

Cost Estimation Model (Cem) For Residential Building: Sensitivity Analysis

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ABSTRACT:- Cost estimation is a practice-based task, which involves evaluation of unknown situations and complex relations of cost-influencing factors. An artificial neural network (ANN) is an analogy-based process, which best suits the cost forecasting domain. The main advantages of ANNs include their ability to learn by examples (past projects), and to generate solutions for forthcoming applications (future projects). ANNs do not require a prerequisite establishment of rules and reasoning which rule relations between a desired output and its significant effective variables. Twenty-three years' data were involved in this study and data were collected from seven parameters from the Schedule of Rate Book (SOR) and general studies. The data were simulated in NEURO XL Version 2.1 for developing ANN architecture. The resultant ANN model practically predicted the total structural cost of construction projects, which is evident from sensitivity analysis that cost of steel (44.129%), cost of cement (16.6%) and skilled labour rate are the major contributors towards the structural cost of project.

Keywords:- Artificial Neural Network (ANN), Correlation Factor, Cost estimation, Sensitivity Analysis

I. INTRODUCTION

Reliable predictions of cost and duration are amongst the highest determinants of success of construction projects. Construction practitioners are aware of uncertainty, incompleteness, unknown circumstances and complex relationships of factors affecting cost and duration of construction projects [1]. True cost estimation of a software development effort is critical for good quality management decision making. The accuracy and reliability of the effort estimation is very important for software production because both over estimates and under estimation of the software attempt are harmful to software company. Thus, from an organizational perspective, an early and exact cost estimate will reduce the opportunity of organizational conflict during the later stages [2].

Artificial neural networks can model complex non-linear relationships and approximate any assessable function. They are particularly helpful in problems where there is a complex relationship between an input and output. The majority commonly adopt architecture for estimate software effort is feed forward multilayer perceptron with back propagation knowledge algorithm and the sigmoid activation function. The main advantage ANNs have more than physically based models is that they are data-driven and underlying contact using examples of the desired input output mapping [3].

Dominic D Ahiaga-Dagbui [2014] make a case for using data to re-examine the sources of cost overrun on construction projects to develop final project cost model base on about 1,600 water infrastructure project. 92% of the validation predictions were within $\pm 10\%$ of the actual final cost of the project [4]. Ines Siqueira [1999] in Canada collected data from 75 building projects, a large manufacturer of prefabricated structural steel buildings, over a 3-month period [5]. Eng. Hasan Abu Jamous [2013] estimated the cost at early step of road projects in Gaza strip using parametric techniques and achieved the facility to estimate the cost of road projects at initial stage and reducing the error rate to reach 5.5% [6].

Ibrahim Mahamid [2013] did formulation of 5 regression models. The coefficient of determination (r^2) of the developed models is ranging from 0.65 to 0.97. This indicator between the dependent and independent relationship variables is good and forecast model fit by the actual-life data [7]. Huseyin Karanci [2010] used data of 41 mass housing project. The techniques of ANN based modelling can be used to compare conceptual range estimation of other types of building projects for example, infrastructural, industrial and other types of building projects [8]. Nedal Salah Jameel Al Sheikh [2013] research aims to predict the parametric cost estimation in building construction project in Gaza Strip using Fuzzy logic Model to predict cost estimate to an acceptable degree of accuracy reached to 88% [9].

Amusan Lekan Murtala[2011] determined the accurate cost of the building projects with average competence of 0.763, coefficient of performance 1.311 and average mean square error (M.S.E) of 0.01136. The research work was to improve the models' validity and stability[10]. Mohamed Zahran et al [2014] generated a parametric cost estimating model by using artificial neural network and inherent algorithms, Past Data of 14 of previous similar project have been collected. The testing shows that the percentage of absolute difference of predicted cost (%Error) ranges from 0.7% to 2.3% with average value of 1.8%[11].

In this study 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. This procedure consists of repeatedly feeding input and output information from empirical observations, propagate the error value, and adjust the connection weights until the error value drop below a user-specified tolerance level. To accomplish this goal, structural cost data from past twenty three years from 1993 to 2015 were collected and simulated in ANN SOFTWARE.

II. METHODOLOGY

The problem formulation of this study was done after detailed literature review. There are lot of parameters on the basis of which researchers have conducted their studies for designing a cost evaluation model. Various analytical tools and methods were used to make the estimation more accurate and precise. The first step was to prepare a survey report in which last year records were taken with the help of internet or other resources like schedule of rates in which the rate of all parameters are yearly provided. To make the approach more realistic, data from Private Companies was also collected to predict the variation of building rates. The graph of deviation in rates for these companies was also analyzed annually. Apart from this the input data was also collected from Local Market to get an idea about the present rate of material, labor and contractor.

