Prediction of Early Stage Construction Cost of Building Projects Using Artificial Neural Network

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Abstract—**Construction process generally depends on the finance management for maintaining the project feasibility and its smooth operations during the entire project execution stages. Prediction of the early stage construction cost of building projects is important during the pre-design stages of any construction projectconstruction project.The conventional and traditional cost prediction method requiresdetailed information about the construction projects.Accuracy in the prediction of construction costat the early stage affects the decisions making process and it gives insight into budgeting and the project feasibility studies. The objective of this paper is to develop early stage cost prediction model for the building construction using artificial neural network (ANN). The resilient back propagation (Rprop) and Levenberg-Marquaedt (LM) algorithms are used and neural network model is developed in Matlab R2013a. Database of 58 buildings is used in this study and it includes residential buildings, public and commercial buildings in the Mumbai and nearby region in the state of Maharashtra, India. The key parameters those influences on the structural skeleton cost of buildings were identified. The input layer of the artificial neural network (ANN) model includes nine parameters, namely; total plot area, ground floor area, typical floor area, height of building, quantity of shear wall, quantity of exterior wall, number of columns, types of foundation, number of householders and total structural skeleton cost estimate of buildings represents output of the ANN model. The developed ANN cost model showedhigher degree of correlation. The result obtained from the trained neural network model shows that, the ANN is able to predict the cost of building projects at the pre design stage.**

Keyword- artificial neural network (ANN); prediction early stage construction cost; estimation

I. INTRODUCTION

Construction cost in early stage of project execution plays a vital role on the project success. In general during early stages of construction projects, detailed design, drawings are not usually available and project cost is required for decision makingin budgeting and knowing project feasibility.Many times due to limited and uncertain information, it is difficult to predict construction costs with better accuracy.Many cost models are available for the construction project cost estimation at the early stage, however development of cost models became challenging due to the influence of several factors affecting project cost and schedule.Better cost estimation accuracy and reliability improves the suitability of resultant designs and actual execution of project.Traditional methods such as regression analysis have limitations due to large number of significant variables involvedin estimating accurate construction costs.Now-a-days the soft computing techniques i.e. artificial neural networks, expert system, case-based reasoning, fuzzy logic, genetic algorithm and decision trees are more effective in prediction of cost than the traditional statistical methods. In this study artificial neural networks

(ANN) isusedfor early stage cost prediction. The main objective of this paper is to develop a pre-design construction project cost. Artificial neural network has potential to learn from the past and capture trends involving complex set of relationship between the dependent variables (i.e. output) and the independent variables (i.e. input). ANN model is designed, trained and tested for prediction of structural system cost for the medium size construction projects in Mumbai and Western Maharashtra, India. Project documents and database were collected from the various stakeholders i.e. consultancy firm, contractors, builders and owner of buildings. Next section discusses in brief literature reviewed related to case studies on early stage construction cost and various tool used.

II. LITERATURE REVIEW

This section discusses the literature reviewed related to cost estimation and applications of soft computing tools in construction management and some of them are mentioned here. Mohammed Arafa et al. (2011) concluded a reasonable concentration of predicted values around the best fit line when compared with the actual. The coefficient of determination between actual value and predicted values was 90% with ANN. Ismaail El Sawy et al. (2011) developed ANN model for site overhead costs for the future projects of building construction projects in Egypt. Wang et al. (2010) used the fuzzy neural network estimation model and shows better estimate of the cost of construction Rifat Sonmez (2004) used neural networks and bootstrap method in estimation of costs. RunZhi Jin et al. (2012) developed a Case Based Resoning model for prediction at early phaseusing data of 41 business facilities and 99 multifamily housing projects. Tawfeket al. (2012) concludes that cost of quality is greatly affected by different project aspects. Rafiq et al. (2001) introduced three types neural network MLP, NRBF and RBF for prediction of design parameters for the slab andconclude that the depth of slab ismost important parameter greatly influences on other design parameters and cost of structural skeleton. Literature reviewed shows that very few studies are done on prediction of early stage construction cost and almost no studies are reported as far as Indian construction is concerned.

III. OBJECTIVE OF STUDY

The objective of this paper is to develop a model based on Artificial Neural Network to estimate the cost of the structural system of the buildings at early stages using limited available data.Next sections discuss in brief about artificial neural network.

