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Conceptual Cost Modelling for Sustainable Construction Project Planning— A Levenberg–Marquardt Neural Network Approach

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Abstract: The main objective of this paper is to develop a systematic neural network model to estimate the conceptual cost for sustainable construction projects. A wide range of influencing factors on micro and macro level has been considered. The proposed engineering approach is pragmatic to model labour and material cost incurred in different stages of construction using the Artificial Neural Network (ANN) technique. The results indicated an acceptable convergence with reasonable generalization capabilities and the results obtained from the neural network model are more accurate and credible. This study contributes to the construction professionals by providing insight for using different ANN activation and transfer functions along with a wide range of influencing factors to benchmark the project manager's conceptual cost predicting capabilities. Moreover, the systematic engineering approach guides the project managers how a readily available practical database can help optimize several objectives. It supports two key factors of sustainable construction: the economic dimension and the social dimension.

Keywords: Sustainable project planning, conceptual cost, systematic approach, neural network model.

1 Introduction

In the present era, sustainable project planning gains momentum and popularity due to growing resource constraints, environmental pollution and waste generation by the construction industry. Nowadays, construction authorities unceasingly promotes the sustainable construction practices towards developing resource efficient and eco-friendly construction projects. The first step in the sustainable construction is the project planning [1–4]. Sustainable construction project planning mainly focuses on planning, monitoring and controlling of projects and their support processes to face sustainability-related problems, particularly for large-scale projects [5]. In order to execute sustainable project planning, conceptual cost modelling is indispensible for resource allocation because financial planning plays a vital role in successful execution and completion of projects integrated with sustainability [6–9].

Construction practitioners have recognized the prominence of early planning to the final outcomes of the project for sustainable construction. Conceptual Cost Estimate (CCE) is prepared during the initial stage of project formulation to appraise the economic viability of proceeding with the project. While preparing conceptual cost estimates planning engineers consider lot of complex factors which decide the cost of project [10, 11].

Conceptual cost estimate is prepared with minimum number of engineering and design data. So conceptual cost planning for sustainable construction projects becomes a crucial task for the estimators and planning engineers [12, 13]. By and large, successful completion of construction projects predominantly depends on the reliable prediction of conceptual cost of the project. Therefore project managers emphasize more on conceptual cost estimate. Since conceptual cost plays a vital role in successful completion of sustainable construction projects, a wide range of techniques are used for modelling the conceptual cost [14].

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Among various prediction techniques, Artificial Neural Network (ANN) is considered as one of the most unswerving technique to model the conceptual cost of the project. Neural network approach does not need any prior assumption of the functional relationship. Artificial neural networks have the ability to learn from examples and it can map their functional properties [15, 16]. In terms of accuracy neural network is found to be competitive with other functional approximation systems. The superior capability of neural network to learn from examples helps in modelling the complex conceptual cost estimate. Among numerous neural networks have been proposed to solve complex problems; away from that back propagation networks have been exceptionally prevalent due to their unique learning capability [17, 18].

2 Neural Network Model for Conceptual Cost Modelling

2.1 Conceptual frame work

This study mainly focuses on neural network-based approach for modelling the conceptual cost estimate for sustainable construction project planning. In order to accomplish the objectives of the study, back propagation neural network methodology was executed [19, 20]. Modelling the conceptual cost using back propagation neural network comprises of four steps:

(1) Ascertaining input variables and choosing appropriate neural architecture
(2) Collection data for training and testing
(3) Training and testing the neural network model
(4) Prediction of conceptual cost using NN model and validation of results.

