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Cost Estimation Model (Cem) for Residential Building using Artificial Neural Network

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*Abstract***— The achievement of any project undertaking is defined by improved quantity and cost estimation technique that facilitates optimum utilization of resources. The objective of this study is to develop a cost estimation technique by using an artificial neural network (ANN) model that will be able to forecast the total structural cost of residential buildings by considering various parameters. In this study, data of last twenty three years has been collected from Schedule of rate book (SOR) and general studies. Eight input parameters, namely, cost of cement, sand, steel, aggregates, mason, skilled worker, non-skilled worker and the contractor per square feet construction were selected. The parameters were simulated in NEURO XL Version 2.1 for developing ANN architecture. The resulting ANN model reasonably predicted the total structural cost of building projects with correlation factor R-0.9960 and RSquared-0.9905 giving favorable training and testing phase outcomes.**

Keywords— Artificial Neural Network (ANN), Correlation Factor, Cost estimation, Model, Variables

I. INTRODUCTION

Cost is probably the first to be considered when it comes to construction projects. Accurate estimation of quantities and costs incurred in a construction project is a crucial factor in its achievement [1]. Because of the complexity of the construction industry and individuality of every project undertaking, several factors may affect the overall project cost. A number of objects, such as the structural, architectural, sanitary, electrical and air-conditioning system workings conclude the total cost of buildings. Olotuah, 2002, observed that building resources incur approximately 60% of the total cost of a residential building [2]. Meanwhile, the structural casing covers 25% of total construction cost in a multi-storey reinforced concrete residential building. Therefore, greatest worry must be exercised in the design of structural systems if a considerable reduction in cost is preferred. However, consistency and accuracy of available cost estimating techniques are matter of concerns presently. Thus, now there is a growing need to deal with the concerns by introducing a new and alternative approach for estimation of cost and to identify the factors responsible for variation of cost.

Usually, the ordinary least squares regression approach is applied and the replica is selected based on the coefficient of determine, R2. However, because of high correlation among a great group of variables, this technique tends to generate regression coefficients estimators that will badly perform in the presence of multi-collinearity [3]. Furthermore, the variance of the usual least squares estimator become inflated, which results in the low prospect of the estimator being close to the correct value of the regression coefficient [4]. This can be rectified by determining uncorrelated variables to be included in the regression model. Lots of quantity and cost estimation models have been developed. Linear regression is a very useful statistical device for analyzing and predicting the input of a potential new item to the overall approximation. Several other methods have been applied for the cost estimation, such as, principle component study, case-based reasoning and ANN.

Artificial neural networks can model complex non-linear relationships and approximate any assessable function. ANN is a powerful means to handle non-linear problems and subsequently map relations between complex input/output data and address uncertainties [5]. They are particularly helpful in problems where there is a complex relationship between an input and output. The main advantage ANN models have over physically based models is that they are data-driven and underlying contact using examples of the desired input output mapping [6].

Ismaail EISawy et al (2011) tried to develop a parametric cost-estimating model fifty-two actual real-life cases of building projects, in Egypt, constructed during 2002-2009 and achieved an accuracy of 80% [7]. Jamshid Sodikov (2005) developed a more accurate estimation technique for highway projects in developing countries at the theoretical phase using artificial neural network [8]. H.Muarat et al (2004) in Turkey, used training and testing data from thirty projects of 4–8 storey reinforced concrete structure by neural network methodology, achieving an average cost estimation accuracy of 93% [9]. Emad Elbeltagi (2014) developed an ANN model to predict the cost of highway structure projects in Libya by considering various factors that influence the highway construction [10].

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The motive of this work is to explore the ANN technique and predict the total structural cost of buildings and to determine the factors which affect the cost of buildings. Hence a cost estimation model (CEM) has been developed using artificial neural networks, particularly multi-layer feed forward neural networks. The back propagation knowledge algorithm is used to instruct the network by iteratively processing a set of training sample and compare the network's prediction with the real. The variation in the estimation is propagated to the input for adjusting the coefficients. To accomplish this goal, structural cost data from past twenty three years from 1993 to 2015 were collected and were used simulated in ANN SOFTWARE.