IV. ARTIFICIAL NEURAL NETWORK

Artificialneural network is a computational system inspired by its learning ability from the pattern similar to the biological nervous system in the humanhaving many applications in science and engineering. Due to its capability in capturing patterns of incomplete and noisy data sets, ANN is becoming popular in engineering day by day.Neural networkis able to generalize from examples and past experience and it effectively provides solutions to the problems. Training process in ANN consists of the presenting set of examples (input vectors) with known target outputand then neural network system assigns weights to the interconnecting link to reduce the errors between network output and target output.In general the network architectures are classified as a single layer feed forward networks, multilayer feed forward networks and recurrent network (Wasserman, 1995). Some of the well-known neural network systems consist of back propagation network, ADALINE (Adaptive Linear Element), associative memory etc. Fig. 1 shows the architecture of an artificial neuron. A neural network basically consists of interconnected neurons and each neuron or node is an independent computational unit (Fig. 1). The total input I received by the soma of the artificial neuron is:

$$I = \mathrm{w}_1\mathrm{x}_1 + \mathrm{w}_2\mathrm{x}_2 + \ldots + \mathrm{w}_\mathrm{n}\mathrm{x}_\mathrm{n} = \sum_{i=1}^{n} \mathrm{w}_\mathrm{i}\mathrm{x}_\mathrm{i} \quad (1)$$

Where $x_1, x_2, x_3, \ldots\ldots xn$ are the n inputs to the artificial neuron and $w_1, w_2, w_3, \ldots\ldots\ldots w_n$ are the weights attached to the input links.

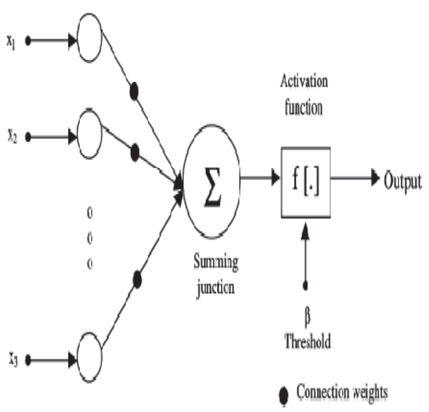


Fig.1.*Working of Neuron*

To generate the final output y, the sum is passed on to a non-linear activation function (∅) or transfer function, or squash function which releases the output $y = \emptyset$.In this paper multilayer feed-forward network is used as shown in Fig. 2.

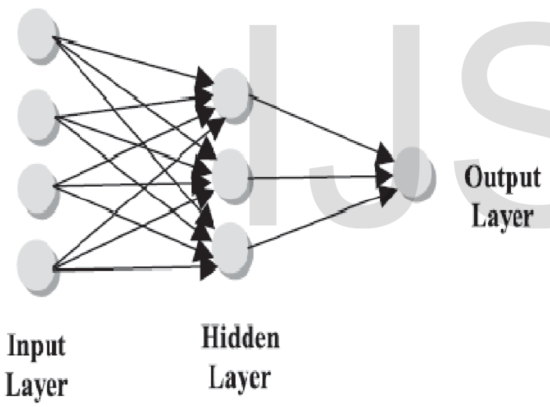


Fig.2.*Typical Feed-Forward Neural Network Model*(Wasserman, 1995)

Each layer has number of neurons or nodes. Each neuron in particular one layer is connected to the every single neuron on the next layer. Due to which, information is fed forward from one layer to next layer. This neural network model consists of an input layer, one or more hidden layer and an output layer and shown by the arrows. Initially random weights are assigned usually in the range of + 1 to – 1 to each interconnection. The hidden layers links the input layers to output layers with function to extract and remember the useful features and sub features from input layers to predict values at the output layers. More details of this can be seen in the standard textbooks of the neural network (Wasserman, 1995).

V. METHODOLOGY ADOPTED

The database and required documents were collected from the engineering consulting firms, architectural firms, contracting companies, builder and developers and owner of the buildings. Around 62 buildings were identified in Mumbai and western Maharashtra region out of which database of 58 buildings of similar nature is used for this study. The factors affectingcost of the structural system of building such as; foundation, columns, plinth beams, beams, slabs, shear walls and masonry works, finishing works includes plastering, painting, tiling, doors and windows, electrical and mechanical work was collected out of these nine important parameters were selected as shown in Table 1 and the range (Min. to Max.) of the inputs and output parameters are also shown in Table 2. Fig.3 shows details of data collected from various civil engineering structures. Height of the building directly influences the vertical section of structural area. Three types of foundation system were considered in this study namely; isolated footing, isolated and combined footing and raft foundation. Quantitiesof shear wall and exterior wall also have impact on total structural skeleton cost.

