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Estimation of Building Construction Cost Using Artificial Neural Networks

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ABSTRACT

The cost estimation of the building construction projects at initial stages with a higher degree of accuracy plays a vital role in the success of every construction project. Based on the survey and feedback of the design professionals and construction contractors, a dataset of 78 building construction projects was obtained from a mega urban city Mumbai (India) and geographically nearby region. The most influential design parameters of the structural cost of buildings (Indian National Rupees: INR) were identified and assigned as an input and the total structural skeleton cost (INR) signifies the output of the neural network models. This research paper aims to develop a multilayer feed forward neural network model trained along with a backpropagation algorithm for the prediction of building construction cost (INR). The early stopping and Bayesian regularization approaches are implemented for the better generalization competency of neural networks as well as to avoid the overfitting. It has been observed during the construction cost prediction that the Bayesian regularization approach performance level is better than early stopping. The results obtained from the trained neural network model shows that it was able to predict the cost of building construction projects at the early stage of the construction. This study contributes to construction management and provides the idea about the entire financial budget that will be helpful for the property owners and financial investors in decision making and also to manage their investment in the volatile construction industry.

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1. Introduction

Cost estimation at an early stage of construction projects along with accuracy has been a major challenge in the construction industry for decades [1,2] The estimates are generally carried out in each and every phases during the project life cycle and it plays an important role in the success of every civil engineering projects [3,4]. During the early stage (feasibility), limited information is available for the cost estimation process and becomes a very difficult task to estimators and project engineers [5]. At such conditions, an appropriate estimation plays an imperative role in the financial management that provides the design of budget to the investors and hence better decisions can be made [6]. It is also helpful to the project manager to manage their available resources and cash reserve funds during the entire project execution stages.

Several prediction modeling techniques have been introduced for construction cost estimation such as statistical regression models, case-based reasoning model, support vector machine model and artificial neural networks (ANNs) [7]. Development of such modeling techniques is generally based on the historical data of the previous projects and construction experience along with prior knowledge of estimators. Based on the literature study, the neural network has the ability to learn effectively from previous work and can be applied as a suitable tool for the development of cost estimation modeling [1].

Generally, the cost of building includes numerous parameters such as; structural skeleton system, interior, and exterior walls, finishing works, mechanical and electrical works, etc. and about 60% cost is the materials used for such construction elements [8]. The structural skeleton system including foundation contributes a major part in the total cost of residential building projects and hence careful attention must be taken by the architect as well as structural designers during the design of all structural members. After completion of successful literature survey and interview with expertise related to the Indian construction industry, the most influential design parameters of the cost of the building were identified. The neural network generally requires a similar type of dataset for better predictions; hence dataset of recently constructed 78 building projects was collected from the design professionals, architects and construction contractors working in the city of Mumbai area India and its nearby regions. The purpose of this research was to identify the most influencing design parameters and attempts to develop neural networks models that can be used further for the estimation of building construction cost during the progress of the construction. The most widely used, multilayer feedforward neural networks along the necessary training associated with backpropagation algorithm are utilized. Early stopping criteria and regularization approaches are applied during the implementation for better generalization and also to avoid overfitting and later outcomes of both the approaches were compared on the basis of regression performance as well as error criteria [9]. Such cost estimation models can be helpful to the design professionals in decision making at the early stage of construction and better control on the project.

2. Literature review

Numerous applications of artificial neural networks in the various field of civil engineering are reported for prediction as well as optimization. Few of them in the construction project cost predictions are discussed in this section. Smith and Mason [10] introduced a cost estimation relationship (CER) by comparing regression as a statistical and artificial neural network model. Adeli and Wu [9] discussed the learning rules as well as weight optimization for the regularization of neural networks. They developed a neural network model that includes the cost factors as a reinforced-concrete pavement quantity and the thickness of the pavement while the unit cost of highway construction was the output. Hegazy and Ayed [4] developed a parametric cost estimation model for highway construction cost using eighteen cases from Newfoundland, Canada. Simplex optimization; and genetic algorithms (GAs) approaches were applied for effective weight optimization during the training of the neural network. Attala and Hegazy [11] compared statistical regression and artificial neural network model for prediction of cost deviations in reconstruction projects. 36 identical factors from the 50 reconstruction projects were identified having a direct influence on cost performance. It has been concluded that the neural network is having better prediction capability as compared to regression if uncertainty in data prevails. Gunaydın and Dogan [8] presented artificial neural network model by utilizing cost factors such as the ratio between typical floor area and total area, the ratio between ground floor area and total area, number of floors, console direction of the building, foundation, etc. for the early stage construction cost prediction. The result showed that 93% accuracy in prediction performance as well as low error criteria (MSE) indicating a good cost estimation. Kim et al. [12] examined three different models such as regression, neural network, and case-based reasoning by using 530 cost historical data set. They used a total of 9 cost factors such as floor area, finishing grades, duration, etc. for their study. The performance of these three approaches is measured on MAER criteria indicating better performance by the neural network estimation compared to the regression as well as case-based reasoning model. Liu et al. [13] discussed an approach of fuzzy neural networks for real estate cost prediction based on hedonic price theory. Lowe et al. [14] designed a framework using a linear regression model to predict the construction cost of the building while incorporating 286 sets of data. They developed the best regression model indicating a better coefficient of determination R^2 of 0.661 along with 19.3% of mean absolute percentage error. Shehab et al. [15] applied a neural network approach versus regression for early and accurate prediction of water and sewer network rehabilitation projects cost. The result was compared and observed that the performance of the neural network approach was better over the regression. Wang et al. [16] contributed a comparative study of neural network and support vector machine for prediction of project cost and schedule success. Naik and Kumar [17] developed an artificial neural network trained with the backpropagation algorithm for prediction of G+3 housing projects utilizing 512 data sets. Gulcicek et al. compared the neural network model with a regression approach for prediction of the unit cost of construction. They identified structural parameters such as the number of floors, earthquake zone, soil type, building importance factor, floor area, and total area for the development of multiple linear regressions as well as investigated the building importance factor as the most influential factor. Further, they have compared regression model with a neural network approach and concluded that ANN model performed better than the other one. Hayeri et al. [6] developed ANN model for the construction cost prediction. The gradient descent (*traingd*), gradient descent with momentum (*traingdm*), variable learning rate (*traingdx*), resilient backpropagation (*trainrp*), Levenberg-Marquardt (*trainlm*) and Powell-Beale restarts (*traincgb*) training algorithms were applied for the development of the neural network. Gardner et al. [18] compared two approaches; artificial neural networks and bootstrap sampling in a case study of 189 highway projects for the development of highway cost estimating the model. The next section discusses the methodology adopted in this research work.