II. METHODOLOGY

In this study a frame work has been developed for estimating the variation & construction cost for residential building. All the models where developed using data of input variables like cost of cement, sand, steel, aggregate, mason, skilled, non-skilled, Formwork, Brick work etc (Table 1). Also the rates of material that is input variables has been taken from Schedule of rate book of last 20 years. Pentium 4 class P.C. with window XP operating system is used to run NEURO XL Version 2.1 Artificial Neural Network software. For all the models, total data set is divided into training set (68%), validation set (16%), and test set (16%).

Table 1 Input parameters for ANN model.

Year	Cement (Rs/bag)	Sand (Rs/ft^3)	Steel (Rs/kg)	Aggregate (Rs/ft^3)	Mason (Rs/day)	Skilled Labor (Rs/day)
1993	80	2	6	2	110	50
1994	90	2	7	2	120	55
1995	100	3	9	2	125	60
1996	110	4	10	3	130	65
1997	120	5	12	3	135	65
1998	125	5	13	4	140	70
1999	130	6	15	4	145	75
2000	135	7	17	5	150	75
2001	135	9	17	5	155	80
2002	140	12	18	6	155	90
2003	145	15	19	6	160	95
2004	145	18	20	7	165	95
2005	150	19	21	7	170	105
2006	155	20	22	8	175	100
2007	160	22	23	8	180	120
2008	178	23	25	9	200	120
2009	190	24	28	10	220	150
2010	200	25	30	12	250	200
2011	200	25	33	16	300	250
2012	225	30	38	18	350	250
2013	260	40	40	20	400	300
2014	260	40	48	40	425	340
2015	290	60	34	23	450	360

Selection of parsimonious ANN structure was accomplished by first fixing the number of hidden layers and then choosing the number of nodes in each of these layers. For larger networks, computational costs are high and might overfit the training data with too many nodes. The presentation of one- hidden layer ANN is found to be better than two hidden layers ANN [11]. Nodes in the hidden layers, are very important for characteristic extraction from the patterns of input time series, they normally have a very small weight changes and learn very slowly [12, 13]. Here single hidden layer is used to generate feed-forward entirely-connected neural network (multi-layer perceptron). For both hidden and output layer hyperbolic tangent activation function is employed. This function has a sigmoid curve and is calculated by using the following formula as in equation 1.1

$$F(x) = (e^{x} - e^{-x}) / (e^{x} + e^{-x}) \text{ ---------------- (Eq. 1.1)}$$

The selected output range is [-1 to 1]. Sum-of-Square is the error function used to rate the quality of the neural network. Training is stopped when the number of iteration become 500. As iteration is a single complete presentation of the training set to the neural network. This is the simplest and the most commonly used condition to stop training. When a neural network begins to over-train (i.e. to memorize data instead of generalizing and encoding data relationships), the validation errors increase while training errors might still reduce in that case, one has to retrain and restore best network. When the training is completed the testing operation was performed. The performance of each network model was then evaluated by computing the mean absolute error for each model.

III. RESULTS AND DISCUSSION

The table 1.2 shows the actual and forecasted structural cost obtained through the ANN model. The output obtained from ANN model also includes Absolute and Relative errors in prediction. From the error percentage it is clear that maximum error is 8.58%, for year 2008, which is less than 10%. Hence the result indicates 'good' estimation values with prediction above 90%.

Table 2 Output parameters obtained through ANN model.