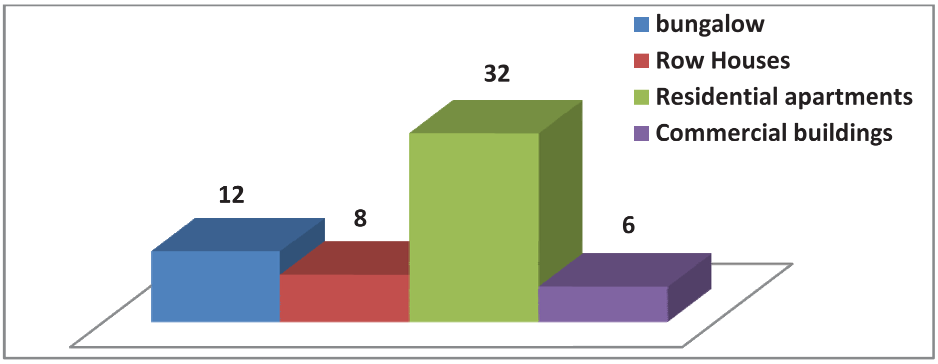


Fig.3.Frequency of Collected Data

Table I. Input and Output Parameters

Sr. No.	Inpuput parameters	Output parameter
1	Total plot area	Total cost of structural skeleton in Rs.
2	Ground floor area	
3	Typical floor area	
4	Height of building	
5	Quantity of shear wall	
6	Quantity of exterior wawall	
7	Number of columns	
8	Types of foundation	
9	Number of householders	

Table II. Range of Inputs and Output Parameters

Sr. No.	Descriptit oion of parameters	Range (Min. – Max.)
1	Total plot area	118.34 – 4785.80 (m^2)
2	Ground floor area	55.46 – 1122.76 (m^2)
3	Typical floor area	0 – 1122.76 (m^2)
4	Height of building	4.15- 38.12 (m)
5	Quantity of shear wall	0 – 295.78 (m^3)
6	Quantity of exterior walall	24.45 – 773.61 (m^3)
7	Number of columns	14 – 134 Nos.
8	Types of foundation	Isolated footing Isolated and combined footing Raft foundation
9	Number of householderers	1– 117 Nos.
10	Total cost of structural l s skeleton	Rs. 921010 – 91469414

VI. ANN MODEL USED

The ANN tool available in the Matlab version R2013a was used to develop early stage cost estimation model. Non-linear tan-sigmoid transformation function was applied in the hidden layers and linear transformation function was employed in output layer. The range of values of tan-sigmoid function is ranged between +1 to -1 and hence normalized data is used.The resilient back propagation (Rprop) and the Levenberg –Marquaedt (trainlm) algorithms are used to train the networks.The ANN model works in three phases i.e. training phase, validation phase and testing phase. The database used for training, validation and testing was 70%, 15%, and 15% respectively. The training sets are utilized to modify the weights and biases for minimization of error. Fig.4 shows ANN model used in the study. The test set was used to check for generalization of ANN that does not have effects on training process. A performance function of mean squared errors (MSE) was used to check the performance of neural network. MSE between target and network yielded early stage cost and is calculated using equation below;

$$MSE = \frac{1}{N}\sum_{j}^{N}\left(T_j - P_j\right)^2 \tag{2}$$

where; N is total number of training set and Tj and Pj are the target and actual output of dataset respectively.

The root mean square error is applicable to iterative algorithms and is a better measure for higher values. It offers a general representation of the errors involved in the prediction. The lower the value of RMSE, the better the prediction is and following formula is used to compute RMSE;

$$\text{RMSE} = \sqrt{\frac{\sum_{i}^{n}(Xi-Yi)}{n}} \tag{3}$$

VI.I.FEED FORWARD NEURAL NETWORK

Multi-layeredfeedforward ANN architecture consisting input layer, one hidden layers and output layer was used to develop the early-cost estimation model. Each layer has a number of neurons (nodes or perceptions). Each neuron in one layer is connected to every neuron in the next layer to forward the information. Fig.4 shows the developed ANNs model.

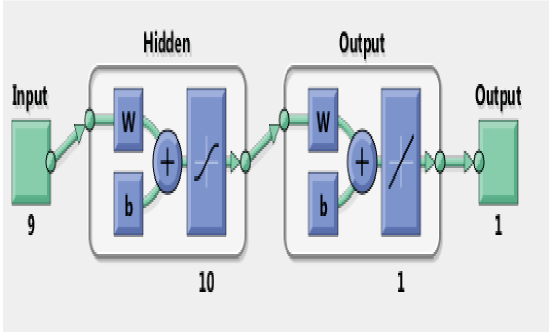


Fig. 4.*ANNModel*(Matlab R2013a)

VII. RESULTS AND DISCUSSION

Twenty trials were run for the prediction of early stage construction costs.Results of ANN outcomes with regression analysis and plots indicate the network outputs with respect to the given targets in training, validation and testing phases. Mean squared error (MSE) performance function which is used to check networks performance during training, validation and testing phases. In each trial number of hidden layers was increased by 1 and maximum of 10 hidden layers were used. The values of sum square error (SSE), coefficient of determination (R-square), root mean square error (RMSE) and overall regression (R) using both the algorithms from 1 to 10 hidden layers are shown in Table 3. As an example network performance with LM and Rprop algorithm is shown for (i) 1 hidden layer in Fig. 5, 6, (ii) for 5 hidden layer in Fig. 7 and 8 and (iii) for 10 hidden layers in Fig. 9 and 10 respectively. From Table 4 it can be confirmed that ANN is able to predict early stage construction cost. The best results were obtained at 10 hidden layers using LM and Rprop algorithms. The size of network was 9-1-1 and number of cycles of 1000. In order to assess the network performance, number of cycles was kept constant i.e. 1000 for hidden layers of 1 to 10. Best result wit LM algorithm gives SSE = 0.0618, R^2= 0.9901, RMSE = 0.0332 and overall R = 0.9950 and same with Rprop algorithm was observed to be 0.3741, 0.9403, 0.0825 and 0.9707 respectively.