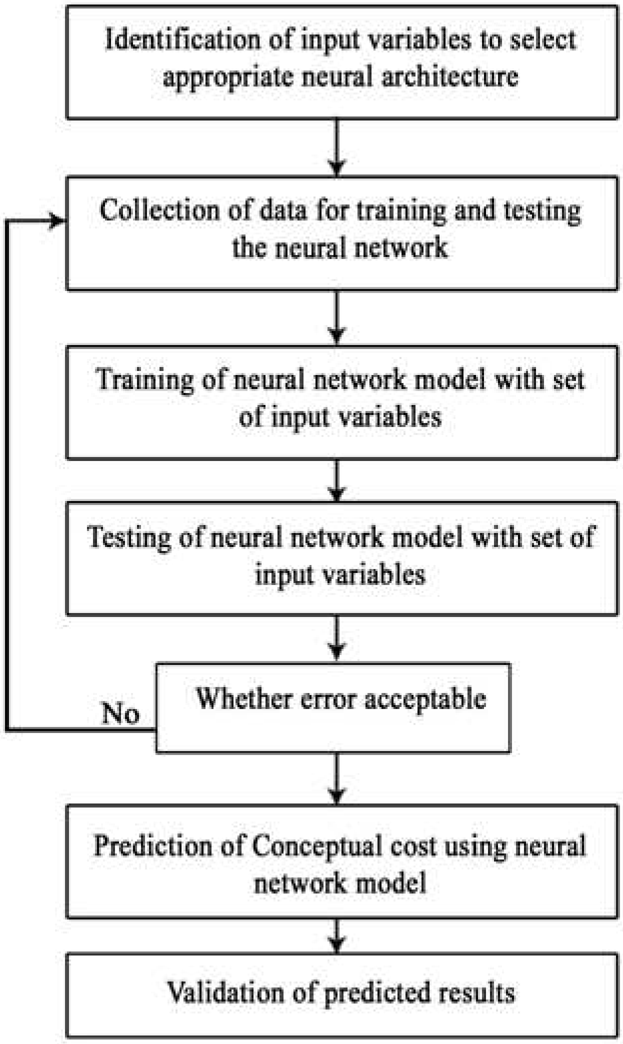

Fig. 1: Conceptual frame work for developing Neural Network Model

2.2 Identification of Input Variables

Identifying the input variables for conceptual cost estimate is the base to implement sustainable project management effectively. Generally, sustainable project planning mainly focuses on project planning practices with contemplation of sustainability. Researchers have been considering several measures for sustainable project planning. From the perspective of sustainable project planning, conceptual cost estimate is the one of key factor to be considered. Conceptual cost mainly depends on area of construction. In order to model the conceptual cost based on the area, material and labour cost data from several construction projects is collected. Area of construction is considered as the input variable to assess the conceptual cost. Material and labour cost details are collected from the senior project managers and the planning engineers. The data used for training are collected from 10 construction projects. Only data for projects that are completed is used for training the neural network. All projects used in this study are considered as a medium-size projects of area between 2,30,000 and 2,50,000 square feet. The type of construction and material used is almost same for the all 10 projects (e.g type of flooring, labour cost, grade of concrete etc). The labour and material cost incurred for various stages of work are collected from the construction sites.

2.3 Development of Neural Network Model

There are several neural network architectures are available, therefore the following principles are considered for the selection of appropriate neural network.

– Number of input nodes is determined based on the number of independent variables used in the model.

– Number of hidden nodes is fixed based on 80% of the input nodes.
– In order to avoid longer training period, the number of hidden layers should be reduced.
– The number of neurons should be sufficient for the network to converge but they should not be exaggerated to make the network memorize [21].

Generally, back-propagation is one of the most common method for training the neural network [22]. In this study MATLAB software is used as a tool to train the neural network. MATLAB is chosen because of its user friendliness and speed in training the networks. Levenberg-Marquardt algorithm is used to train the network. Based on above principles, a single layered feed-forward neural network is developed. Based on Mean Absolute Percentage Error (MAPE) and R^2 value, the performance of single-layered feed-forward network is analysed. Basically neural network consist of input layer, hidden layers and an output layer. Through weights, bias and activation function hidden layer is connected with other layers. Each layer consists of several numbers of neurons. Each neurons get input from data set. Weighted inputs are combined and processed by an activation function and output is produced. The structure of ANN model is shown in Fig. 2.

3 Training and Testing Neural Network

The developed model comprises of an input layer with 10 nodes, and an output layer with 14 nodes. Generally, one hidden layer is apt for the neural network model for most of the application in construction [23], the model is fixed with one hidden-layer neural network. In order to maintain accuracy in designing the neural network architecture and fixing its parameters some trial and error is required. The neural network is experimented with five, seven and ten hidden nodes. Out of these trials, the neural network with ten hidden nodes show the best performance, in terms of the associated value of MAPE. The structure of the developed ANN model in MATLAB is shown in Fig. 3.