3. Methodology adopted

The research method adopted in this study indication with important stages is given in Fig. 1.

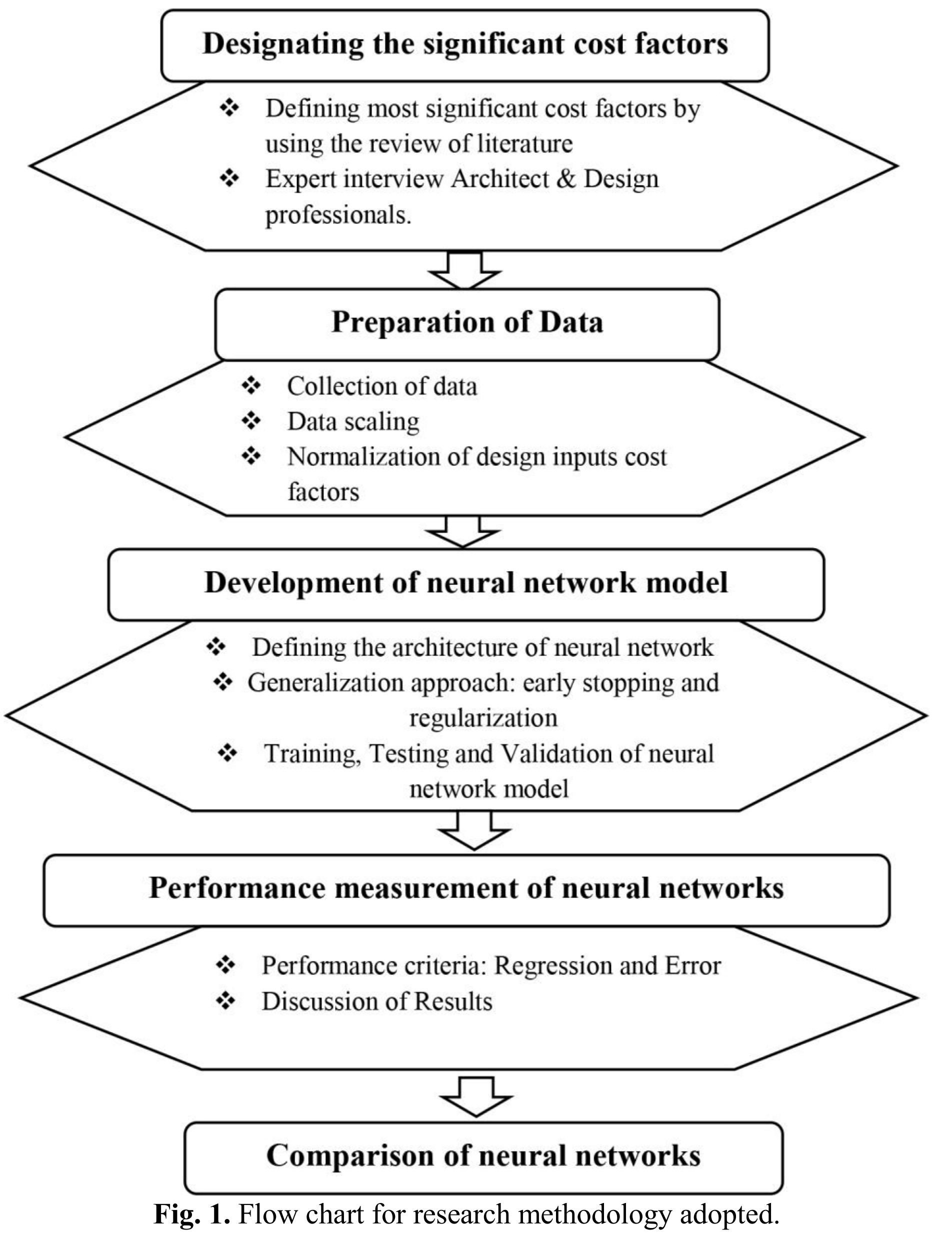

Fig. 1. Flow chart for research methodology adopted.

4. Designating the significant cost factors

Identification of the most important factors having a greater impact on building construction cost is essential to develop a neural network model. Investigating the most influential cost parameters has been done based on the literature review. Some of the cost parameters were identified by conducting expert interview and recommendation taken from the engineering firms, architects and design professionals of construction industries in India. It includes a total of six structural skeleton cost factors and other four having a major impact on cost as well as finishing work cost factors. Table 1 gives the most significant parameters that were implemented in this research and used as design input parameters for the development of neural network models.

Table 1
Inputs and Output Design Parameters.

Sr. No.	Portrayal of Input-Parameters	Data Range involved
X_1	Ground Floor Area	55.46 - 1409.86 (m^2)
X_2	Typical Floor Area	0 - 1801.21 (m^2)
X_3	Number of Floors	1 - 15 Nos.
X_4	Structural Parking Area	0 – 571.66 (m^2)
X_5	Quantity of Elevator Wall	0 – 374.61 (m^3)
X_6	Quantity of Exterior Wall	24.45 – 842.94 (m^3)
X_7	Quantity of Exterior Plaster	59.68 – 2001.83 (m^3)
X_8	Area of Flooring	95.37 - 11491.71 (m^2)
X_9	Number of Columns	14 – 138 (Nos.)
X_{10}	Types of foundation	Isolated footing Isolated and combined footing Raft foundation
X_{11}	Number of householders	1 – 129 (Nos.)
Y	Total cost of project	1,46,6277 – 21,79,59,593 (INR) INR= Indian National Rupees

5. Preparation of database

Data was collected from the under construction 78 building projects and required important documents were also collected from the various engineering firms, architectures, contracting companies, builder and developers as well as the owner of the buildings in and around the city of Mumbai, India. The collected dataset includes a housing bungalow, small and medium scaled apartment projects which were recently constructed [7] and some of them having a time schedule of completion between the years 2017-2019. Asymmetry types of buildings are usually avoided [1] during the collection of data for self-learning by the network and better prediction.