International Journal of Scientific & Engineering Research, Volume 5, Issue 7, July-2014
ISSN 2229-5518

Table III. Performance of Artificial Neural Network

Sr. No.	Algorithm	Network	Hidden layers	No. of Epoch	Sum Square Error (SSE)	Coefficient of Determination (R-square)	Root Mean Square Error (RMSE)	Overall Regression (R)
1	L-M	9-1-1	1	1000	0.4369	0.8777	0.8830	0.9368
	Rprop				1.6067	0.7344	0.1694	0.8569
2	L-M	9-2-1	2	1000	0.7226	0.8800	0.1136	0.9380
	Rprop				0.3769	0.7613	0.0820	0.8725
3	L-M	9-3-1	3	1000	0.8583	0.9018	0.1238	0.9496
	Rprop				0.7685	0.8039	0.1182	0.8963
4	L-M	9-4-1	4	1000	0.4409	0.9024	0.0887	0.9499
	Rprop				0.8203	0.8545	0.1210	0.9243
5	L-M	9-5-1	5	1000	0.5431	0.9316	0.0985	0.9652
	Rprop				0.1710	0.8811	0.1969	0.9386
6	L-M	9-6-1	6	1000	0.6609	0.9378	0.1086	0.9683
	Rprop				1.0547	0.8906	0.1385	0.9419
7	L-M	9-7-1	7	1000	0.1970	0.9584	0.0593	0.9789
	Rprop				0.6130	0.9111	0.6130	0.9481
8	L-M	9-8-1	8	1000	0.1764	0.9651	0.0561	0.9823
	Rprop				0.6076	0.9060	0.1051	0.9484
9	L-M	9-9-1	9	1000	0.1044	0.9813	0.0432	0.9906
	Rprop				0.4110	0.9461	0.0872	0.9666
10	L-M	9-10-1	10	1000	**0.0618**	**0.9901**	**0.0332**	**0.9950**
	Rprop				**0.3741**	**0.9403**	**0.0825**	**0.9707**

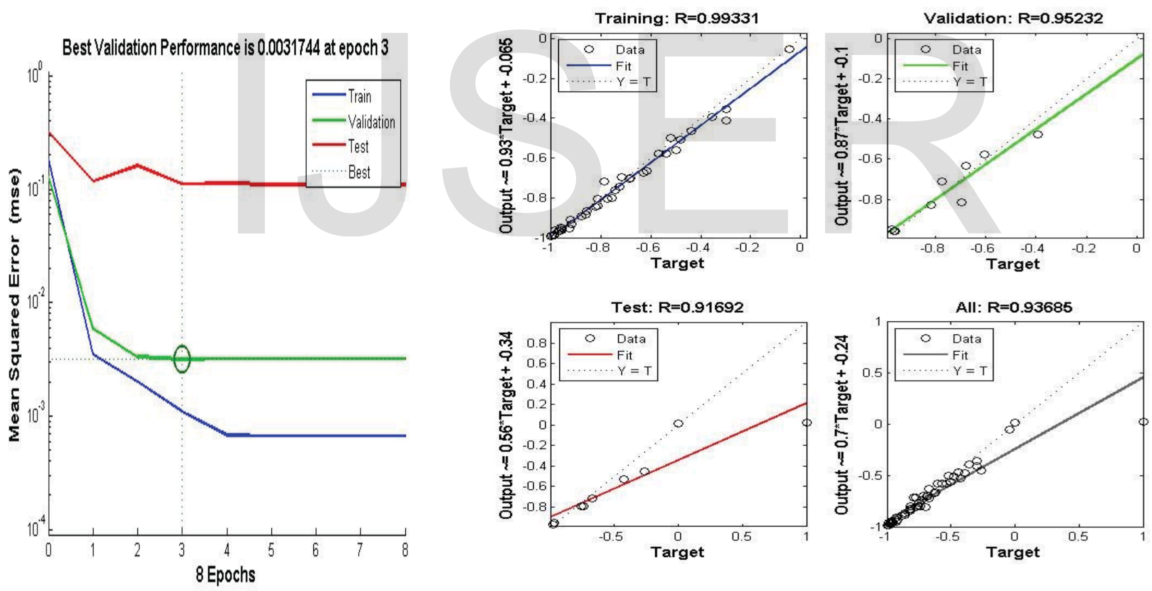
Fig. 5 shows network performance according to (a) MSE and (b) regression (R) between outputs and targets using Levenberg-Marquaedt (LM) algorithms for hidden layer 1 and same with resilient back propagation (Rprop) algorithms is shown in Fig. 6 (a) and (b). Similar plots can be seen in Fig. 7 (a) for MSE and (b) for regression (R) between outputs and targets using Levenberg-Marquaedt (LM) algorithms using 5 hidden layers and same with resilient back propagation (Rprop) algorithms is shown in Fig. 8 (a) and (b).

