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PRELIMINERY PROJECT COST ESTIMATION MODEL USING ARTIFICIAL NEURAL NETWORKS FOR PUBLIC SECTOR OFFICE BUILDINGS IN SRI LANKA

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Abstract

Cost estimating is a critical due to incomplete project details and drawings and has become a similar issue in Sri Lanka. Since, cost of a building is impacted by decisions made at the design phase, efficient cost estimation is essential. Therefore novel cost models have identified as simple, understandable and reliable. Thereby, Artificial Neural Networks (ANN) have established having the ability to learn patterns within given inputs and outputs and the end result was developed as the preliminary project cost estimation model for public sector office buildings in Sri Lanka. To accomplish the above aim, the survey approach was selected and semi structured interviews and documentary review were conducted in collecting data. Then training and testing of the Neural Networks (NN) under ten design parameters was carried out using the cost data of twenty office buildings in public sector. The data was applied to the back propagation NNtechnique to attain the optimal NN Architectures. The empirical findings depicts that the success of an ANN is very sensitive to parameters selected in the training process and decreasing learning rate makes Mean Square Error smaller but with considerably larger number of iterations up to certain point. It has been gained good generalization capabilities in testing session achieving accuracy of 90.9% in validation session. Ultimately, NN has provided the best solution to develop a cost estimation model for public sector as accurate, heuristic, flexible and efficient technique.

Keywords: *Artificial Neural Networks (ANN), Cost Estimation Models, Office Buildings, Preliminary Project Estimate, Public Sector.*

1. Introduction

In early stages unavailability project information was the major problem faced in cost estimation. Therefore, parametric cost estimation models were very useful (Kim et al., 2004).According to Ashworth (1999), cost modeling is the symbolic representation of a system which exists or is planned, and which in terms of its significant cost, features for the reasons of display, analysis, evaluation or control. Therefore, model based cost estimation has become the best to overcome the difficulties faced by the estimators. A wide range of cost forecasting techniques have been exploited in the construction industry namely statistical based analysis techniques and artificial intelligence based technique (Kim, Seo, & Kang, 2005; Elhag, Boussabaine, &Ballal, 2005; Lowel, Emsley, & Harding, 2006; Sonmez , 2008). Currently historical cost data is the most popular source in cost estimating at the early stage of a project since there are incomplete project details.

Yet, the performance of usage of historical cost data in cost forecasting in Sri Lankan consultancy practice is poor. In the meantime, Ferry & Brandon (2000),stated that the private and public sectors are differentiatedin terms of cost targets. In public sectorPreliminary Project Estimates (PPE) are prepared to get the estimated project cost approved from the Cabinet of the government, after completing the preliminary designs. Therefore, the need for an accurate and reliable cost estimate prior to the actual design of the project has been increased in public sector. Although there are number of cost estimating and modeling software in the international market, they are difficult to be adopted for Sri Lankan context.Therefore, those models have limited usage and the availability of the cost models are very much less in number, when applying to current status of Sri Lankan construction industry. Accordingly, main research problem is arising "How to develop a Preliminary project cost estimation model for public sector office buildings in Sri Lanka?".

Therefore the research aim is todevelopa preliminary project cost estimation model for public sector office buildings in Sri Lanka by investigate different types of construction cost estimation techniques and models and its suitability, current Sri Lankan practices in public sector projects while conducting a thorough analysis of the collected data.

2. Construction Cost Estimating

Cost planning is an attempt used to bridge the gap in cost information between the time of the preliminary estimate and the receipt of the tender (Odeh&Battaineh, 2001). According to the Yu (2007), in preparingan estimate, it is necessary to appreciate the employer's requirements and how they are translated into substance, the business considerations affecting that translation and the source and nature of the data upon which estimates are based to the form of estimate and its reliability (Cheung et al., 2012). Even though there are incomplete project information at the early stage of a project, it is mandatory to predict the cost since it established the budget and it would be the employer's first impression on the project. Hence, parametric cost estimation techniques are most appropriate for cost estimation at the early stages. Among the cost estimation techniques qualitativeand quantitativemethods are the major categories. There the historical cost data and expert experience is used for the Qualitative cost estimation techniques. While, quantitative techniques not only rely on historical cost data and expert knowledge, hence it can also be analysed project processes, designs, and unique features (Berny & Townsend, 1993). However, systematically analyses cost data of historical projects are highly useful in both qualitative and quantitative techniques and it acts as roots for cost modeling and provides cost controlling at the design stage.

