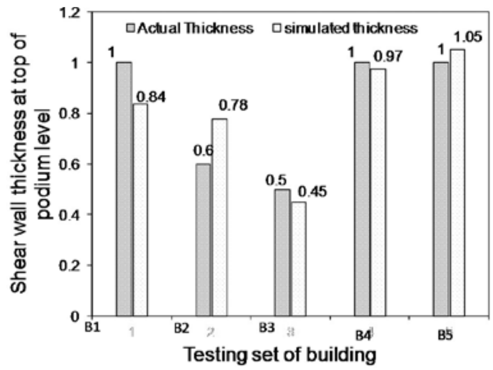

Figure 4.6 Comparison of actual shear wall thickness of test building with simulated from artificial neural network.

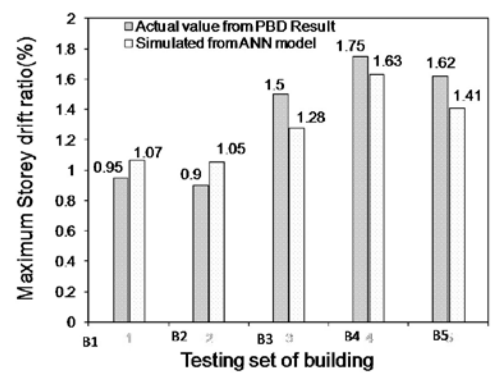

Figure 4.7 Comparison of actual Maximum storey drift ratio of test building with simulated from artificial neural network.

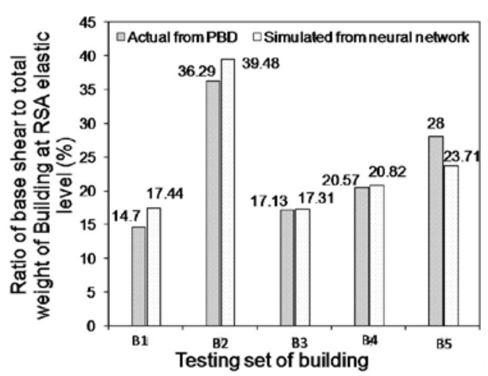

Figure 4.8 Comparision of actual ratio of base shear to total weight of building at RSA elastic level and simulated from artificial neural network.

Figure 4.5-8. Comparison of actual and simulated output values from ANN models (Source: AIT-Consulting)

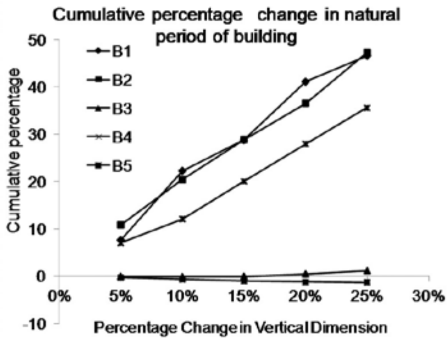

Figure 4.9 Changed in Natural period of building simulated by **Network I** with vertical dimension of building keeping horizontal dimension of building and dimension of shear wall constant.

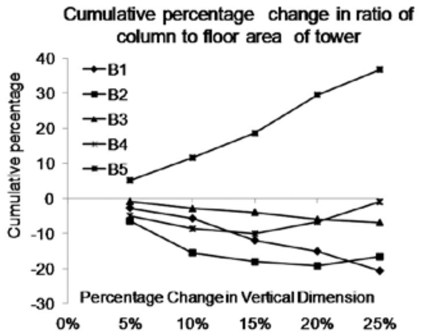

Figure 4.10 Changed in ratio of total area of column to total area of tower of test building simulated by **Network II** with vertical dimension of building keeping horizontal dimension of building and dimension of shear wall constant

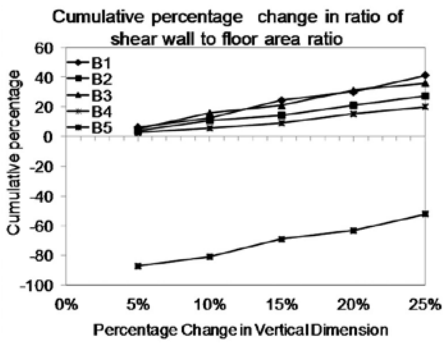

Figure 4.11 Changed in ratio of total column area to floor area of tower at top of podium level of building simulated by Network II with vertical dimension of building keeping horizontal dimension of building and dimension of shear wall constant.