It has been observed that as the number of hidden layers increases, error between target and observed in training, validation and testing decreases. Fig. 9 (a) MSE and (b) regression (R) (Levenberg-Marquaedt (LM) algorithms) and Fig. 10 (a) MSE and (b) regression (R) with resilient back propagation confirms the reduction in error in training, validation, testing and overall network at 10 hidden layers. It has been observed that the performance of ANN increases with the increase in number of hidden layers in the network.

Fig.11 shows error histogram during design phase using (a) Levenberg -Marquaedt (LM) algorithms and (b) resilient back propagation (Rprop) algorithms at hidden layer 10. The orange color line in Fig. 11 (a) and (b) indicates the line of zero error for 10 hidden layers in the network. The summary of best results obtained is given in the Table 4 including the zero error value at hidden layer 10. Both error values are near about zero and it indicates that the total errors occurred during training, validation and testing phase are eliminated and it has reached to near about zero. Error histogram is used to obtain verification of network performance during training, validation and testing phase. The blue, green and red bars represent the data used during training, validation and testing phase respectively.

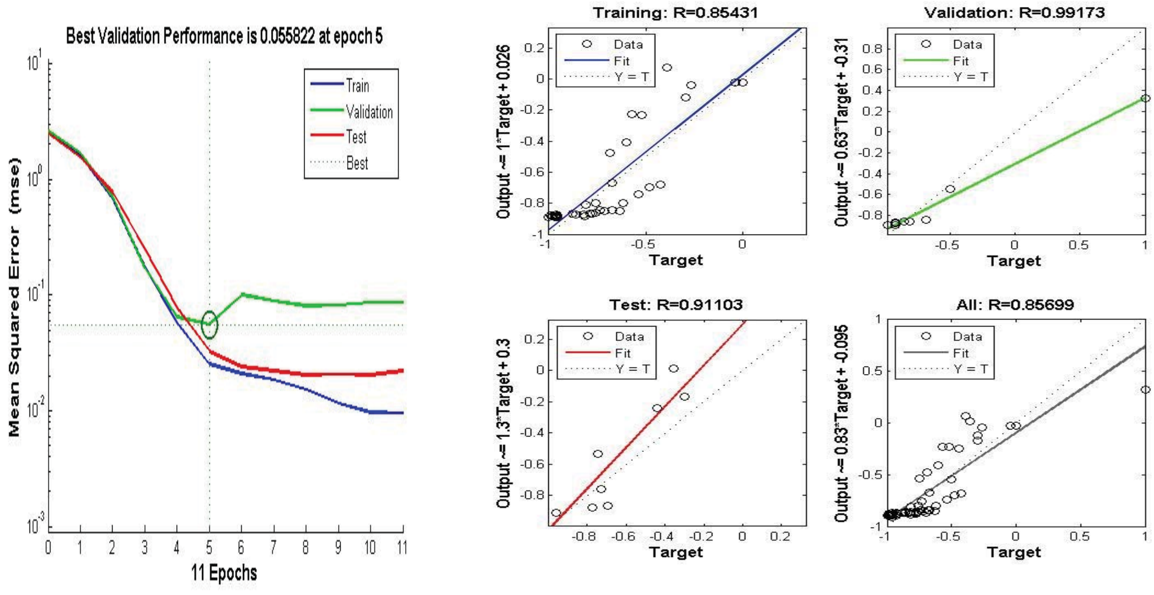
Table IV. The summary of best results.