The network istrained to fit inputs and the targeted output. Normally, generalization stops improving automatically network stops training. This is shown by an increase in value of Mean Squared Error (MSE). Mean squared error (R) is an average squared difference between input and the targeted output. R value shows the correlation between output and targets.

The following equation is used to calculate the output

$$f_i = \frac{1}{1+\exp\left(\sum w_{ji} o_i + b\right)}$$

where, w_{ji} is the weight assigned to the connection neuron i in lower layer to j neuron connected in upper layer. Bias value is denoted as b and o_i is the output of i neuron. Error of network is propagated backwards from output to the input layer. Based on learning strategies, the weights are modified to minimize the error to an acceptable level. The error occurred during training and testing of network is expressed as Root Mean Square Error (RMSE) value. RMSE is calculated using the following equation:

$$R = \sqrt{\frac{1}{p}\sum_j \|t_j - o_j\|}$$

$$R^2 = 1 - \frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2}$$

The Mean absolute Percentage Error (MPE) is calculated using the following equation

$$MPE = \frac{o-t}{t} \times 100$$

where, o is the predicted output and t is the actual output of the network, p is the total number of patterns used for training and testing. The regression plot of the network is shown in Fig. 4.

In general, back-propagation training adapts a gradient-descent approach of adjusting the neural network weights. The data of hundreds of training cycles (called epochs) are processed during the training phase of the neural network. After the completion of each cycle, the error between the neural network outputs and the actual outputs are propagated backward to regulate the weights for higher accuracy. The training process consist of 143 epochs for testing. The status of the neural network is shown in Fig. 5.

4 Results and Discussions

Developed ANN model establishes a set methodology which can provide an economical and rapid means of cost estimating of future building construction processes. The major disadvantage of conventional cost estimate includes the need for detailed project information, uncertainties regarding project development, changes in some design parameters, etc. However, the model has been developed for early-cost estimation of buildings by applying the principles of supervised learning of neural networks. This model proved that neural networks are capable of reducing uncertainties related to the cost of a building. For validation of the neural network models, 80% of the data is considered from the original data set for training the network and R value of 0.999 is obtained for testing. 10% of the data is considered for testing and R value of 0.999 is obtained for testing and remaining 10% of data is considered for validation. Neural network model is trained using the save training data set for 143 epochs. The error is minimised at epoch 5. The best validation performance of the network is shown in Fig. 6.