The data collected through internet, local market and the private companies was then compared to determine effect of rate variation on the cost of residential buildings. After collecting the data a table was drawn in which rate of all input parameters like cement, sand, steel, aggregate, and the cost of mason, skilled and non-skilled labor were filled. Than all the data was inserted in the software artificial neural network to predict the result. After inserting the data, input parameters were divided into training set 68%, validation set 16%, and test set 16%. A correlation graph was setup correlation between actual and predicted structural cost. A sensitivity analysis was finally done to identify the contribution of various input parameters on the total evaluation model.

The Multilayer Perceptron Neural Network Model

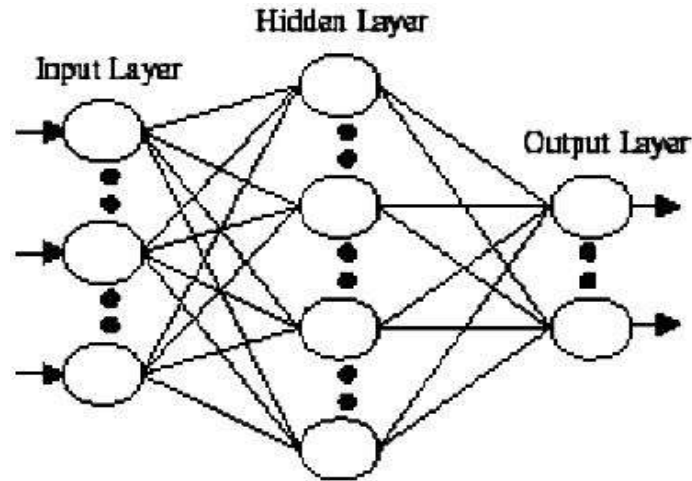
The Multi-Layer Perceptron (MLP) is one of the most popular networks. It consists of layers of parallel processing this elements are known as neurons, in this network each layer fully interconnected to proceeding layer by interconnection strength or weights (w). There are following diagram in which figure 1 shows a perceptron network with three layers. On the left side the network show input layer, in the middle side one hidden layer with three neurons and on the right side there is an output layer with two neurons.

Input Layer

In the input layer a vector of predictor variable value are present ($x_1 \dots x_p$). The input layer standardizes these values or processing before the input layer so that the range of every variable is 1 to 1. The input layer distributes the values to every neuron in the hidden layer. In addition to the predictor variables, there is a stable input, called the bias that is fed to each of the hidden layers; the bias is multiplied by a weight and additional to the amount going into the neuron. The weighted sum is fed into a transfer function, resulting in function output. The outputs from the hidden layer are spread to the output layer.

Hidden Layer

Introducing at a neuron in the hidden layer, the value from each input neuron is multiplied by a weight, and the resulting weighted values are added together producing a combined value. The weighted sum is fed into a transfer function, resulting in functioned output. The outputs from the hidden layer are distributed to the output layer.



Output Layer

Arriving at a neuron in the output layer, the value from each hidden layer neuron is multiply by a weight, and the resultant weighted value are added together producing a combined value. The weighted sum is fed into a transfer function, which results in functioned output.

III. RESULTS AND DISCUSSION

The output results obtained has already been showed in previous paper of the author. Figure 2 shows the error between actual and forecasted structural cost obtained through the ANN model. The main aim of training is to minimize error in the results obtained. 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%.



Figure 1 Error Prediction

Table No.1 show the sensitivity analysis of various input parameter like cost of cement, sand, steel, aggregate, mason labour, skilled labour, and non-skilled labour. From the sensitivity table it is clear that, cost of steel i.e. 44.129 is contributing majorly in structural cost analysis. Also influence of cost of cement and skilled labour is 16.605 & 24.315 respectively.

Table 1 Sensitivity Analysis

Input	Value, %
Cement in beg	16.605
Sand in cubic ft	7.767
Steel in per kg	44.129
Aggregate in cubic ft	0.002
Mason Cost of per day	7.178
Skilled cost of per day	24.315
Non Skilled cost of per day	0.004



Figure 2 Sensitivity Analysis

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, From sensitivity analysis or input importance table it is clear that cost of steel (44.129 %), cost of cement (16.6%) and Skilled labour rate are the major contributor towards the structural cost of residential building, 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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