Sr. No.	Error criteria	Algorithm	Network	Value
1	Sum Square Error (SSE)	LM	9-10-1	0.0618
		Rprop	9-10-1	0.3741
2	Coefficient of Determination (R-square)	LM	9-10-1	0.9901
		Rprop	9-10-1	0.9403
3	Root Mean Square Error (RMSE)	LM	9-10-1	0.0332
		Rprop	9-10-1	0.0825
4	Overall Regression (R)	LM	9-10-1	0.9950
		Rprop	9-10-1	0.9707
5	Zero Error	LM	9-10-1	0.000687
		Rprop	9-10-1	-0.00154



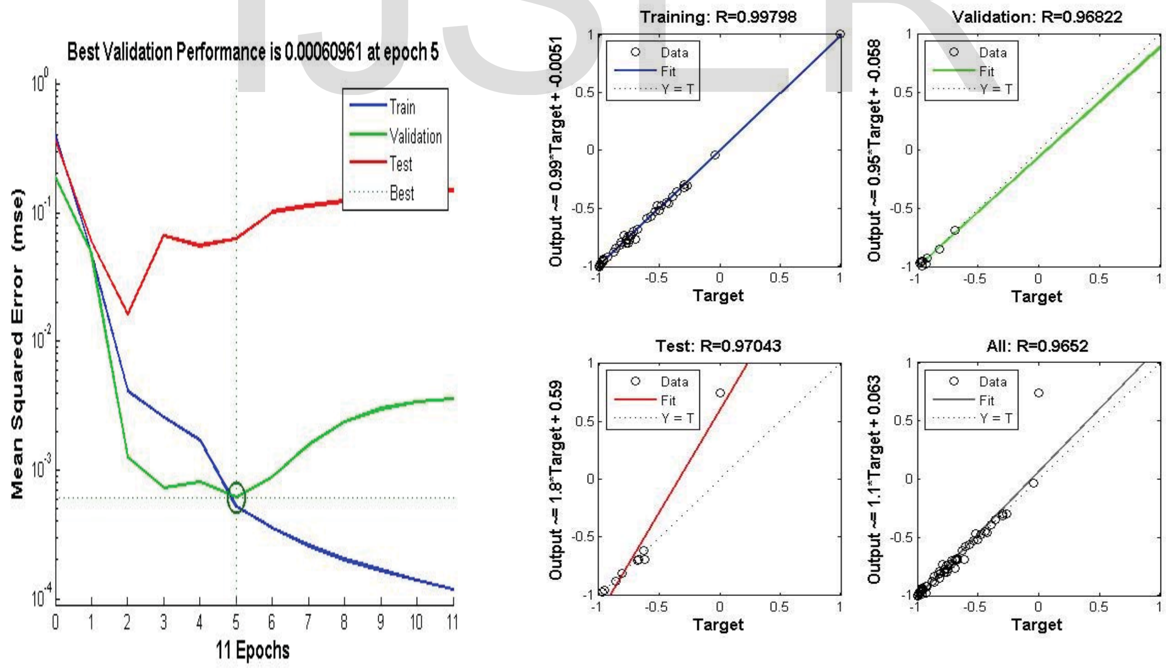
(a) (b)

Fig. 5. (a) Network's performance according to the MSE and (b) Regression (R) between outputs and targets using Levenberg -Marquaedt (LM) algorithms at hidden layer 1



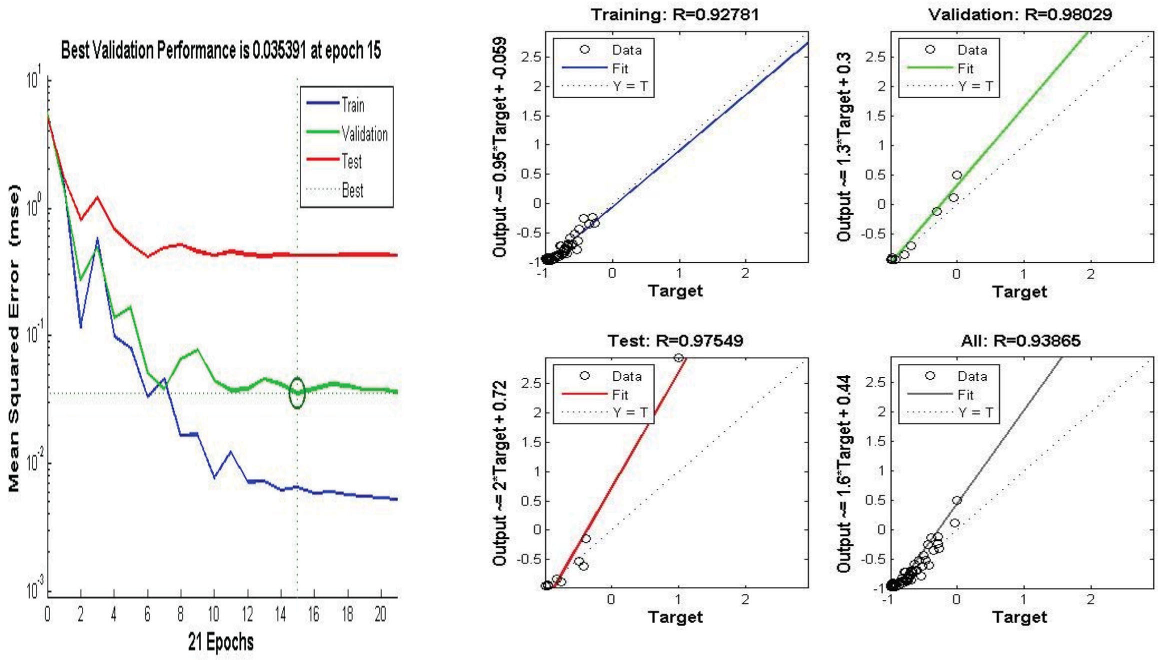
(a) (b)

