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An Artificial Neural Network approach for Cost Estimation of Consultancy Services of Building Projects in Kathmandu Valley

Prajjwal Moktan [a], Mahendra Raj Dhital [b], Nagendra Bahadur Amatya [c]

[a, b] *Department of Civil Engineering, Pulchowk Campus, IOE, Tribhuvan University, Nepal*
[c] *Department of Applied Sciences & Chemical Engineering, Pulchowk Campus, IOE, Tribhuvan University, Nepal*
[a] prajjwalmtn95@gmail.com, [b] mrdhital@ioe.edu.np, [c] nagendraamatya@gmail.com

Abstract

Cost estimation of an engineering projects comprises of, but not limited to, construction costs and consultancy services costs with the amount of former being more than that of later. With the advent of Machine Learning (ML) techniques, the cost estimation now has become more efficient in the availability of very limited data in compared to traditional cost estimation techniques. Many cost estimation models focus on construction phase where a little to no consideration is given to the engineering services costs. The nature of engineering service is different to that of the construction process as they are less tangible and less material based. This makes it essential to use the ML based techniques of cost estimation in the field of engineering service cost. This paper uses the Artificial Neural Networks (ANNs), a form of ML based techniques for the cost estimation of engineering service cost of building projects in Kathmandu valley. Firstly, 6 influential factors were identified through Expert opinions. Then the data of 70 building projects were collected and fed for ANN model development. Finally the results show that the fairly accurate predictions can be obtained even with small datasets. The model developed in this study showed a 12.51% Mean Absolute Percentage Error (MAPE) error.

Keywords

Cost Estimation, Consultancy Services, Artificial Neural Networks

1. Introduction

Cost estimation is essential process at the initial stage of any engineering projects. Cost plays a vital role in today's competitive markets also while maintaining the quality of any projects [1].Cost estimates enable project managers to assess the project's viability and successfully manage costs [2]. Also it may influence the client's decision to go on with the implementation of the projects. A proper cost estimation ensures the clients satisfaction and also have control over the cost throughout the project and can be an indicator for the project success.

Various methods of cost estimation are present and have been developed overtime. Yet the traditional methods fail to utilize the organizational knowledge that arises from the past projects so they are insufficient [2]. Estimation methods need to be quick, realistic ad reasonably accurate [3]. With the advent of powerful computations recent cost estimating approaches can incorporate large volume of data and form complex relationships between the data. Artificial Intelligence (AI) techniques have been used in the recent years proving more accuracy even with limited numbers of information [1].Machine learning (ML), knowledge-based systems (KBS), evolutionary systems (ES), and hybrid systems are a few examples of AL techniques (HS) [4].

There are many ML-based methods for estimating contractor costs, however there are few studies on using these techniques to determine the cost of engineering services. Accurately estimating the engineering cost is in contrast with the construction cost as there are less tangible and material components. The study of Hyari [5] is, to the best of authors' knowledge, one of the few studies on the use of ML based models for the cost estimation consultancy services within the construction industry where 5 influence factors have been used to predict the cost of engineering services. Also others literatures are there for the cost estimation models using of building construction projects, (namely Luu

& Kim, 2009, Cheng, 2010; Günaydin & Doğan, 2004; Huawang & Wanqing, 2008; G.-H., 2013; Mohammed & Mamoun, 2011; Richa Yadav, 2016) but not for the consultancy services in this particular field of interest.

The research aims to investigate the potentials of developing an accurate ANN model utilizing the past data to estimate the cost of consultancy services of private building projects.Even in the early stages of the design process, when appropriate information is not available, it is still possible to obtain a fairly accurate prediction [6]. This strategy promotes a feedback loop that could aid designers in finding the best solution. [1]