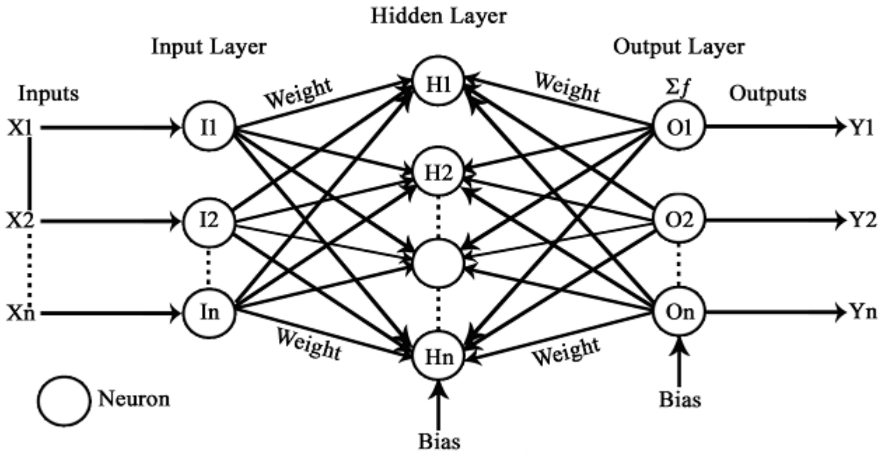

Fig. 2: Structure of ANN model

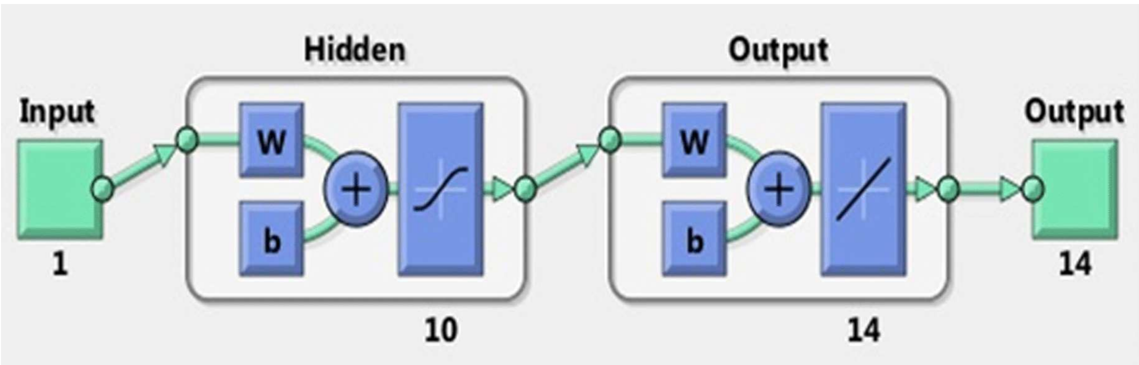

Fig. 3: Structure of developed ANN model in MATLAB

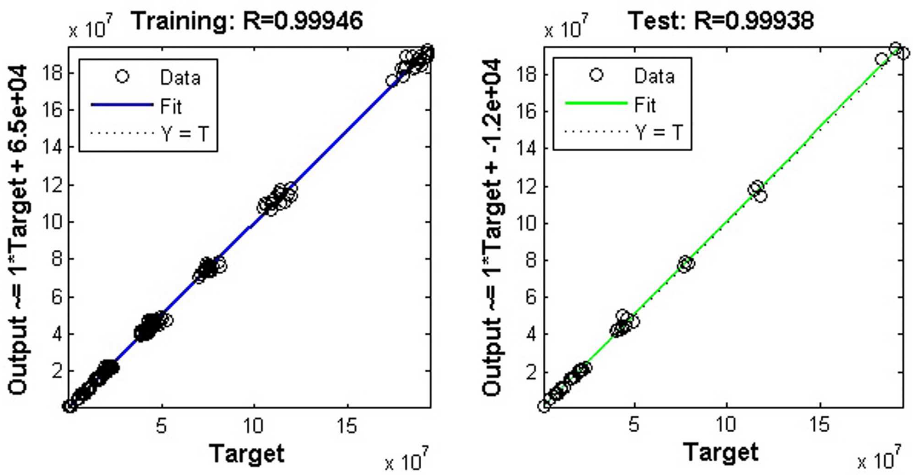

Fig. 4: Regression plot of the neural network

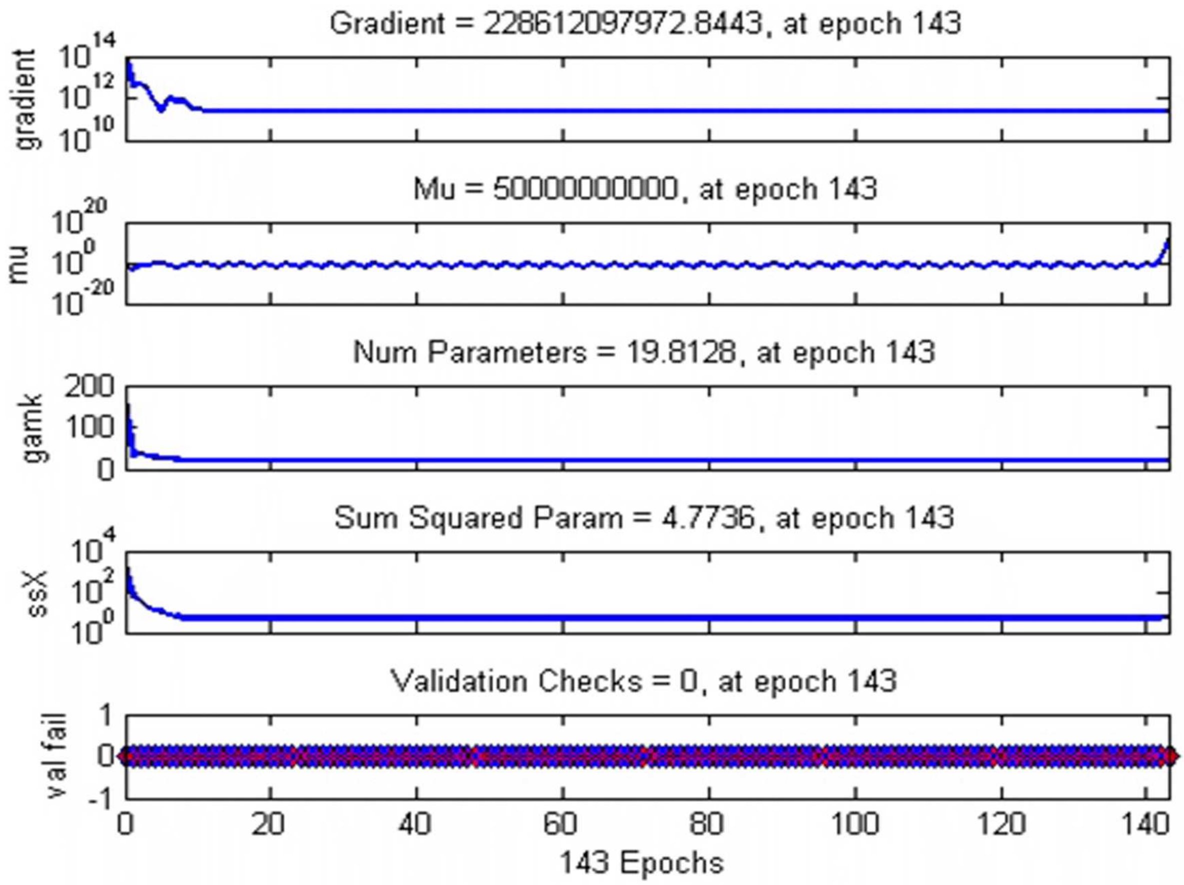

Fig. 5: Overall status of the neural network

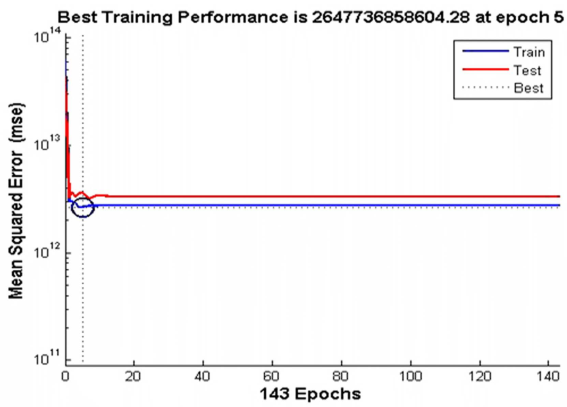

Fig. 6: Best validation performance of the network

The predicted output values are closer to the actual values. Percentage of error between the actual values and the predicted values is calculated. The percentage error variation ranges between 6.48 to-7.05 for substructure, for super structure 4.67 to-3.68, for flooring 6.52 to-7.99, for plastering 8.98 to-6.17, for tiles fixing 5.64 to-7.67, for electrical and plumbing 7.87 to-8.12, for painting 3.98 to-7.56. Table 1 gives the comparison of actual and ANN results.

5 Conclusion

This paper summarizes the development of a cost estimation model using artificial neural networks and a back-propagation algorithm. Sustainable construction cost plays a vital role in sustainable development. A systematic approach is essential to model the conceptual cost for sustainable construction project financing. The development of neural network model to estimate the conceptual cost of construction projects for sustainable project planning has gained considerable interest among researchers and practitioners. The best prediction of conceptual costs helps the project managers in taking proactive actions for execution of sustainable construction. An ANN model can be a useful tool to assist the project managers in predicting the conceptual cost. The developed model in this paper is valuable and provides a holistic view for the construction professionals regarding sustainable construction planning, thereby enhancing their capability in this regard.