6. The architecture of multilayered feedforward network

The backpropagation learning algorithm was used to train the multilayer feedforward neural networks. A typical feedforward neural network generally includes an input layer, one or more hidden layers, and an output layer. The total eleven cost parameters were designated as input and weighted with an appropriate weight '*w*'. The sum of the weighted inputs and the bias forms the input to the transfer function '*f*' to generate the output which is the total cost of project [19].

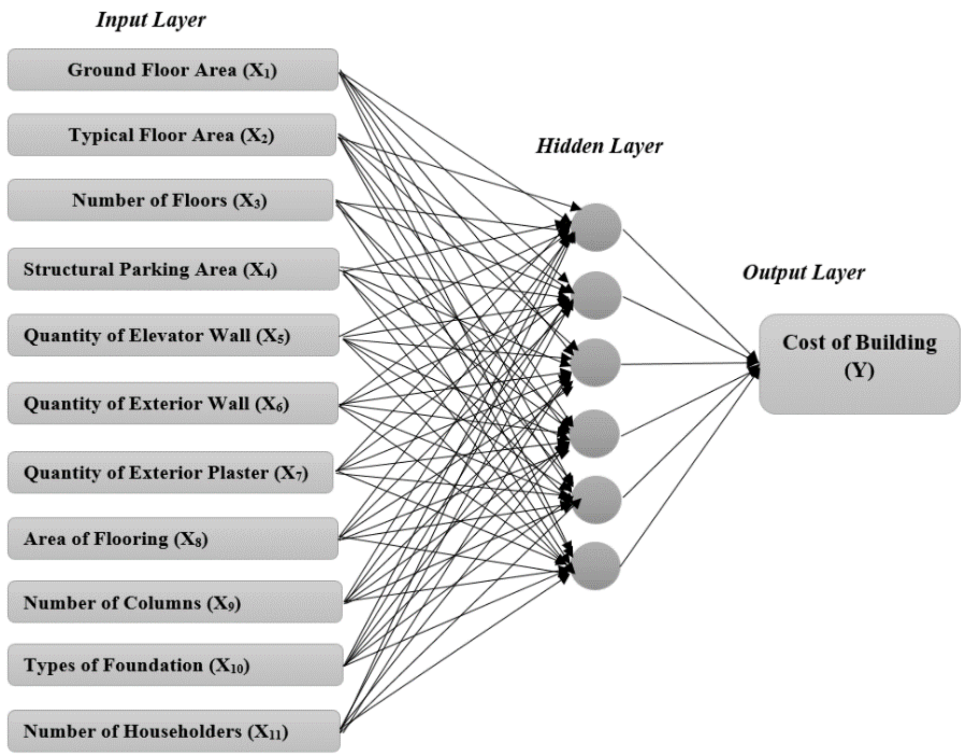

Fig. 2. The architecture of a single layer Feed-forward back propagation network (11-6-1).

The sample architecture of a single-layer feedforward network having eleven inputs (input layer), a single hidden layer and a single output (output layer) is shown in Fig. 2.

The analysis is implemented with two layers (one hidden layer) as well as three layers (two hidden layers) to check the performance of networks. The increment in a number of neurons applied through hidden layers increases the strength of network [19], but for adequate fitness, neurons are set as 5, 10 and 15. The various combinations of log-sigmoid (*logsig*), tan-sigmoid (*tansig*) and linear (*purelin*) activation functions are utilized for multilayer networks. Three different network architectures, according to neuron's arrangement in the hidden layer as 1, 5 and 10 are developed to measure the performance of the neural network model. A sigmoid transfer function is applied in the hidden layer and a linear transfer function for the output layer of the neural network.

6.1. Training of the neural network model

The most widely used backpropagation algorithm is used during the training of feedforward neural network. The neural network toolbox of the MATLAB R2015a version software is used to create a network architecture, training, validation, and testing of the networks [19]. The most important steps involved during the training phase of the feedforward neural network are shown in Fig. 3.

Over-fitting or poor generalization is the major problem because of over learning of network during its training and it may result in less performance on the new state of affairs. The early stopping and regularization [19] approaches are applied for the better generalization capability of neural networks as well as to avoid the overfitting.