Table 1: Land use of Kathmandu Valley

Land Use Classes	Area (sq.km)			Acreage (%)		
	1990	2000	2012	1990	2000	2012
Agricultural	421.60	394.12	342.08	58.40	54.60	47.39
Built-up	**38.09**	**66.54**	**118.65**	**5.28**	**9.22**	**16.44**
Commercial	0.20	0.37	0.37	0.03	0.05	0.05
Industrial	0.79	1.01	1.00	0.11	0.14	0.14
Institutional	3.70	4.29	4.45	0.51	0.59	0.62
Military	1.21	1.21	1.20	0.17	0.17	0.17
Mixed Residential/ Commercial	0.91	2.76	5.69	0.13	0.38	0.79
Public Utilities	0.26	0.30	0.30	0.04	0.04	0.04
Residential	21.83	46.18	94.19	3.02	6.40	13.05
Rural Settlement	1.17	1.13	1.86	0.16	0.16	0.26
Special Area	0.87	0.87	0.87	0.12	0.12	0.12
Transportation	7.15	8.41	8.71	0.99	1.17	1.21
Forest	253.34	253.56	251.08	35.10	35.12	34.78
Others	2.96	3.48	6.07	0.41	0.48	0.84
Recreational / Open Space	2.39	2.03	2.01	0.33	0.28	0.28
Water body	3.50	2.14	1.98	0.48	0.30	0.27
Total	**721.87**	**721.87**	**721.87**			

As shown in Table 1, more number of private residential buildings have been built in Kathmandu valley with the rapid urbanization due to rapid increase in in-migration to Kathmandu valley from other parts of the country. It can also be said as urban migration from rural parts of Nepal. So more number of people are acquiring the consultancy service of preparation of design and drawings of their buildings which is the scope of this research. The service cost is varied due to competitive markets and general public who wish to acquire this services are unaware of how much is the justifiable cost they wish to expend. So the proposed model will be new of its kind to the author's knowledge in this scope that will help for creating a data driven model for the cost estimation. The remaining sections of the paper includes a literature review, identification of factors influencing the cost of consultancy services, data collection and preparation, and model development.

2. Literature Review

2.1 Cost estimation methods in building projects

For cost assessment of residential building projects, G. H. Kim [7] tested three algorithms: regression, neural networks, and case based reasoning. Year, gross floor area, floors, total unit, duration, roof types, FND types, basement usage, and finishing grades are used as input parameters, while actual cost is used as an output parameter. Estimation error is used to evaluate 75 proposed neural network models.

The neural network approach presented by the authors Günaydin & Doğan [1] for cost estimation of structural systems in building construction projects. The NN model with 8-4-1 produces the best results, with 8, 4 and 1 representing input neurons, hidden neurons, and output neurons, respectively.

Luu and Kim [8] developed a neural network for apartment construction project cost prediction. Mean percentage error (MPE) and mean absolute percentage error (MAPE) are used to evaluate the proposed neural network model (MAPE).

The authors of Cheng [9] proposed evolutional fuzzy hybrid neural network cost estimation for building construction projects. Impact factors from seven engineering categories are used in the proposed approach. The proposed evolutional fuzzy hybrid neural network (EFHNN) model combines four artificial intelligence techniques: neural networks, high-order neural networks, fuzzy logic, and genetic algorithms. The estimation error is used to assess performance.

For cost estimation of school building construction projects, G.-H. Kim [7] introduced three algorithms: regression, neural network, and support vector machine. Year, budget, school levels, land acquisition, class number, building area, gross floor area, storey, basement floor, and floor height are used as input elements, while total construction cost is used as an output parameter. Actual error rate, mean absolute error (MAER), and standard deviation are used to evaluate the proposed neural network model. Analysis of variance is used to compare MAER of three outcomes (ANOVA). The NN model, which has an MAER of 5.27 and a standard deviation of 4.13, produces the best results.

2.2 Cost Estimation methods in consultancy services

Few literatures have been found to estimate the cost of engineering services by the help of data driven machine learning methods.

Hyari [5] developed a conceptual cost estimation model for engineering services in a public construction project. They used 5 input features, namely, project type, engineering services category, project location, total construction costs, and project scope. The model was trained on a data set obtained from the Government Tenders Department in Jordan. The optimal network architecture consisted of 15 neurons in hidden layer that uses nonlinear sigmoid function and a linear single neuron output layer. The obtained average accuracy percentage was 26.3% and 28.2% in training and testing set respectively. Recommendation to conduct such research using different data set of various engineering projects form different places was made by the author.

Another research by Matel [2] developed and optimizes a neural network model to estimate the preliminary cost of engineering services, which showed about 14.5% improvement in the accuracy of the model as compared to Hyari. The study mainly contributes in the analysis of 7 relevant and important variables for the cost estimation namely, intensity, number of project team members, project duration, collaborating disciplines, contract type, project phases and scale of work. The study pointed out the need of large number of sample, external validation by applying to new projects and comparing to estimates done by experts and also further research in the field of ML based cost estimation in engineering services.