Year	Contractor (Rs/ft^2)	Forecast	Abs. Error	Rel. Error	Estimate
1993	290	312.40957	22.409572	7.73%	Good
1994	320	325.48742	5.4874173	1.71%	Good
1995	350	355.31718	5.3171772	1.52%	Good
1996	370	378.10013	8.1001263	2.19%	Good
1997	400	409.25739	9.2573891	2.31%	Good
1998	425	425.69218	0.6921805	0.16%	Good
1999	450	460.90113	10.90113	2.42%	Good
2000	475	490.3637	15.363698	3.23%	Good
2001	500	500.56361	0.5636101	0.11%	Good
2002	525	550.93636	25.936358	4.94%	Good
2003	550	591.69713	41.697126	7.58%	Good
2004	600	614.38795	14.387947	2.40%	Good
2005	650	655.11369	5.1136869	0.79%	Good
2006	700	668.14794	-31.85206	4.55%	Good
2007	750	735.36585	-14.63415	1.95%	Good
2008	850	777.0985	-72.9015	8.58%	Good
2009	900	881.23432	-18.76568	2.09%	Good
2010	1000	980.20803	-19.79197	1.98%	Good
2011	1070	1028.7587	-41.24135	3.85%	Good
2012	1100	1102.7111	2.7111141	0.25%	Good
2013	1200	1238.3095	38.309463	3.19%	Good
2014	1300	1314.485	14.485034	1.11%	Good
2015	1400	1303.8944	-96.10563	6.86%	Good

The results were then plotted on the scatter graph between actual and forecasted values of last 23 years. The forecasted values generated through the ANN model were found to have very high correlation coefficient. The estimated correlation coefficient and R-squared coefficient for the results obtained were 0.9960 and 0.9905 respectively as shown in Fig. 1.

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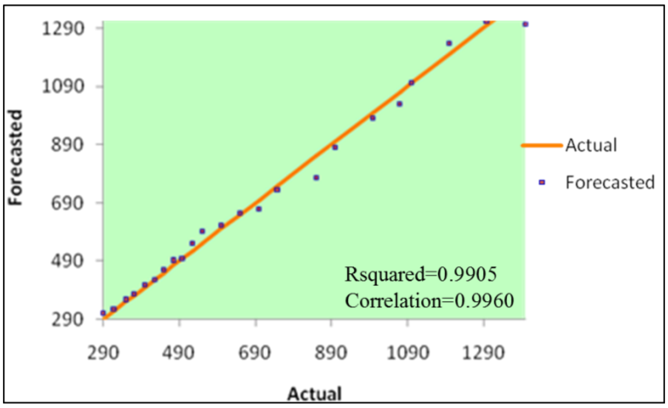

Fig. 1 The scatter graph between actual and forecasted values.

The Table 3 shows the summary of the co-relation factor between actual and predicted structural cost. The average Absolute Error (AE) obtained for Training Set and Test Set were 21.436 and 27.183 respectively. The predictions for each year from 1993 to 2015 indicated Good Forecasts for both Training (100%) and Test Set (100%), where the Tolerance level was 10% for Training Set.

Table 3 Summary of the results.

	Training Set	Test Set
No of Rows	19	4
Average AE	21.436	27.183
Average MSE	932.1315	1477.6754
Tolerance	10%	30%
No of Good forecasts	19 (100%)	4 (100%)
No of Bad forecasts	0 (0%)	0 (0%)

IV. CONCLUSION

The motive of this work was to explore the ANN technique and predict the total structural cost of buildings and to determine the factors which affect the cost of buildings. The developed cost estimation model (CEM) with back propagation knowledge algorithm was used to instruct the network by iteratively processing a set of training sample and compare the network's prediction with the real. The generated model fairly forecasted the structural cost, where the correlation coefficient and R-squared coefficient were found to be 0.9960 and 0.9905 respectively. The average absolute error of training set 21.43 and that of test set was 27.18, with the error varying from 8.58% (maximum) to 0.11% (minimum), indicating 'good' error deviation during training. The accurate conversion of practical field data into real time data can bring major change in the construction industry by forecasting the cost of any project. Artificial neural networks can model complex non-linear relationships and approximate any assessable function. The advance prediction of overall residential building cost can help the user in decisive planning. This model can also be used in future by various stakeholders, to study variation in the project cost, if the cost of various important resources like steel, cement, labor, etc. is changed.

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