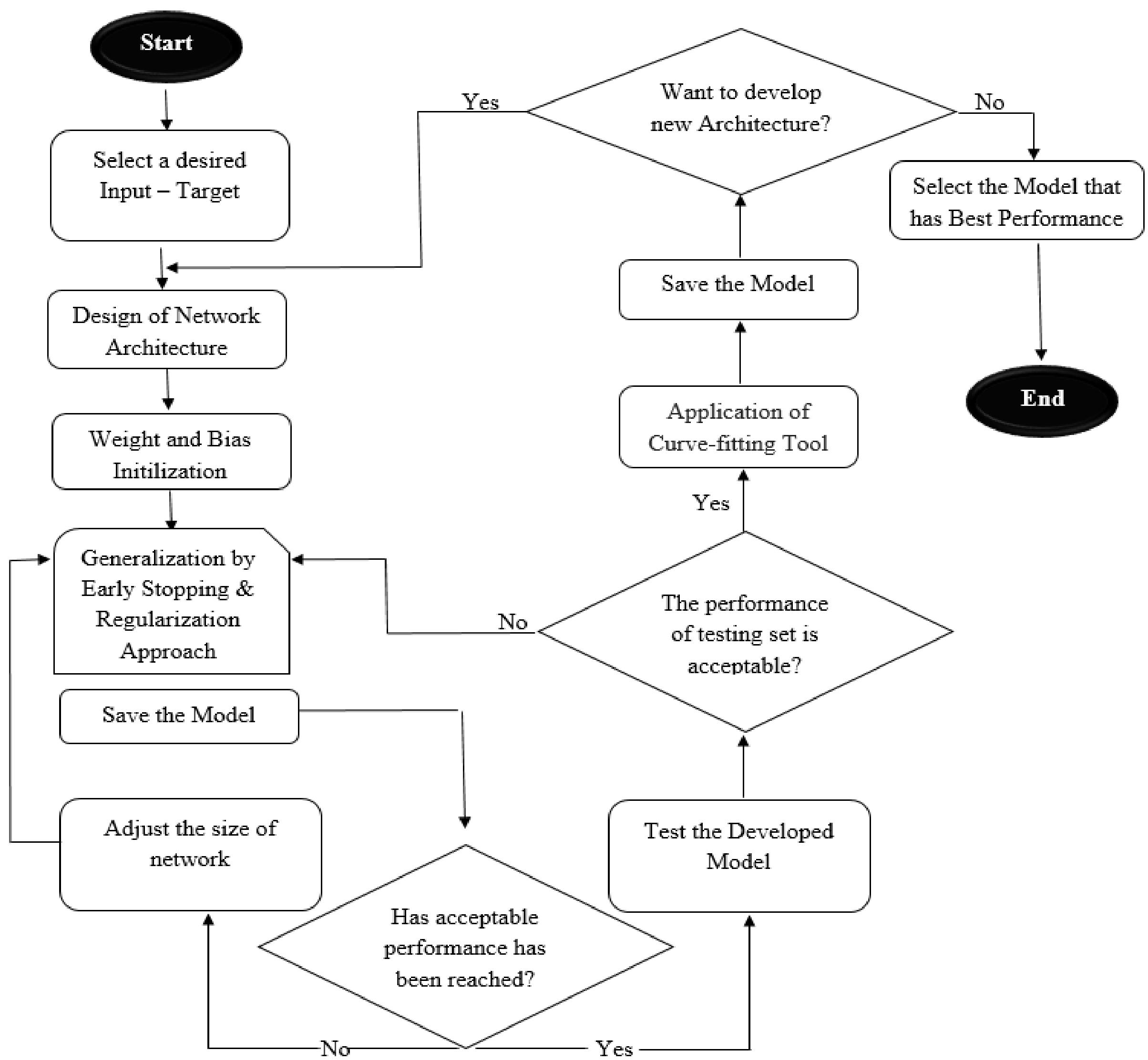

Fig. 3. Training procedure of feedforward neural network.

6.2. Early stopping approach

The first approach is implemented is early stopping as it is most widely used to avoid the network from overfitting with effective manner. The data set is divided into three subset categories. The first subset is implemented as the training set and it plays an important role in the computation of gradient as well as initialization of weights and biases to the network. The second subset, the validation set monitors the error occurring through the training procedure. During the training process of network, the validation error generally decreases at the early phase, but when the network starts overfitting of the dataset, the validation error increases. The training process is stopped after reaching specified numbers of repetitions, the weights and biases are initialized at a minimum level. The third subset, the test set is generally not used during the training, but it is very suitable to compare different networks as well to check the design and performance network. The training functions are applied for early stopping approaches are; Levenberg-Marquardt (*trainlm),* scaled conjugate Gradient (*trainscg*) and gradient descent (*traingd*).

6.3. Regularization approach

The second approach implemented is regularization to modify the performance function in order to achieve the best generalization. The regularization is carried out in an automated approach [20] giving the mean sum of squares performance function as utilized throughout the training process of feedforward neural networks to investigate network errors. The Bayesian regularization (*trainbr*) training function is implemented to carry out the regularization approach.

7. Performance measurement of ANN model

The performance of neural network models is carried out on the basis of error criteria and regression criteria which plays an important role in the comparison of developed neural networks. Following are the important criterion and it is implemented in this study;

7.1. Mean squared error (MSE)

The performance of the trained neural network model was measured by mean squared error (MSE) performance function. *MSE* between targeted cost and predicted cost developed by the neural network is calculated using equation 1;

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

where;

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

7.2. Root mean squared error (RMSE)

The root mean square error is used to offer an overall illustration of the errors occurred during the prediction and also plays a significant role in judging the model. The adequate fit of the trained network represents the lower value of RMSE. Equation 2 is used to determine the *RMSE*;

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(fi\ .\ Oi)^2} \tag{2}$$

where, N = prediction /observation pairs, f = prediction and O = Observation.

7.3. Regression (R)

The regression (R) value represents the correlation between the outputs (predicted cost) and targets (actual cost). The value regression (R) characterizes the precise linear association between outputs and target. If the value of (R) is near about one, then it is the indication of a robust linear relationship between outputs and target and vice-versa.

$$R = \frac{\Sigma(x.y)}{[(\Sigma x^2 \Sigma y^2)^{1/2}]} \tag{3}$$

where, $x = X - X'$, X is the target output (actual cost); X' is the mean of X and

$y = Y - Y'$, Y is the network output (predicted cost); Y' is the mean of Y.

7.4. Coefficient of determination (R^2)

Coefficient of determination (R-squared) [19] designates the proportional sum of the difference between the outputs (predicted cost) and targets (actual cost). R-squared is the amount of the total sum of squares and property of R-squared is categorized in two fields;

- Ordinary — Ordinary (unadjusted) R-squared [19]

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \tag{4}$$

- Adjusted R-squared adjusted [19]

$$R^2_{adj} = 1 - (\frac{n-1}{n-p})\frac{SSE}{SST} \tag{5}$$

where SSE is the sum of squared error, SSR is the sum of squared regression, SST is the sum of the squared total, n is the number of observations, and p is the number of regression coefficients [19].