SONA
MINIMUM DESIGN CONSULTING FEES

FOR BUILDING DESIGN AND MASTER PLANNING

1 RESIDENCE DESIGN / MIXED USED RESIDENTIAL BUILDINGS

Proposed Cost:

NRS 100 per Sq. Ft for Built Up Area Up to 3500 Sq. Ft.
NRS 80 per Sq. Ft for Built Up Area above 3500

Cost Distribution

Architecture	Structure	Sanitation	Electrical	BoQ, Specification and Contract Documents
50%	20%	10.00%	10.00%	10.00%

Figure 1: Minimum Consultancy Fees

Further in the context of Nepal, Society of Nepalese Architects (SONA), an umbrella organization of all practicing architects, has recently endorsed the minimum consulting fees for various building types, where one can take the reference for their new project which is shown in the Figure 1.

2.3 Artificial Neural Networks (ANNs) for Cost Estimation

The first inspiration for ANNs came from research on brain functions. [1] ANNs consist of nodes (neurons in ANNs) grouped in interconnecting layers and sets of layers to form a network [10].There are three different types of layers, namely, input, hidden and output layers. The layout or architecture of a network is shown in Figure 2

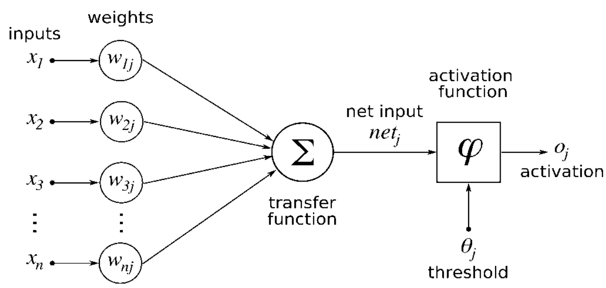


Figure 2: Structure of Multilayer Perceptron

The potential of ANN to deal with the intricate and nonlinear relationship between input and the predicted outcome is its key highlights .Previous research has demonstrated that the neural network model is superior to conventional regression methods for cost estimates. The ANN model showed that neural networks can reduce cost-related uncertainty in construction projects. Finally, more research is being conducted in order to create a comprehensive and practical model for accurately predicting construction costs [7].

The problem in this study i.e. estimating conceptual cost based on past data of completed projects, is based on feed-forward neural network architecture and back-propagation technique. The structure of NN is made up of three main layers: input, hidden, and output. Except for the output layer, which includes one neuron that represents the training process's output, each one comprises many neurons. In a construction project, a cost estimation model is used that is based on an artificial neural network that adjust to cost estimation better [11].

3. Research Methodology

Quantitative approach was used for this study. First of all the influencing factors of the cost estimation of preparation of design and drawings of private building projects were identified. These variables were validated through expert opinions. Finally data were collected through survey forms form the private consultancy firms and ANN models were developed. The research methodology framework is shown in the figure 3.

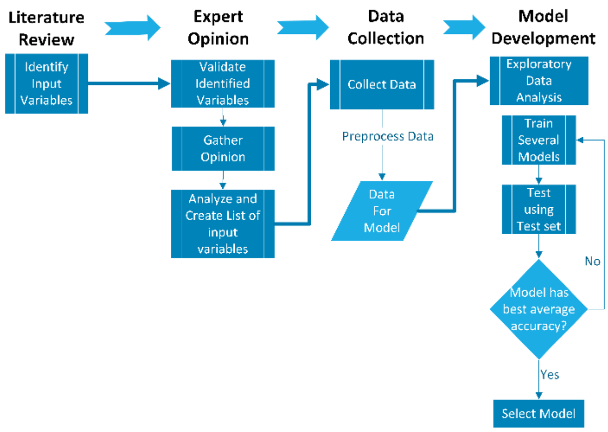


Figure 3: Research Methodology

3.1 Expert Opinion

When obtaining research evidence, the expert opinion technique ensures the validity and reliability of the research. As a consequence, the outcomes of expertise, i.e., the evaluation and opinion of qualified and experienced experts on the subject area, serve as the foundation for making important decisions [12].

6 influencing factors were identified through the expert opinions. 3 experts with more than 15 years of experience were selected for the expert opinion and verification of the factors obtained. The odd number of experts is preferred as there is always majority by one. The identified factors are presented in Table 2.