3. Building Cost Estimation Models

Cost modelling is a symbolic development of a structure and enclosed the factors which are affecting to the cost (Holm, Schaufelberger, Griffin, & Cole, 2005). It can be categorized in to two ways, as one based on historical development of the cost models such as first-generation models, second generation models and third-generation models and the other method is according to their characteristics such as traditional cost models, non-traditional cost models and new wave models **(Seo, Park, Koo, & Kim, 2008)**.Traditional and non-traditional Cost Estimation models have briefly listed out in Table 1.Meanwhile, such estimates cater in evaluating project feasibility and effective cost control during detail project designing while preventing re-budgeting, re-designing and project cancellations.

3.3 NEW-WAVE MODEL

Neural Network (NN): NNs are a computer system based on the abilities of the human brain. A group of simulated neurons is interconnected and NNmodels consist of simple computational units organized into a sequence of layers and interlinked by a system of connections (Kim, Seo, & Kang, 2005). A typical parametric NN model includes the parameters in the input layer, and cost in the output layer. It also includes at least one hidden layer between the input and output layers to represent the relations between the parameters and cost (Sonmez & Ontepeli, 2009). Table 2 indicates the Advantages and limitations of neural networks.

Table 1, Traditional and Non-Traditional Cost Estimation Models

Traditional Cost Estimation Models	Non-Traditional Cost Estimation Models
Unit method**:** Cost per functional unit of the buildingto confirm that the costs are reasonable with other similar nature buildings (Seo, Park, Koo, & Kim, 2008). ***Approximate quantities*****:**Mmost reliable and accurate under sufficient information. Measurement can be carried out using composite rates to save time. ***Storey enclosure method***: Considers thevariations in plan shape and storey height (Seo, Park, Koo, & Kim, 2008). ***Cubic method of estimate***: Relates the cost of a building to its calculated volume (Akinsiku, Babatunde, & Opawole, 2011). ***Elemental cost analysis method***: Unit cost is broken down into elements and sub-elements in a flexible, easily understandable manner (Akinsiku, Babatunde, & Opawole, 2011)	***Regression analysis:*** Statistical computer system approach is utilized in Multiple Regression Analysis to forecast change in a dependent variable on the basis of change in one or more independent variables (Garza &Rouhana, 1995). The equation is used in fitting a curve or line to points of data, such that the differences in the distances of data points from the curve or line are minimized (Bode, 1998). ***Probabilistic Treatments:*** Probability theory and random number generation produce cost models with risk profiles which recognize the inherent variability and uncertainty of design cost modeling, due to its predictive nature (Skitmore& Ng, 2003). ***Simulation Models:*** In Monte Carlo simulation, a mathematical model is constructed based on pre-specified probability distributions, where the possible outcomes of major cost elements are described, and operates to check the

Table 2, Advantages and limitations of neural networks

Advantages	Limitations
• The neural network does not use pre-programmed knowledge base • Suited to analyze complex pattern • Have no restrictive assumptions (Bode, 1998) • Allows for qualitative data (Bode, 1998) • Can handle noisy data • Can overcome autocorrelation User-friendly, clear output, and robust and flexible (Bode, 1998) • The numbers of inputs and outputs are not restricted (Smith & Mason, 1997)	• Requires high quality data Variables must be carefully selected a priori • Risk of over-fitting • Requires a definition of architecture • NNs are in a sense the ultimate 'black boxes' • Time consuming in determining the number of the neurons • Possibility of illogical network behavior • Large training sample required

4. Identification of Suitable Technique for Public Sector Building Projects

Cost models provide a powerful alternative for conceptual estimation of construction costs. However, development of cost models is critical task due to several factors affecting the cost of a project (Sonmez, 2011). NNis accepted as a germane and precise technique used at the preliminary stage based on the available data and it can perceive the relationship and pattern between the inputs which are parameters and the outputs which are costs. However, the details of the project at the early stage are limited to handful ofparameters such as floor height and floor area. Thus, NN delivers an effective output based on the details of previous projects. Even though there are several new wave models, NN is the most appropriate technique for cost estimation due to the complexity of the other new wave techniques (Bode, 1998). In Sri Lanka, there was a considerable development in public sector office buildings in recent years and a critical need for a proper cost model is initiated to estimate project cost at early stages. Therefore, this researchfocuses on public sector office buildings available in the industry. Here the public sector constructions projects are essential to submit an accurate estimate to obtain the Cabinet approval at the preliminary stage, one of the critical issue faced is the prepared estimate is not up to the required standard due to lack of detail drawings and specification. Hence it is clear that, even though some systematic procedures,and models are being used in other sectors, public sector consultancy firms are currently practicing the taking off method using the incomplete drawings, where it is not catering for the accuracy of the estimate using the available set of drawings and specifications. Therefore a question is aroused as, “How to build a preliminary estimating model to cater the current demand in public sector office buildings in Sri Lanka?”. Thereby the data collection and analysis is conducted to fulfil the given deficiency.