8. Results and discussion

Several trials topologies were conceded in this study to get the most appropriate one along with a higher degree of accuracy. The mean square error (MSE) is utilized as a performance function to investigate the error between target and network output, as well as with the help of curve fitting tool the Root Mean Square Error (RMSE) and Sum Square Error (SSE) are also calculated. The regression criteria; Overall Regression (R), Coefficient of Determination (R-square) and R-Adjacent (R^2_{adj}) are applied to find the correlation between target cost vs. predicted cost (network output).

According to the thumb rule, the product of input layer neurons, hidden layer neurons, and output layer neurons represents the number of required samples for the development of neural network architecture [21]. Total 36 trials were run for the generalization of neural network and the characteristics of most suitable feed-forward backprop neural networks (early stopping and regularization approaches). The training functions, activation functions, number of hidden layers, the arrangement of the neurons' in the hidden layers and performance measurement criteria are given in Table 2. The database of 78 building projects is divided into three subsets, where 70% of the data set (54 sample sets) is used during the training phase, 15% (12 sample sets) for validation phase and remaining 15% (12 sample sets) for the testing purpose.

Table 2
Performance of the Different Networks.

Sr. No.	Training Function	Transfer Function	Hidden Layer	Neuron's Arrangement	Mean Square Error (MSE)	Root Mean Square Error (RMSE)	Sum Square Error (SSE)	Overall Regression (R)	Coefficient of Determination (R-square)	R-Adjacent (R^2_{adj})
1	*Trainlm* (Early Stopping)	*tansig, logsig, purlin.*	1	11-1-1	-0.0010	0.1377	1.422	0.8248	0.6804	0.6762
				11-2-1	-0.0111	0.09675	0.7114	0.9487	0.9002	0.8989
				11-3-1	-0.0213	0.2155	3.528	0.8538	0.7291	0.7256
				11-4-1	0.01016	0.07633	0.4427	0.9663	0.9339	0.933
				11-5-1	-0.0114	0.0790	0.4752	0.9597	0.9211	0.9201
				11-6-1	**-0.0051**	**0.02469**	**0.0463**	**0.9959**	**0.9920**	**0.9919**
				11-7-1	-0.0093	0.0943	0.6759	0.9530	0.9084	0.9072
			2	11-1-1-1	0.00376	0.07307	0.4057	0.9445	0.8922	0.8908
				11-2-2-1	-0.0108	0.09211	0.6448	0.9575	0.9169	0.9158
2	*Trainscg* (Early Stopping)	*tansig, logsig, purlin.*	1	11-1-1	-0.0087	0.09076	0.6261	0.9411	0.8857	0.8842
				11-2-1	**-0.0042**	**0.04943**	**0.1857**	**0.9774**	**0.9554**	**0.9548**
				11-3-1	-0.0031	0.08407	0.5371	0.9254	0.8565	0.8546
				11-4-1	-0.0007	0.08058	0.4935	0.9294	0.8639	0.8621
				11-5-1	-0.0171	0.14410	1.577	0.8767	0.7688	0.7657
				11-6-1	0.0012	0.05915	0.2659	0.9715	0.9438	0.9431
				11-7-1	-0.0105	0.1056	0.8469	0.9317	0.8682	0.8664
			2	11-1-1-1	-0.0171	0.1085	0.8943	0.9399	0.8835	0.882
				11-2-2-1	-0.0071	0.08189	0.5096	0.9404	0.8845	0.8829
3	*Traingd* (Early Stopping)	*tansig, logsig, purlin.*	1	11-1-1	-0.0401	0.1476	1.655	0.8737	0.7635	0.7604
				11-2-1	-0.0002	0.1067	0.8649	0.8727	0.7617	0.7585
				11-3-1	**-0.0073**	**0.09819**	**0.7327**	**0.9320**	**0.8686**	**0.8669**
				11-4-1	-0.0528	0.1904	2.7540	0.8467	0.7170	0.7132
				11-5-1	-0.0171	0.07732	0.4543	0.9079	0.8243	0.822
				11-6-1	-0.0103	0.09759	0.7238	0.9207	0.8477	0.8457
				11-7-1	0.03484	0.1237	1.164	0.8891	0.7907	0.7879
			2	11-1-1-1	-0.0255	0.1552	1.831	0.8594	0.7309	0.7273
				11-2-2-1	-0.0090	0.07923	0.4771	0.8922	0.7961	0.7934
4	*Trainbr (Regulari -zation)*	*tansig, logsig, purlin.*	1	11-1-1	-0.0001	0.06835	0.3551	0.9626	0.9268	0.9258
				11-2-1	-0.0020	0.03678	0.1028	0.9902	0.982	0.9817
				11-3-1	**-0.0022**	**0.02469**	**0.04633**	**0.9960**	**0.9922**	**0.9921**
				11-4-1	-0.0072	0.04768	0.1728	0.9860	0.9723	0.972
				11-5-1	-0.0034	0.06703	0.3415	0.9733	0.9478	0.9471
				11-6-1	0.0094	0.04758	0.1721	0.9855	0.9712	0.9708
				11-7-1	-0.0113	0.09308	0.6584	0.9572	0.9164	0.9153
			2	11-1-1-1	-0.0060	0.05905	0.265	0.9736	0.9479	0.9472
				11-2-2-1	-0.0144	0.1038	0.8195	0.9483	0.8994	0.8981

During the early stopping approach, networks are trained with three different training functions are; '*trainlm', 'trainscg'* and *'traingd'*. In the training process of single hidden layer neural networks, the tan-sigmoid (*tansig*) activation function is applied in the hidden layer as well as in the output layer and during the training of two hidden layer neural networks, the tan-sigmoid (*tansig*) activation functions are applied in hidden layer and the linear (*purelin*) was in output layer. This study attempts to investigate the effects of a number of neurons in the hidden layer on the training process of the neural network.