Table 2: Design Parameters

Design parameter (1)	Definition (2)	Type
x1	Building_Purpose	Residential (0), Commercial (1)
x2	Plinth_Area (Sq. ft)	Numeric
x3	No. of storeys	Numeric
x4	Builtup_Area (Sq.ft)	Numeric
x5	Years of expertise on the field	Numeric
x6	Scope of Work Packages	ASE (0), ASE3D (1)

3.2 Data Collection

Secondary data from the records of various private buildings were collected from various private consultancies working in Kathmandu valley. These consultancies maintain the database that comprises of design and drawing details of the project and also bills for the cost data. Those data of readily available were collected. The number of sample collected was 70.

3.2.1 Data Processing

The data needs to be processed before to the ANN model. The model does not handle the categorical/ text values and will only handle numerical value for model development. Following steps were carried out before feeding to the model.

Step 1: The categorical values were transferred to numerical variable using one hot encoding.

Step 2: The actual cost was transformed into Base year cost 2014/15 AD using Consumer Price Index (CPI) index of KTM valley provided by Nepal Rastra Bank (NRB) as shown in Table 3 . Equation 1 is used to compute the Base year cost is given as:

$$Base\ year\ cost = \frac{Actual\ Cost}{Corresponding\ CPI} * 100 \quad (1)$$

Table 3: CPI of KTM Valley

Fiscal Year	CPI
2014/15	100.0
2015/16	111.6
2016/17	115.0
2017/18	118.8
2018/19	124.5
2019/20	133.2
2020/21	137.6

Step 3: The data were then manually inspected to find and eliminate outliers.

3.3 Model Development

This phase consists of 3 process namely, training of model, optimization of model and testing of model. The data sets were divided into the ratio of 70-30 as training and testing sets respectively. The training and testing processes were run through iterative process to achieve best model with least Mean Absolute Percentage Error (MAPE) on total prediction set.

3.3.1 Training of Data

The data after being preprocessed were fed into the model. For modelling Statistical Packages for Social Science (SPSS) software package was used. This provided a user friendly built in option for modelling a neural network under multilayer perceptron. Data are generally normalized for confidentiality and for effective training of the model being developed which improves the performance of trained networks.

In essence, a neuron adds up its weighted inputs, deducts its threshold from the total, and then transmits the results using an activation function[1]. All neurons are interconnected creating a deep networks each having the value of weightages. The activation function adopted was a hyperbolic tangent given by following equation 2:

$$Activation\ function\ (x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{2}$$

The back propagation algorithm is the most widely used training technique. This algorithm has been shown to be theoretically sound [13]. Gradient descent algorithm is used to minimize the errors and admission of suitable weights.

Identify function was used in the case of output node. The training done was of batch type. The training of all cases in a training set is called an epoch [14]. This number was set to 1000 in order to avoid over-training of the model.

Other two important network training parameters are the learning rate and the momentum coefficient which was set to 0.01 and 0.9 respectively. Slow learning rate was chosen since large learning rates leads to oscillation and divergence in algorithm. [15]The learning rate is compensated by the momentum hence the value is introduced. The training was done till the threshold value was reached i.e 0.0001 change in training error.

3.3.2 Optimization of Data

The number of neurons in hidden layers is set as a parameter for the optimization of the model. Hegazy & Moselhi, stated that one hidden layer with a number of hidden neurons as 0.5 m, 0.75m, m, or 2m+1, where m is the number of input neurons, is suitable for most applications [16]. So as per our 6 input parameters then we can derive 3,4,5,6 and 13 neurons for our study to optimize the training set. So our 5 models are:

- 6-3-1
- 6-4-1
- 6-5-1
- 6-6-1
- 6-13-1

The first, second and third number representing the number of neurons in input, hidden and output layer respectively.

3.3.3 Testing of Data

To measure the accuracy of the neural network model Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) were used. Values of these errors were computed for each model and model with less sum of error was used.

4. Results and Discussion

4.1 Model Selection

After the iteration was completed on five model sets, the one with the least MAPE was selected. Form the table 3, it is seen that (6-4-1) model has least MAPE of 12.51%. So, the model has 6 input neurons, 1 hidden layer with 4 neurons and 1 output neuron.

Table 4: Errors of Overall Prediction

CASE	MSE	MAPE
6-3-1	22351.3	17.85%
6-4-1	19016.73	12.51%
6-5-1	24323.03	20.29%
6-6-1	18932.26	15.61%
6-13-1	24422.37	21.14%

4.2 Model Description

Among 70 data collected 51 were used in training set and 19 were used in the testing set. The sum of squares error of test and training sets were 0.123 and .081 respectively which is low.