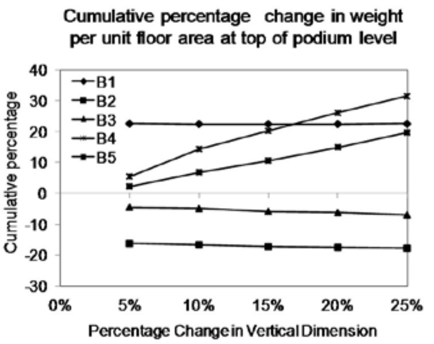

Figure 4.12 Changed in weight perunit floor area at top of podium level of building simulated by Network IV with vertical dimension of building keeping horizontal dimension of building and dimension of shear wall constant.

Figure 4.9-12. Sensitivity of output from ANN models with varying height of building (AIT-Consulting)

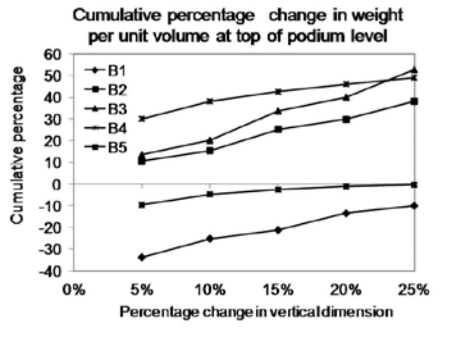

Figure 4.13 Changed in weight perunit volume of tower at top of podium level of building simulated by Network V with vertical dimension of building keeping horizontal dimension of building and dimension of shear wall constant.

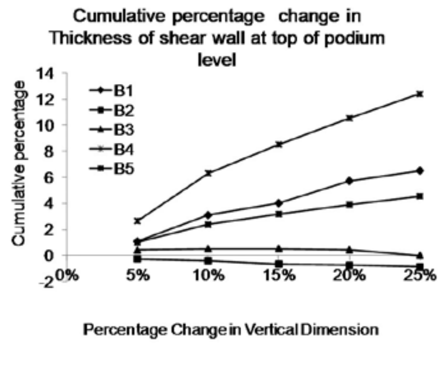

Figure 4.14 Changed in Thickness of tower at top of podium level of building simulated by Network VI with vertical dimension of building keeping horizontal dimension of building and dimension of shear wall constant.

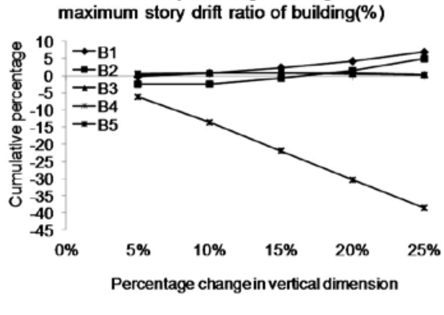

Figure 4.15 Changed in maximum story drift ratio at top of podium level of building simulated by Network VII with vertical dimension of building keeping horizontal dimension of building and dimension of shear wall constant.

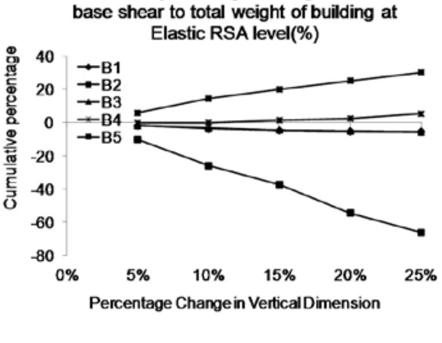

Figure 4.16 Changed in ratio of base shear to total weight of building at RSA elastic level of test building simulated by Network VIII with vertical dimension of building keeping horizontal dimension of building and dimension of shear wall constant.

Figure 4.13-16. Sensitivity of output from ANN models with varying height of building (Source: AIT-Consulting)

Model III: Model Assessment for the Ratio of Core Wall Area to Floor Area at the Top of the Podium Level

ANN Model III was trained with the architectural dimensions of tall buildings to the ratio of core wall area to the floor area of the tower at the top of the podium level. Model III can be used to simulate the ratio of total core wall area to floor area of tower at the top of the podium level for new tall buildings in the preliminary design stage. The area of the shear wall for target variables were taken from the results of code based design procedures.