During the training of all network, it was observed that the Levenberg-Marquardt (*trainlm)* with network architecture 11-6-1 (eleven inputs, six neurons in the single hidden layer and one output) gives the best results as compared to other ones. The best training performance is based on the average mean square error (MSE) as is shown in Fig. 4. After 18 epochs the network achieved the best validation performance. The properties of validation, as well as testing performance, look similar and acceptable. The next performance measurement is the regression plots between target and network output as shown in Fig. 5. The regression plot includes; the overall correlation coefficient (R) = 0.9959; indicating the strong relation between the target and output. The output is calculated by multiplying target with slope (0.97) and the addition of y-intercept (0.016) of linear regression. The dashed line represents the 45degree fit line indicates the best fit, where the dataset should fall along with it and the value of correlation coefficient (R) and y-intercept of linear regression should be near about 1 and zero respectively.

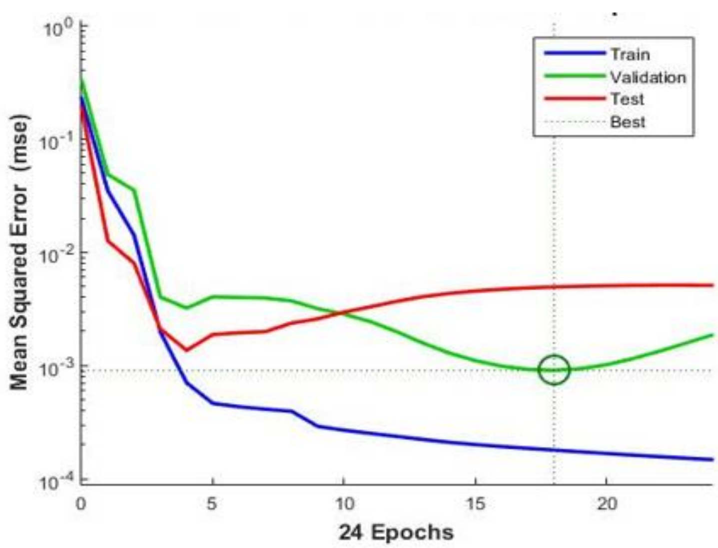

Fig. 4. Network Performance associated with 11-6-1 network (*trainlm*); Best validation performance is 0.0009034 at epoch 18.

As shown in Fig. 5, the network architecture (11-6-1) has satisfied the values of correlation coefficient (R), slope and y-intercept during training, validation and testing phase. The curve fitting tool provides the coefficient of determination (R-squared) and it designates the proportional sum of the difference between the outputs (predicted cost) and targets (actual cost) as shown in Fig. 6.

The MSE performance function and Bayesian Regularization (*trainbr*) training function was implemented during the regularization approach. It is observed during the training of different network that the network architecture, that the performance of all networks are satisfactory but 11-3-1 architecture generates the best performance and also there was no change in increment in hidden neurons in hidden layers. In the training process of single hidden layer neural networks, the log-sigmoid (*logsig*) activation function is applied in the hidden layer as well as in the output layer. During the training of two hidden layer neural networks, a log-sigmoid (logsig) activation function is applied in hidden layer and the tan-sigmoid (*tansig*) was in the output layer. Also, another activation function was implemented with hidden and output layer but no such difference was observed.

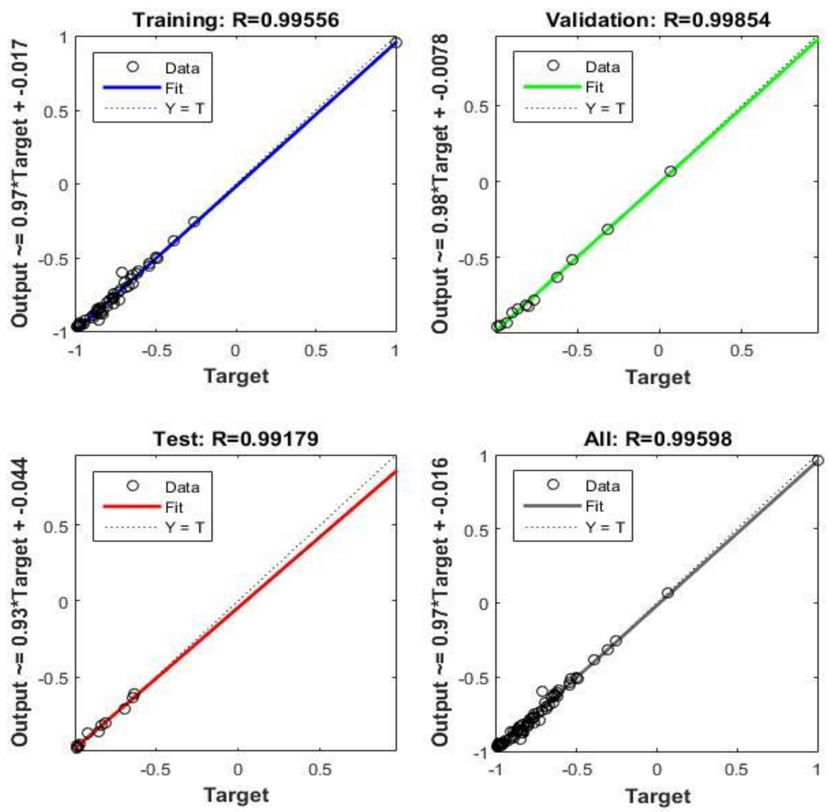

Fig. 5. Regression plot associated to 11-6-1 network (*trainlm)* (MSE = -0.0051).