5. Research methodology

The survey approach is identified as the optimum method and inbetween, document review and semi structured interviews were conducted. the collected data in interviews were analysed using both content analysis and neuroph studio was used as the quantitative data analysis method. training and testing of the neural network is done with the neuroph studio application using six steps. then the findings were geared towards achieving the ultimate outcome by developing a preliminary cost estimation models using the method of nn using the java programming language which carries number of advantages as easy to write, compile, debug, and learn, it is robust, multithreaded and secure.

6. Data Analysis andResearch Findings –

Interviews Semi-structured interviews have been carried out with four key individuals of public sector consultancy organizations in Sri Lanka. Expert opinions were gathered to explore current practice of cost estimation and the necessity of a cost estimation model at the preliminary stage. Further expert opinions were gathered to identify variables for the model preparation and relationships between parameters. Table 3 shows the profile of the respondents.

Table 3, Respondents' profile

Code	Designation	Experience in the construction industry (yrs)
A	Deputy General Manager (Contracts and Quantity Surveying Unit)	16
B	Chief Quantity Surveyor	18
C	Quantity Surveyor	15
D	Quantity Surveyor	10

Majority expressed that the method used for the preparation of preliminary estimate, varies depend upon the availability of data about the project. according to respondent a "*we do predictions up to the maximum level, on the basis of whatever the information we have*". on the other hand majority of the respondents pointed out, that four major items they have readymade analysis prepared by themselves based on the past projects and subjecting to changes they used such estimates for current projects and several mistakes have also been identified by the respondents. accordingly, as emphasized by the respondent a "*if we have reasonable time to prepare estimates with the use of designs developed by architecture and engineering departments of the organization it will result in better estimates*". however, oftenat the preliminary stage of the project architects are reluctant to put their decisions to design since they are not thorough with project details. the necessity of preparing an advanced cost estimation model originated through the importance of obtaining the cabinet approval for the allocated budget for the project especially in public sector projects. even though the probable estimates are prepared by the practitioners based on their skill and experience, there is a possibility of occurring errors in such estimates. therefore majority highlighted that, though it provides the user an easier environment, reluctance to change, traditionally embossed practices and lack of knowledge had become major barriers in the implementation.According to the respondents the parameters were selected for the accuracy of the cost model depending on the availability of data, cost significant items and selection of independent and dependent variable. However the majority commented that for the reliability and accuracy of cost estimation model it is important to used actual rates and costs incurred for the particular works and the respondents further stressed that, to get parametric details it is essential to refer the architectural and construction drawings. However, finding of final bills and related drawings of particular office developments was hard and difficult when it comes to the public sector consultancy organizations, due to poor documentation and unavailability of soft copies of each document.

7. Research Findings and Data Analysis – Document Review

Twenty office buildings, constructed during last 10 years were selected. Most of the them were 2-5 storied having strip foundations with column footings. Only two buildings with the pile foundations were found. According to the opinions of the experts and experienced obtained through documents, cost of main elements and suitable parameters were collected and thereby the data base was developed. The data base developed using the MS Excel Moreover, it easy to feed data from MS Excel sheet to the Neuroph Studio which is the software used for data training and testing. Prior to that parameters which are expected to relate for selected structural elements are selected and presented in the Table 4.

Table 4, Parameters and their Expected Relationship

Element	Expected Relationship (Inputs)
Substructure	Gross Floor Area, Ground Floor Area, Type of Foundation
Super Structure Concrete Works	Gross Floor Area, Ground Floor Area, Number of Stories, Average Storey Height, Building Height
Masonry Works	Gross Floor Area, Number of Stories, Average Storey Height
Water Proofing	Gross Floor Area, Ground Floor Area, Upper Floor Area
Roof structure including, Covering and Plumbing	Ground Floor Area, Roof type
Floor, Ceiling & Wall Finishes including Painting	Gross Floor Area, Wall area, Doors & Windows Area
Doors and Windows	Wall area, Doors & Windows Area

In order to generate most reliable cost estimate, separate NNs was created for each elements. Then the data from projects were trained and tested within each NNs. Each elements were trained and tested with different hidden layers, momentums and learning rates. Ten the results were presented and discussed for each elements separately as shown in Figure 1.