Table 1: Comparison of actual and ANN results

S.No	Area (Sq.ft)	Stage of construction	Labour Cost (Rs)	Predicted Cost (Rs)	Material Cost (Rs)	Predicted Cost (Rs)
		Substructure	1,58,62,500	1,63,67,721	1,06,51,170	1,05,83,200
		Superstructure	10,57,50,000	10,96,45,267	17,98,97,061	1836,10,372
		Flooring	1,52,28,000	1,52,38,473	7,61,40,000	7,32,34,946
1	2,35,479	Plastering	3,90,02,000	4,02,74,194	84,90,660	79,44,912
		Wall tiles	5,60,400	10,42,040	4,34,32,800	4,55,65,107
		Electrical & Plumbing	234,14,375	2,24,21,820	4,23,19,689	4,27,02,585
		Painting	51,02,489	52,04,642	1,98,12,378	1,92,41,385
		Substructure	1,76,23,125	1,70,31,471	1,09,13,475	1,08,46,467
		Superstructure	11,74,87,500	11,48,14,095	18,09,43,933	18,79,18,872
		Flooring	1,68,58,600	1,58,73,685	8,12,02,400	7,65,30,454
2	2,41,613	Plastering	4,32,38,000	4,16,41,501	73,15,080	79,63,875
		Wall tiles	15,59,700	13,01,848	5,28,15,560	4,74,32,569
		Electrical & Plumbing	2,13,75,000	2,19,83,649	4,40,12,300	4,38,62,470
		Painting	51,14,516	52,51,680	2,04,41,379	1,98,46,392
		Substructure	1,67,45,208	1,63,99,691	99,05,616	1,05,95,905
		Superstructure	10,99,05,168	10,99,36,160	18,08,95,416	18,40,72,928
		Flooring	1,62,73,512	1,52,69,250	7,21,69,488	7,34,64,361
3	2,35,848	Plastering	3,84,43,224	4,03,56,474	82,54,680	79,44,813
		Wall tiles	16,50,936	10,56,373	4,33,96,032	4,56,47,381
		Electrical & Plumbing	2,35,84.800	2,24,29,177	4,29,87,112	4,27,82,509
		Painting	47,16,960	52,07,186	1,91,03,688	1,92,71,163
		Substructure	1,61,05,527	1,68,98,538	1,03,36,383	1,07,90,121
		Superstructure	11,94,69,357	11,38,95,071	19,03,81,752	18,72,82,461
		Flooring	1,56,24,765	1,57,51,360	7,59,60,396	7,59,65,182
4	2,40,381	Plastering	4,30,28,199	4,14,05,482	88,94,097	79,46,701
		Wall tiles	7,21,143	12,51,994	4,47,10,866	4,71,09,479
		Electrical & Plumbing	2,28,36,195	2,21,25,474	4,20,66,675	4,36,71,713
		Painting	55,28,763	52,41,919	1,92,30,480	1,97,10,225
		Substructure	1,70,00,427	1,73,66,665	1,08,40,852	1,10,23,403
		Superstructure	11,92,49,372	11,67,03,137	19,24,25,123	19,14,75,265
		Flooring	1,72,46,810	1,61,22,021	8,08,13,624	7,81,72,966
5	2,46,383	Plastering	4,23,77,876	4,21,20,810	86,23,405	81,46,517
		Wall tiles	17,24,681	14,37,929	4,92,76,600	4,72,51,833
		Electrical & Plumbing	2,14,35,321	2,16,66,272	4,43,48,940	4,43,99,360
		Painting	54,20,426	52,87,807	2,09,42,555	2,03,62,325
		Substructure	1,70,69,580	1,61,20,078	1,03,80,150	1,04,70,894
		Superstructure	10,91,06,910	10,70,65,006	17,39,25,180	17,54,01,024
		Flooring	1,47,62,880	1,50,18,289	6,96,62,340	7,02,69,774
6	2,30,670	Plastering	3,89,83,230	3,94,23,120	80,73,450	79,14,637
		Wall tiles	6,92,010	8,99,319	4,47,49,980	4,53,01,272
		Electrical & Plumbing	2,02,98,960	2,19,70,189	4,10,59,260	4,17,27,588
		Painting	48,44,070	51,80,561	1,84,53,600	1,89,31,519
		Substructure	1,66,61,190	1,66,23,223	1,04,72,748	1,06,82,093
		Superstructure	10,97,25,837	11,18,19,543	18,77,95,413	18,60,52,098
		Flooring	1,45,19,037	1,54,86,693	7,35,47,253	7,47,41,488
7	2,38,017	Plastering	4,14,14,958	4,08,66,315	78,54,561	79,40,653
		Wall tiles	11,90,085	11,48,001	4,80,79,434	4,62,96,649
		Electrical & Plumbing	2,38,01,700	2,23,61,388	4,37,95,128	4,32,37,342
		Painting	52,36,374	52,23,273	1,90,41,360	1,94,65,463
		Substructure	1,72,19,020	1,73,49,208	1,18,07,328	1,10,12,037
		Superstructure	11,48,75,462	11,66,33,752	19,45,74,926	19,11,76,784
		Flooring	1,59,89,090	1,61,14,160	7,94,53,478	7,80,76,180
8	2,45,986	Plastering	4,28,01,564	4,21,04,382	76,25,566	81,25,953
		Wall tiles	9,83,944	14,30,035	4,59,99,382	4,73,53,580
		Electrical & Plumbing	2,09,08,810	2,16,73,119	4,35,39,522	4,43,63,106
		Painting	49,19,720	52,84,963	2,04,16,838	2,03,22,966