The most appropriate artificial neural network models among several architecture network and learning algorithms were chosen based on the mean square error and correlation coefficient between the actual and simulated value of training, testing and validation sets during the training processes. For network Model III, an architecture network of (14:5:1) with a L-M learning algorithm shows higher correlation to training and testing sets. Figure 4.3 shows that the simulated outputs of Model III are very close to the actual value from code based design. The outputs of the networks that are modified with changing the vertical dimension of the building are shown in Figure 4.11.

Model IV: Model Assessment for the Weight Per Unit Floor Area Ratio of the Tower (KN/m2)

The most appropriate artificial neural network model was selected from a different architecture network and learning algorithm based on the least mean square error and highest correlation coefficient between the actual and simulated values of training, testing and validation sets during training. For network Model IV, architecture network (14:15:1) with a L-M learning algorithm shows a higher correlation to the training and testing sets. The simulated output and actual output from code based design are much closer to each other, and can be seen in Figure 4.4. From Figure 4.12 the simulated output by Model III is changed when the height of the building is increased.

Model V: Model Assessment for the Weight of the Building Per Unit Volume Ratio of the Tower (KN/m3)

The simulated value of weight per unit volume of the tower by network Model V and from code based design are close to each other with architecture network 14:10:5:1. Two hidden layers and 15 numbers of hidden nodes with L-M algorithms give better performance to test buildings and can be shown in Figure 4.5. The simulated output of network Model IV with a changing the vertical dimension of the buildings can be seen in Figure 4.13.

Model VI: Model Assessment for the Thickness of the Shear Wall (m)

The minimum mean square error for both training and testing sets were found with 25 hidden nodes in a single hidden layer architecture network. The network architecture 14:25:1 with the L-M learning algorithm was selected for the simulation of new data. The actual shear wall thickness from code based design and simulated from network Model VI is shown in Figure 4.6. The change in the simulated value of outputs with increases in the height of the building can be shown in Figure 4.14.

Model VII: Model Assessment for the Maximum Storey Drift Ratio

The network Model VII with architecture network 14:10:1 and the L-M learning algorithm shows the minimum mean square error for both the training and testing sets was selected for the simulation of maximum storey drift for the new buildings and is shown in Figure 4.7. When input parameters are modified by the changing height of the building the network output for testing the building were also changed as per Figure 4.15.

Model VIII: Model Assessment for the Ratio of Base Shear to the Total Weight of the Building

The artificial neural network with architecture network 14:5:1 and the L-M learning algorithm was selected with minimum mean square error for both training and testing sets. The actual and simulated values of the percentage of base shear to total weight at the RSA elastic level of the test building can be shown in Figure 4.8. The simulated output of the networks with changing building height was observed, and the simulated values are shown in Figure 4.16.

Conclusions and Recommendations

- From eight ANN models result an artificial neural network with supervised learning which can be used in the preliminary design of tall buildings. Applications of an Artificial Neural Network that simulates basic structural design and response parameters of new buildings is very useful to select the appropriate structural components in preliminary building design. The output of Artificial Neural Network models can be used in starting preliminary design with the most appropriate size of structural components and also to check the result of the structural design very quickly.
- A properly trained Artificial Neural Network can reliably predict the key structural parameters from architectural drawings. The developed ANN models can map architectural data to begin structural designs, providing results through a heuristic approach. The trained network reliably predicts the output for various ranges of data and outputs can be shown from the sensitivity of network models with different input variables.
- Different neural network model sets need to be trained for each parameter to improve reliability. Results of eight different ANN models for test buildings shows that the predicting capacity of Artificial Neural Network models for new buildings were close to structural design results. For new building sets, the Pearson correlation coefficient was found to be over 80%. Very small deviations between actual and simulated results shows the high performance of the network. The uniform distribution of input vectors leads to good network performance.
- The performance can be improved by increasing training data sets of tall buildings in the Philippines or a similar seismic region.
- Earthquake and wind loading parameters can be added if sufficient building data of different seismic zones and exposure conditions are available and also utilized in the results of a performance based design for higher accuracy.
- Bayesian bootstrapping can be applied in future studies. To evaluate the sensitivity and optimum input nodes, principal component analysis and genetic algorithms can also be used.

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