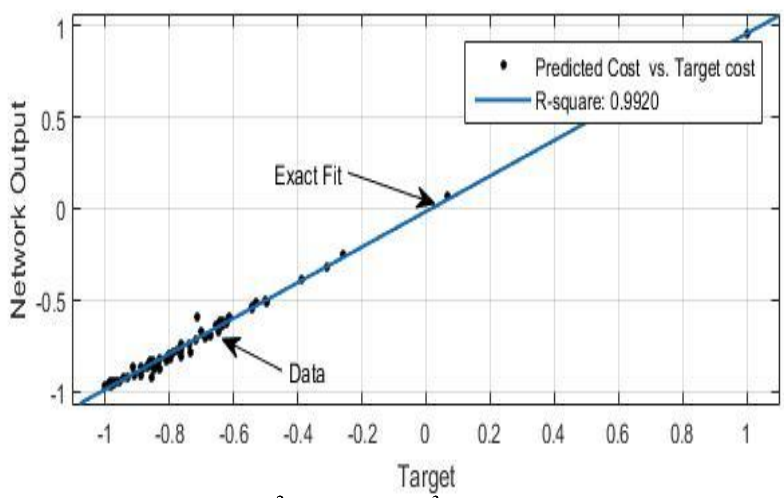

Fig. 6. Predicted Cost vs. Target Cost. (R^2 = 0.9920, R^2_{adj} = 0.9919, RMSE = 0.02469and SSE = 0.0463).

During the training process of Regularization approach, the network architecture11-3-1 has the best training Performance is 0.0002454 at epoch 197 training performance is shown in Fig. 7.

The regression plot having correlation coefficient (R), slope and y-intercept values of 0.9944, 0.98 and 0.010 indicates that it has satisfied all the best-fit criteria shown in Fig. 8. Fitness between the network outputs (predicted cost) and target (actual cost) with respect to the coefficient of determination (R-squared) is shown in Fig. 9.

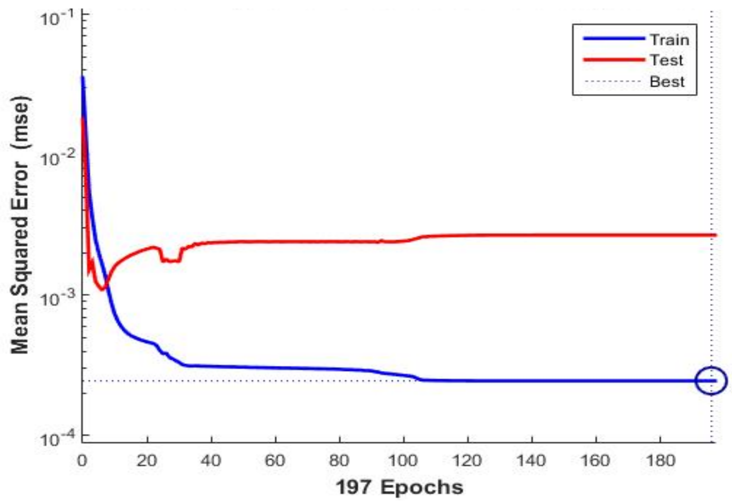

Fig. 7. Network Performance associated with 11-3-1 network (*trainbr*); best training performance is 0.0002454 at epoch 197.

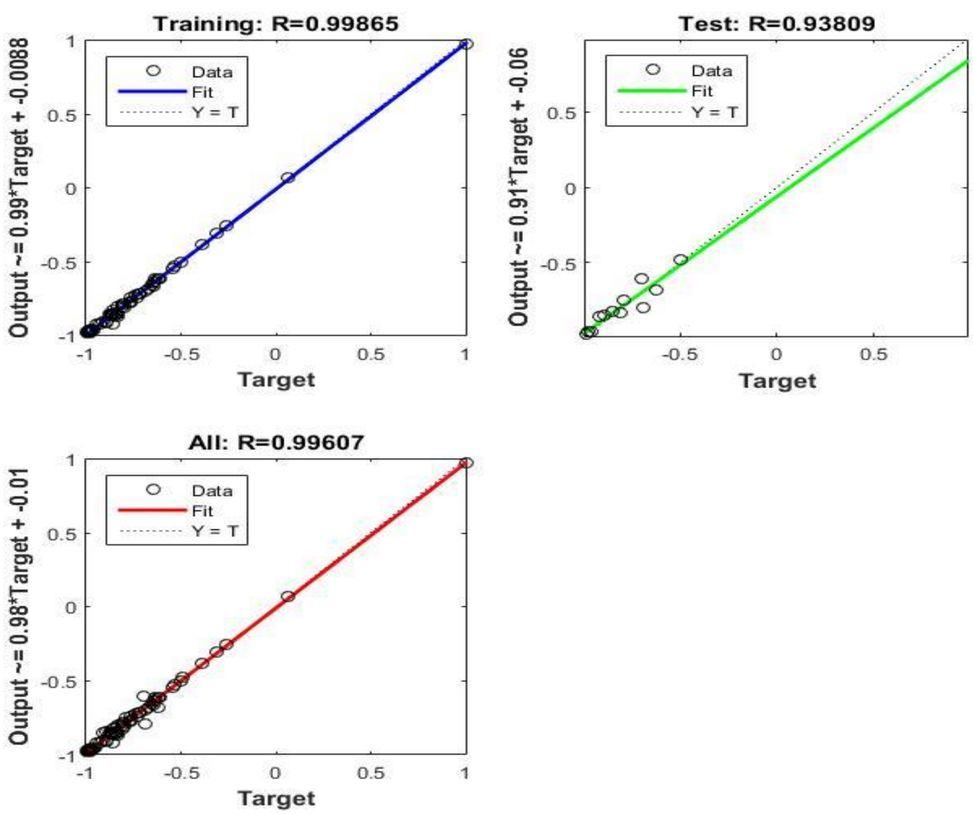

Fig. 8. Regression plot associated to 11-3-1 Bayesian Regularization network (trainbr) (MSE = -0.0022).