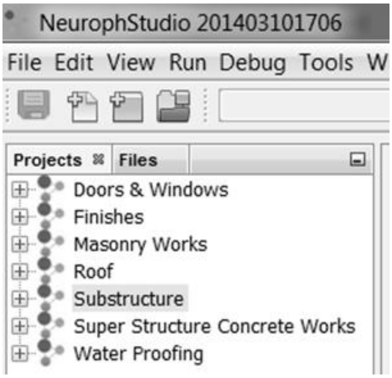

Figure 1, Neuroph Projects Created for Data Analysis

Among the basic elements, sub elements were clearly identified. For an example in substructure, Topsoil excavation, Removal of ground water, Column footings and etc., have identified as the sub elements. Six number of NN architectures were created and tested to obtained optimal NN for sub structure. Number of hidden neurons were taken to range from one to three, while numbers of input and output neurons were three and one respectively.Most of the attempts of training with learning parameters ranging from 0.1 to 0.3, with the momentum rate of 0.6 to 0.7. However, one to three hidden neuron were unsuccessful and some of them were not trained. According to Table5the best combination is the network comprising of two hidden neurons, 0.1 of learning rate and 0.6 of momentum which gives the minimum Mean Square Error (MSE).

Table 5, Sub-Structure Neural Network Training and Testing Results

Training attempt	Inputs	Outputs	Hidden layers	Learning rate	Momentum	Iterations	MSE
1	3	1	1	0.1	0.6	10000	-
2	3	1	2	0.1	0.6	8287	0.0140
3	3	1	3	0.1	0.6	3450	0.0159
4	3	1	1	0.2	0.6	10000	-
5	3	1	1	0.3	0.6	10000	-
6	3	1	1	0.1	0.7	10000	-
7	3	3	2	0.1	0.7	10000	-

However, it reads high amount of iterations and it can be identified from the total network error as the graph shown in Figure 2. The relatively high number of iterations indicated that network is hesitant to learn from the data set. This may due to: poor relationship between selected parameters, the cost of sub structure and insufficient data. However it has been trained at certain network architecture, since there is a minor relationship between parameters.

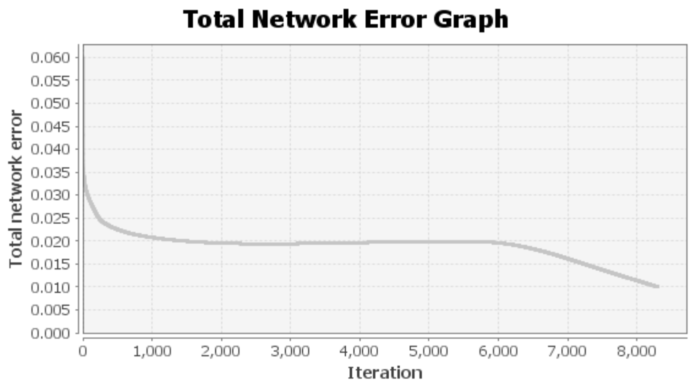

Figure 2, Total network error graph for the optimum neural network

Since the elements coverdifferent sub elements, the relationship between inputs and outputs were hard to identify. The special highlights identified in each basic element is presented in the Table 6.

Table 6, Significant Findings of Each Basic Element

Element	Significant Findings
Sub Structure	Due to several requirements of the design and ground conditions topsoil excavation is not proportionate to the Gross Floor Area (GFA). Type of foundation and ground floor area has the relationship with the cost of sub structure (it is not revealed due to: insufficiency of data set and foundation type).
Super Structure Concrete Works	Quantity of superstructure concrete works are more related to the gross floor area, ground floor area, upper floor area, number of stories, average storey height and building height (Ex: Slabs Concrete Staircases etc.)
Masonry Works	Network shows the relationship between input parameters and the cost of masonry works. GFA, number of stories, average storey height and the building height were used as input parameters
Water Proofing	A relationship between the GFA and the washroom areas in an office buildingis proportionate to the ground floor area (Due to typical shape of most office buildings)
Roof Structure and Plumbing	Area of roof may not related to any of the factors.