Fig.6.(a) Network's performance according to the MSE and (b) Regression (R) between outputs and targets using resilient back propagation (Rprop) algorithms at hidden layer1



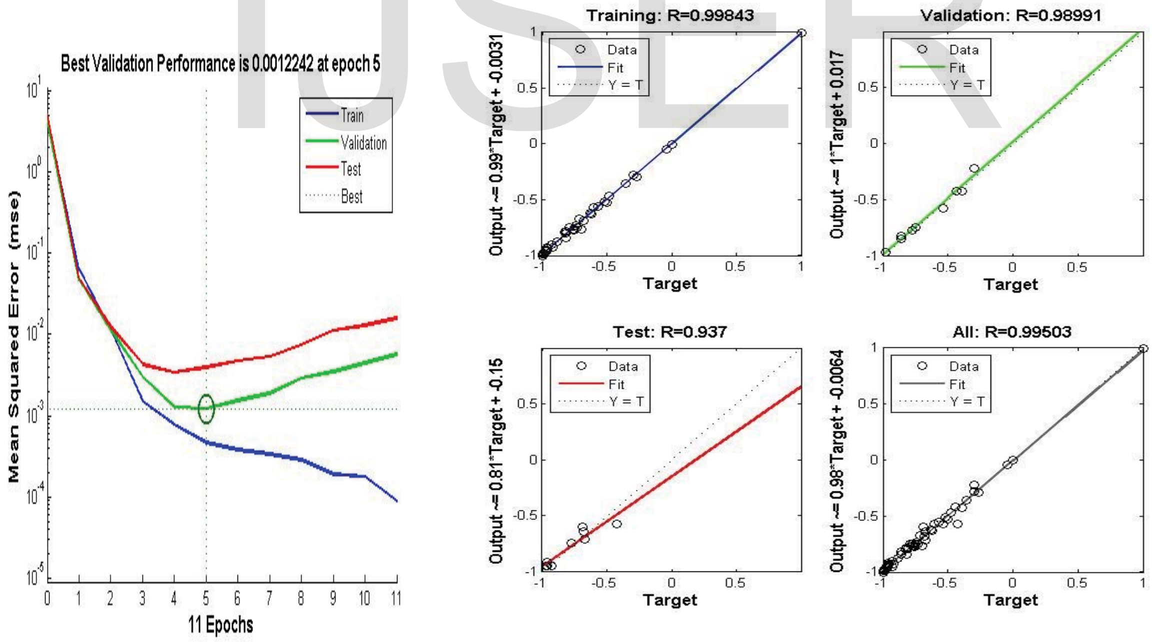
(a) (b)

Fig.7.(a) Network's performance according to the MSE and (b) Regression (R) between outputs and targets using Levenberg -Marquaedt (LM) algorithms at hidden layer 5



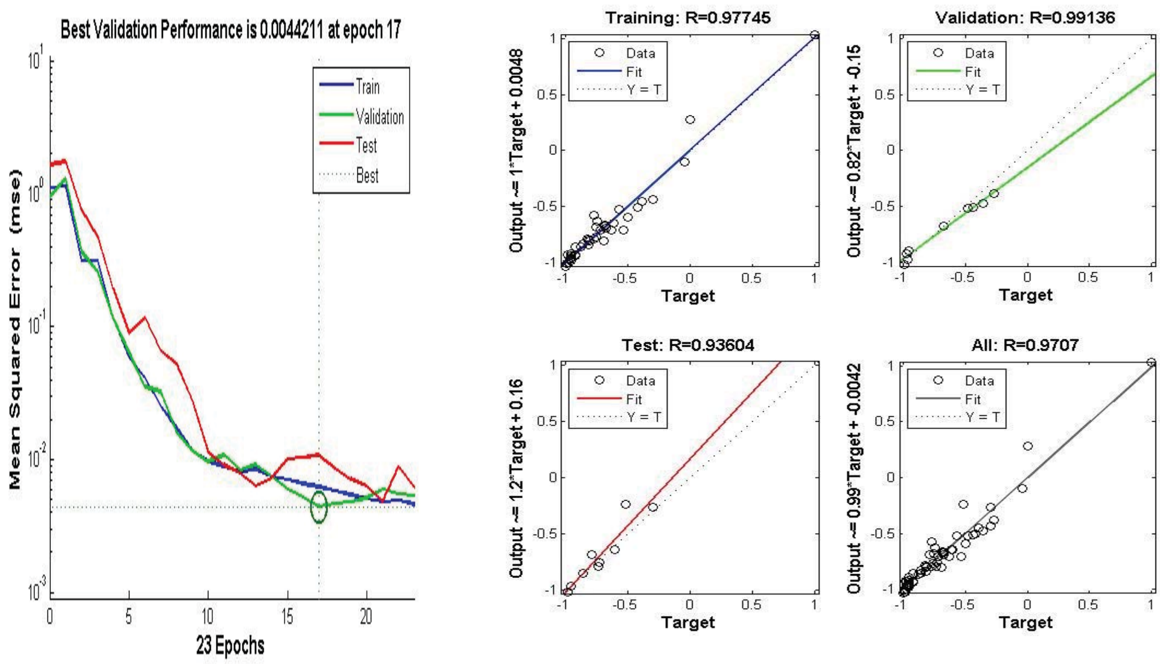
(a) (b)