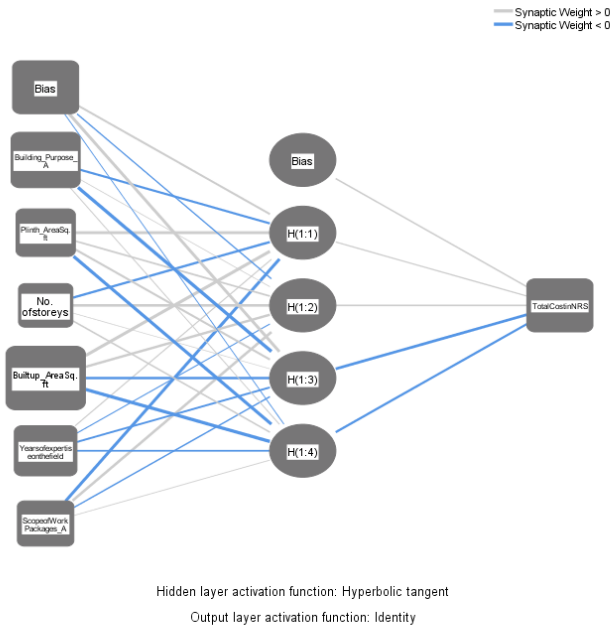
Table 5: Model Summary (6-4-1)

Training	Sum of Squares Error	.123
	Relative Error	.054
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.00
Testing	Sum of Squares Error	.081
	Relative Error	.131

Dependent Variable: Total Cost (in NRS)

a. Error computations are based on the testing sample.

Table 6: Multilayer Perceptron



4.3 Independent Variable Importance

SPSS provides with the analysis of importance factors when modelling a neural network multilayer perceptron. According to Table 4, the most important independent variable is the Built up Area with importance index value of 0.416. This can be justified with the fact that the total cost is calculated by multiplying the rates with the built-up area. So higher the built-up area higher is the cost. The least important factor is number of storeys of the building which had importance index of 0.022.

	Importance	Normalized Importance
Building_Purpose	.254	61.1%
Plinth_Area (Sq. ft)	.100	24.0%
No. of storeys	.022	5.4%
Builtup_Area (Sq.ft)	.416	100.0%
Years of expertise on the field	.152	36.6%
Scope of Work Packages	.056	13.4%

Figure 4: Independent Variable Importance

The table gives us the idea of which factors have significant role in the model that influence the cost of consultancy services. Furthermore this helps in reduction of least important factors form the model without abruptly changing the prediction of the model.

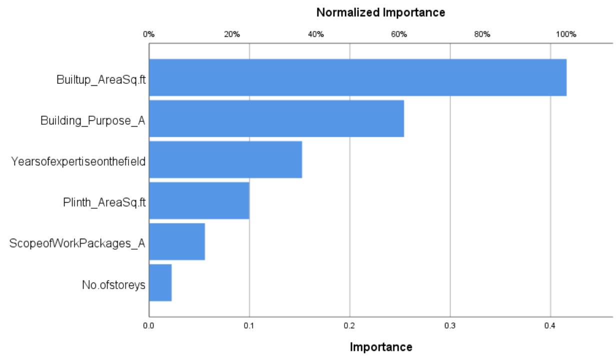


Figure 5: Independent Variable Importance

5. Conclusion

The aim of this research was to develop an ANN model for the cost estimation of the consultancy services of private building projects. Though there are numerous ML based methods for the estimation of construction cost of the building projects, very limited resources is found for the context of consultancy cost. The model was developed in SPSS software packages with 70 data samples. The yield a MAPE of 12.51% while prediction was done for overall datasets. This shows that even with small amount of influencing factors and data samples a good result can be yield. So a fairly justifiable model of cost estimation is developed. This can be used by the general public with no little knowledge on engineering service cost yet know about their demands regarding their buildings and this way can be used to predict the cost of consultancy services.

However there are number of limitations with the present research. Firstly the scope of this project is fairly limited to private buildings projects of mostly residential types and only the cost of preparation of drawings and designs is included. But, most of the consultancy cost is not limited to these only but wide range of other services such as site supervisions and survey, geotechnical investigations and social surveys. Also varieties of buildings types such as intuitional, high rise buildings and apartments that may incur heavy cost of consultancy services did not fall under the scope of this study due to the limited resources in hand. Having said this, it could act as a research gap for further studies.

Also the given the nature machine learning based methods used in this research, more amount of data can be incorporated to increase the accuracy of the model proposed.

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