Continued ...

Table 1 continued ...

S.No	Area (Sq.ft)	Stage of construction	Labour Cost (Rs)	Predicted Cost (Rs)	Material Cost (Rs)	Predicted Cost (Rs)
		Substructure	1,72,19,020	1,73,49,208	1,18,07,328	1,10,12,037
		Superstructure	11,48,75,462	11,66,33,752	19,45,74,926	19,11,76,784
		Flooring	1,59,89,090	1,61,14,160	7,94,53,478	7,80,76,180
8	2,45,986	Plastering	4,28,01,564	4,21,04,382	76,25,566	81,25,953
		Wall tiles	9,83,944	14,30,035	4,59,99,382	4,73,53,580
		Electrical & Plumbing	2,09,08,810	2,16,73,119	4,35,39,522	4,43,63,106
		Painting	49,19,720	52,84,963	2,04,16,838	2,03,22,966
		Substructure	1,69,49,880	1,63,62,380	1,01,22,845	1,05,81,059
		Superstructure	10,61,72,165	10,95,95,982	17,89,15,400	18,35,26,345
		Flooring	1,57,72,805	1,52,33,350	7,65,09,875	7,31,94,885
9	2,35,415	Plastering	4,19,03,870	4,02,60,117	94,16,600	79,44,896
		Wall tiles	16,47,905	10,39,600	4,51,99,680	4,55,51,811
		Electrical & Plumbing	2,28,35,255	2,24,19,988	4,21,39,285	4,26,88,699
		Painting	58,85,375	52,04,208	2,00,10,275	1,92,36,317
		Substructure	1,55,55,012	1,63,85,061	1,01,34,326	1,05,90,113
		Superstructure	11,35,98,724	10,98,03,906	18,52,46,052	18,38,69,495
		Flooring	1,46,12,284	1,52,55,146	7,28,25,738	7,33,61,500
10	2,35,682	Plastering	3,84,16,166	4,03,19,229	80,13,188	79,44,897
		Wall tiles	7,07,046	10,49,870	4,83,14,810	4,56,09,192
		Electrical & Plumbing	2,23,89,790	2,24,26,549	4,33,65,488	4,27,46,590
		Painting	54,20,686	52,06,033	1,90,90,242	1,92,57,649

References

[1] R. Gareis, M. Huemann and A. Martinuzzi, Project Management and Sustainable Development Principles Project Management Institute: Philadelphia, PA, USA. (2013).

[2] P. Soundarrajan and N. Vivek, Green finance for sustainable green economic growth in India. Agric. Econ. (Zemed. Ekon.), vol. 62, pp. 35–44 (2016).