Fig.8.(a) Network's performance according to the MSE and (b) Regression (R) between outputs and targets using resilient back propagation (Rprop) algorithms at hidden layer 5



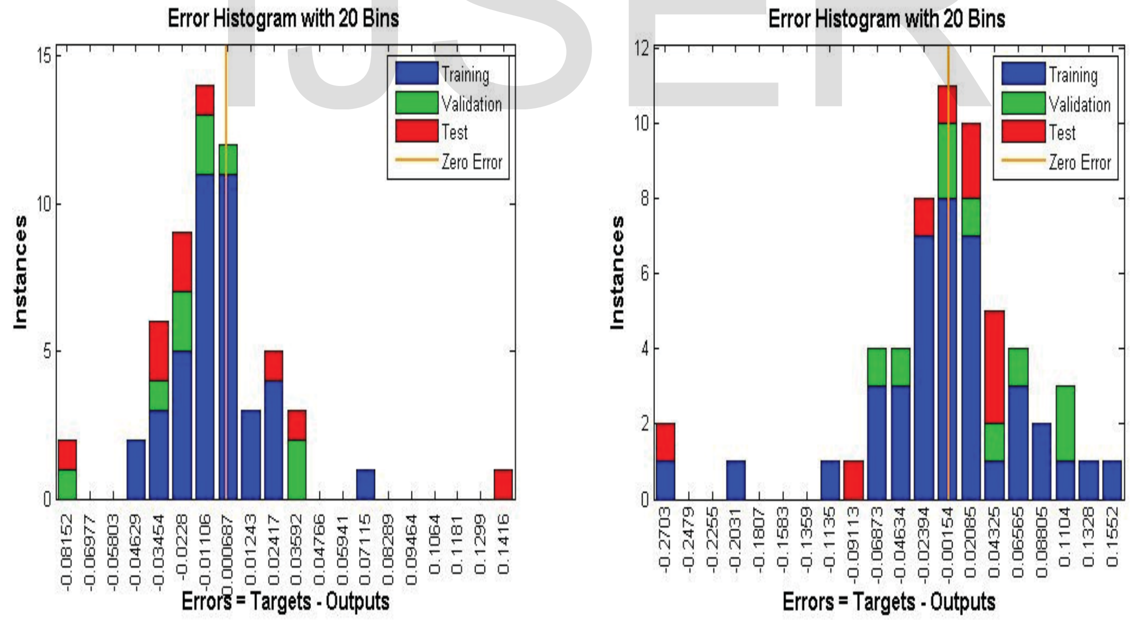
(a) (b)

Fig. 9.(a) Network's performance according to the MSE and (b) Regression (R) between outputs and targets using Levenberg -Marquaedt (LM) algorithms at hidden layer 10



(a) (b)

Fig. 10.(a) Network's performance according to the MSE and (b) Regression (R) between outputs and targets using resilient back propagation (Rprop) algorithms at hidden layer 10



(a) (b)

Fig. 11.(a) Error histogram during design phase using Levenberg -Marquaedt (LM) algorithms and (b)Error histogram during design phaseusing resilient back propagation (Rprop) algorithms

VIII. CONCLUSION

Prediction of the early stage construction cost of building projects is important during the pre-design stages of any construction project. Being a Meta heuristic approach, the convergence criteria adopted significantly reflects on the final prediction. The prediction of early stage construction cost of structures in Mumbai and western Maharashtra of India is done using ANN and following conclusions are drawn.

- Trained neural network can successfully predict early stage construction cost and accuracy in prediction increases with the data size.
- Result obtained also shows higher regression coefficient (R^2, R) and lower root mean squared error (RMSE), mean square error (MSE) and sum square error (SSE).
- A data-mining approach of ANN can predict early stage construction cost of building construction project satisfactorily.

Acknowledgment

Authors wish to thanks all the Consulting agencies, Architectural and contracting firms for sharing the projects data of Mumbai and Western Regions.

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