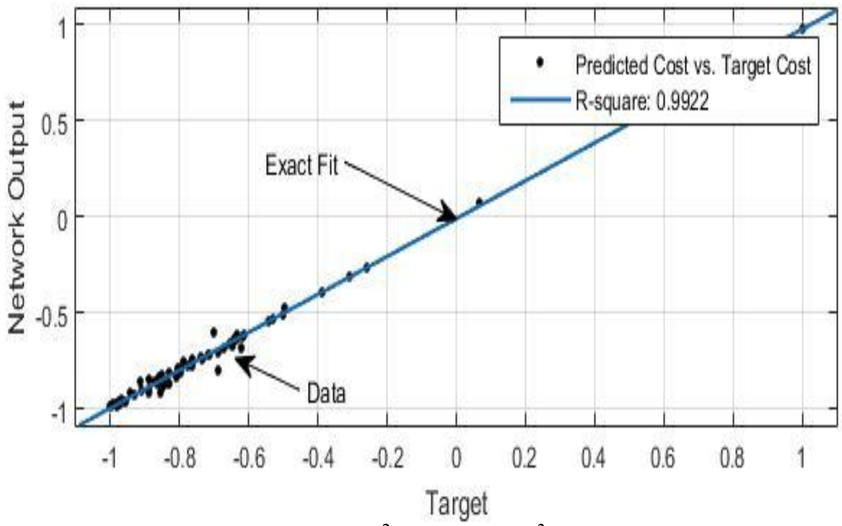

Fig. 9. Predicted Cost versus Target Cost. (R^2 = 0.9922, R^2_{adj}= 0.9921, RMSE = 0.02469and SSE = 0.04633).

The matrix of weights initialized to inputs and bias connected to the neuron of the neural network architecture 11-6-1 (*trainlm*) and the neural network architecture 11-3-1 (*trainbr*) are given in Table 3 and Table 4 respectively.

Table 3
Connection weights and bias for each input parameters of 11-6-1 network (*trainlm*)

Sr. No.	Connections	Weights to Hidden Layer	Bias	Sr. No.	Connections	Weights to Hidden Layer	Bias	Sr. No.	Connections	Weights to Hidden Layer	Bias
1	1-1	-0.37142	1.445	2	1-2	0.47012	-0.96307	3	1-3	0.47938	0.35444
	2-1	0.25008			2-2	0.61968			2-3	0.68250	
	3-1	0.13277			3-2	0.41823			3-3	-0.51876	
	4-1	0.19299			4-2	0.35377			4-3	0.38275	
	5-1	0.18028			5-2	0.15753			5-3	0.75394	
	6-1	-0.6226			6-2	0.38243			6-3	-0.52233	
	7-1	-1.1335			7-2	0.46605			7-3	-0.009603	
	8-1	-0.76879			8-2	0.12490			8-3	-0.50504	
	9-1	-0.26825			9-2	0.09796			9-3	0.15243	
	10-1	0.86943			10-2	-0.73889			10-3	0.029262	
	11-1	0.022039			11-2	-0.05330			11-3	-0.13558	
4	1-4	0.61946	0.00170	5	1-5	0.3486	1.6206	6	1-6	0.026296	-1.5086
	2-4	0.67337			2-5	-0.083759			2-6	028154	
	3-4	-0.70191			3-5	1.0362			3-6	0.095937	
	4-4	0.30923			4-5	-0.74929			4-6	-0.84083	
	5-4	1.0064			5-5	0.65212			5-6	0.95576	
	6-4	-0.72625			6-5	0.28556			6-6	0.7033	
	7-4	-0.81784			7-5	-0.36366			7-6	-0.48618	
	8-4	-0.41426			8-5	-0.085608			8-6	0.81102	
	9-4	0.26346			9-5	-0.48268			9-6	0.85018	
	10-4	-0.14971			10-5	0.10596			10-6	-1.5587	
	11-4	-0.45857			11-5	-0.64942			11-6	-0.28107	

Table 4
Connection weights and bias for each input parameters of 11-3-1 network (*trainbr*)

Sr. No.	Connections	Weights to Hidden Layer	Bias	Sr. No.	Connections	Weights to Hidden Layer	Bias	Sr. No.	Connections	Weights to Hidden Layer	Bias
1	1-1	0.70605	0.79567	2	1-2	0.79101	-1.8344	3	1-3	1.0582	-1.5078
	2-1	1.9581			2-2	0.44727			2-3	1.1108	
	3-1	-0.81162			3-2	-1.3146			3-3	-2.2292	
	4-1	-0.45154			4-2	-0.62523			4-3	-0.94512	
	5-1	-0.51705			5-2	-1.6696			5-3	1.0175	
	6-1	-0.97715			6-2	-0.058074			6-3	1.5513	
	7-1	1.4975			7-2	1.035			7-3	-0.49419	
	8-1	0.24203			8-2	-0.57201			8-3	-0.025767	
	9-1	0.67613			9-2	0.32479			9-3	0.48716	
	10-1	0.2406			10-2	-0.32418			10-3	-1.6128	
	11-1	-1.4344			11-2	-0.48961			11-3	1.1898	

9. Conclusion

The basic aim of this research was to develop a neural network based self-learning model for estimation building construction cost at an early stage of construction. The most important and significant cost factors were identified on the basis of literature as well as from the construction industry professionals and these are the deciding factors as input parameters for the development of a feed-forward multilayer back propagation neural network. 78 building's database and required important documents were collected from the various engineering firms, architectures, contracting companies, construction builders and developers as well as the owner of the buildings from the city of Mumbai, India.

Two different approaches are introduced for the development of ANN model; the early stopping and regularization for the better generalization capability of neural networks as well as to avoid the overfitting. Several trials were run to and identified the most appropriate network architecture. The performance measurement of the developed ANN models is carried out on the basis of error and regression criteria. The outcome of the study indicates that the regularization approach performs better than the early stopping approach. The network architecture 11-3-1 along with the training function the Bayesian Regularization (*trainbr*) perform better in terms of the best results as compared to others. Result obtained has also demonstrated higher regression coefficient (R^2, R) and lower root mean squared error (RMSE), mean square error (MSE) and sum square error (SSE).

A trained neural network can successfully predict early-stage construction cost and it is also observed that the accuracy in prediction increases with the data size. A data-mining approach of ANN can predict early-stage construction cost of building construction project satisfactorily that can be useful to the stakeholders including financial investors in the construction industry.

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