[3] Q. He, G. Wang, L. Luo, Q. Shi, J. Xie and X. Meng, Mapping the managerial areas of Building Information Modeling (BIM) using scientometric analysis. Int. J. Proj. Manag, vol. 35, pp. 670–685 (2017).

[4] R.Y.J. Siew, Integrating sustainability into construction project portfolio management. KSCE J. Civ. Eng., vol. 20, pp. 101–108 (2016).

[5] A.J.G. Silvius, R. Schipper, J. Planko, J. van den Brink and A. Kö hler, Sustainability in Project Management; Gower Publishing: Farnham, UK, (2012).

[6] R.D. Chang, V. Soebarto, Z.Y. Zhao and G. Zillante, Facilitating the transition to sustainable construction: China's policies. J. Clean. Prod., vol. 131, pp. 534–544 (2016).

[7] O.A. Olubunmi, P.B. Xia and M. Skitmore, Green building incentives: A review. Renew. Sustain. Energy Rev, vol. 59, pp. 1611–1621 (2016).

[8] R.Y.J. Siew and M.C.A. Balatbat, D.G. Carmichael, A review of building/ infrastructure sustainability reporting tools (SRTs). Smart Sustain. Built Environ, vol. 2, pp. 106–139 (2013).

[9] R.Y. Siew, Alternative framework for assessing sustainable building funds: Green Building Fund.Build. Res. Inf., vol. 43, pp. 160–169 (2015).

[10] R.Y. Siew, Alternative framework for assessing sustainable building funds: Green Building Fund.Build. Res. Inf., vol. 43, pp. 160–169 (2015).

[11] E. Sfakianaki, Resource-efficient construction: Rethinking construction towards sustainability. World J. Sci.Technol. Sustain. Dev, vol. 12, pp. 233–242 (2015).

[12] G. Silvius, Sustainability in project management: A literature review and impact analysis Soc. Bus., vol. 4, pp. 63–96 (2014).

[13] J. Zuo, Green building research—Current status and future agenda: A review. Renew. Sustain.Energy Rev, vol.30, pp. 271–281 (2014).

[14] V.L.M. Schropfer, J. Tah and E. Kurul, Mapping the knowledge flow in sustainable construction project teams using social network analysis Eng. Constr. Archit. Manag., vol. 24, pp. 229–259 (2017).

[15] H. Adeli, Regularization neural network for construction cost estimation, Journal of Construction Engineering and Management, vol. 124, no. 1, pp. 18–24 (1998).

[16] M. Arafa and Alqedra, 'Early Stage Cost Estimation of Buildings Construction Projects using Artificial Neural Networks Journal of Artificial Intelligence, vol. 4, no. 1, pp. 63–75 (2011).

[17] N.I. El-Sawalhi and O. Shehatto, A neural network model for building construction projects cost estimation, KICEM Journal of Construction Engineering and Project Management, vol. 4, no. 4, pp. 9–16 (2014).

[18] N.B. Chaphalkar, K.C. Iyer and S.K. Patil, Prediction of outcome of construction dispute claims using multilayer perceptron neural network model, International Journal of Project Management, vol. 33, no. 8, article no. 1808, pp. 1827–1835 (2015).

[19] M. Mady, Prediction model of construction labor production rates in Gaza strip using Artificial Neural Network, M.Sc Thesis, The Islamic University Gaza, (2013).
[20] C.G. Wilmot and B. Mei, Neural network modeling of highway construction costs, Journal of Construction Engineering and Management, vol. 131, no. 7, pp. 765–771 (2005).
[21] S. Muqeem, M. Idrus and F. Khamidi, Construction labor production rates modeling using Artificial Neural Network, Journal of Information Technology in Construction, vol. 16, pp. 713–725 (2011).
[22] D.K.H. Chua, Y.C. Kog, K. Loh and E.J. Jaselskis, Model for construction budget performance–neural network approach Journal of Construction Engineering and Management, vol. 123, no. 3, pp. 214–222 (1997).
[23] B. Hola and K. Schabowicz, Estimation of earthworks execution time cost by means of artificial neural networks, Automation in Construction, vol. 19, no. 5, pp. 570–579 (2010).

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