Element	Significant Findings
Floor, Ceiling & Wall Finishes including Painting	Wall finishes-kind and quality of internal and external finishes are varied and wall finishes may not directly proportionate to the wall area off the building. Direct relationship is between floor finishes and the GFA, but the cost can be changed due to different types of finishes.
Doors and Windows	Though the door and window areas used as an input parameter, network was not trained properly (Due to varied amount of door and window areas with wide range of types and designs)

8. User Interface of Developed Cost Estimation Model and Validation

After selecting the optimum NN architectures, "Office Building Estimation Application" was built up. According to Figure 3 user interface developed with another two successive windows. Once clicking "Getting Started" in the initial interface, category selection interface appears as in Figure 3. After selecting a category by clicking the selected button the third interface arrives (When selecting a super structure third interface appears. This interface may vary from one another since it has different parameters to enter.

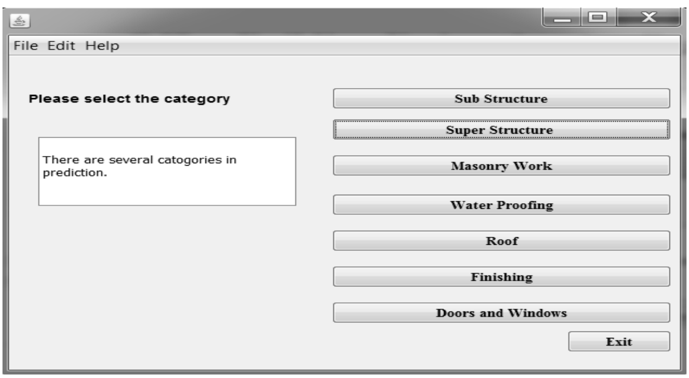

Figure 3, Category Selection Window

After entering relevant parameters then just want click the "predict" button. It predicts the expected cost for the relevant element. This was a user friendly interface and easy to understand.The final step of the NNmodelling was the validation of the model. Since software has already developed in model validation can be done through the developed model. Otherwise, data can be validate with Neuroph Studio by selecting optimum NN architectures for eachelements.

Table 6, Validation of Cost Model

Element	Actual Amount (Rs.)	Predicted Amount	Difference	Percentage Error
Sub structure	3,429,144.00	3,785,265.00	356,121.00	10.39%
Super structure	12,664,566.00	13,828,344.00	1,163,778.00	9.19%
Masonry works	3,878,231.00	4,202,098.00	323,867.00	8.35%
Water proofing works	1,460,808.00	1,360,435.87	100,372.13	-6.87%
Roof	4,552,049.00			
Finishes	57,614,688.00	53,345,987.00	4,268,701.00	-7.41%
Doors and windows	4,375,635.00			

According to the Table 6, when considering all the percentage errors, almost all the percentage errors of each elements were in the range of ± 10.00%. This error value is within the maximum error (10%), which was the initially established percentage. Hence, it can be concluded that ANN model has reached the expected performance in the study.

9. Conclusions

In Sri Lankan construction industry the role of public sector is crucial since preparing a well accurate estimate at the preliminary stage is an essential and transparency of transactions are also vital from the beginning to the end. However, preparing preliminary estimate is crucial since the available data are very less at this stage.Therefore, necessity of a cost model to prepare the preliminary estimate for office buildings in public sector has identified.

Despite drawbacks such as lack of the interpretability of the built model that NNs have, still widely used and included in most data analytics frameworks. However, there are number of advantages in NNs such as data driven, self-adaptive of driven data, approximate functioning - linear as well as non-linear NNs classify objects rather simply - they take data as input, derive rules based on those data, and make decisions. Further, the ability of pattern recognition and generalization of ANN and suitability to predict preliminary project estimates concluded to use NNs. Meanwhile, since the industry is fed up with not having standard practice for preparing estimates at this stage requirement of efficient and reliable cost estimation models were initiated.

Additionally, cost significant items and parameters were selected based on the correlation of variable to the construction cost, retrievable of variables from the past projects and the availability of the variables at the preliminary stage. ANN highlighted as, very sensitive to parameters selected in the training process where the learning rate must not be too high or too low.

Further the decreasing learning rate have made MSE smaller but with considerably larger number of iterations up to certain point. During the testing and training, it was found that each network have obtained MSEs approximate to 0.01 and ANN model effectively learned during training stageand gained generalization capabilities in testing session while achieving the accuracy of 90.9% in validation session. Unfortunately NNs` black box nature may obscure the reason behind the estimate, not display the underlying processes and cost drivers as well as the current cost estimation software. Ultimately all advanced improvements poured in the developments of ANN cost estimation model for preparing PPEs of apartment buildings in Sri Lanka.

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