Sustainable Solutions in Structural Engineering and Construction
Edited by Chantawarangul, K., Suanpaga, W., Yazdani, S., Vimonsatit, V., and Singh, A.

ISBN: 978-0-9960437-0-0

IDENTIFICATION OF THE KEY FACTORS FOR ACCURATE LIFE-CYCLE COST ESTIMATION FOR CONSTRUCTION

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A major limitation of Life-Cycle Cost (LCC) estimation/prediction modelling is the current typical reliance only on those factors that can be readily quantified and come easily to hand. While estimation of the cost of the most common labor, material and plant resources receive consideration because of their high visibility factor, there are several non-cost factors (low visibility factors) affecting the estimate that are often overlooked and, it is argued here, require equal consideration in estimation processes that seek optimum accuracy. Unfortunately, such (low-visibility) factors are neglected or ignored by current prediction models. Identification of these non-cost factors (low visibility factors) affects LCC estimate accuracy and can improve estimation process confidence. This paper critically reviews secondary research on identification of these important non-cost factors and subsequently determines their influence on the accuracy level(s) of construction cost estimation.

Keywords: Life-Cycle-Cost (LCC), non-costfactors, estimation cost, construction/ building projects.

1 INTRODUCTION

There is ongoing growth in construction projects and investment in numerous countries. Organizations and agencies must estimate respective whole-life costs and benefits to assess the desirability of projects. This information helps in shaping the opinion of financial and banking institutions that are associated with the project. Life-cycle cost (LCC) analysis can assist organizations and agencies make informed decisions. LCC is deemed to be one of the fundamental foundations of asset management; the application of which requires various types of (significant input) cost-in-use information. Identification of such key/significant factors greatly affects the output of a LCC analysis (i.e., affects the final whole-cost figure for the project over its usable life), and is the most important step before embarking upon the collection of progress (cost) information. To this end, the main aim of this paper is to critically review the applicability of past studies in determining the most important key/significant factors affecting the overall accuracy of the construction cost estimating process.

2 REVIEW OF SECONDARY RESEARCH

Non-cost factors can affect the accuracy of estimating tools such as life-cycle costing, and cover a multitude of variables that are often difficult to categorize (Alqahtani and

Whyte 2013). Liu and Zhu (2007) classified the variables that influence cost estimation as idiosyncratic, control factors. Control factors are those that the estimators must determine to improve the performance accuracy of estimation. Idiosyncratic factors are factors affecting cost estimation processes somewhat outside the control of (early-stage) estimators such as project complexity, weather, resource availability, type of procurement system, contract type and the like (Liu and Zhu 2007). Elhag et al. (2005) state that the most important factors that influence estimation cost are qualitative, including client priority on construction time, procurement methods, and market conditions including the level of construction activity. This extends the discussion that the most important and considerable factors are related to the idiosyncratic factors as described by Liu and Zhu (2007), as factors outside the control of the estimator; Elhag at al. (2005) identified 67 factors and classified these into six categories. They conducted a questionnaire survey and comparison analysis of respective impact towards reliable costing. They found that consultant and design parameters are the most important category, with an average severity index of 82%, with contractor-attributes category scoring the least average severity index of 67%.

The research above builds upon work by Akintoye (2000), who sought to gain an understanding of the factors influencing contractors' cost estimating practice. He used a comparative study of eighty-four UK contractors. He initially considered 24 factors in the study and found 7 main factors relevant to the cost estimating practice, namely: complexity of the project, scale and scope of construction, market conditions, method of construction, site constraints, client's position, build-ability, and the location of the project. The caveat is that his study focused only on the contractor. Citing this and other studies, Liu and Zhu (2007) noted that most previous research into cost estimation paid attention to specific estimation approaches, with little focus on unique requirements at each project stage. This motivated them to identify the critical factors for effective estimation at numerous phases of typical construction projects. Based on organization control theory and cost estimating literature, they created a theoretical framework that identifies 19 factors for effective cost estimation throughout every project stage of a conventional construction project. These factors were grouped to 6 categories: project information, team experience, cost information, estimation process, and team alignment, and estimation design.

Identification of the major cost overrun factors in the construction sector of Pakistan was the main aim of the study conducted by (Azhar et al. 2008). They identified 42 factors by review of past research and asking expert opinions. Their survey questionnaire asked respondents to rank and score those 42 factors according to their experience. They stated that both internal and external aspects of business settings are present as the major factors behind cost overruns. Their results show that fluctuations in prices of raw materials, unstable costs of manufactured materials, high costs of machinery, additional work, improper planning, the lowest-bidding procurement method, the long period between design and time of bidding/tendering, inexact methods of cost estimation, and inappropriate government policies were the top ten factors behind cost overruns.

Most prior research, including those reviewed above, identified and ranked the important factors based on expert opinion; this technique is straightforward, easy to utilize and commonly available. However, this method is not fully suitable for explicitly displaying relationship factors and cost estimation.

Some researchers have used non-traditional methods, such as multiple-regression and a case-based reasons (CBR) and experts system, to identify key non-cost factors affecting the accuracy of the estimation process. Thalmann (1998) developed a hedonic model for Swiss residential properties based on a (small) sample size of 15 properties. An application of this model for early cost estimates was not possible because the database was small and the developed model was not aligned to it. However, its independent variables are interesting for this present study's direction.

Later Wheaton and Simonton (2007) developed hedonic cost models for residential and office properties. Their study was based on data available for over 60,000 properties (with 42,000 residential properties) and was primarily concerned with six American markets. The focus of their work was on the "true" trends of the cost during a period of 35 years. In addition, they analyzed the correlation between costs and building activity. However, the supply of cost indicators and their drivers was not central to their study. It is argued here that the present study can address this gap, and can work with the developed semi-log regression models and their five independent variables, not least by looking at Artificial Neural Networks (ANN).

Elhag's (1998) work assessed 30 projects to develop two ANN models predicting the lowest tender price of primary and secondary school buildings. The first consisted of four cost-influencing factors as input attributes. They represented types of building, gross floor area, number of stories, and project duration. The second had 13 input-cost variables. They concluded that the more significant the factors contributed in developing an ANN model, the better the outcomes (Elhag and Boussabaine 1998).

Similarly the study of Emsley et al. (2002) was based on a data pool of 288 properties. They worked with regression analyzes as well as with neural networks to compare the two statistical methods. Up to 41 independent variables were included in the developed models, and in the best case the developed model supplied a mean absolute percentage error (MAPE) of 17%. The practical application of the models was made more difficult due to this comparatively large error. Also, the necessary input (41 independent variables) was extensive, making it difficult to apply in early design stages.

Attalla and Hegazy (2003) identified 18 factors affecting the cost performance of reconstruction by means of literature reviews, discussion with construction professionals, and a questionnaire survey. They compared the ANN model with the regression model, and concluded that both models produced relatively close levels of predictability of cost deviation. However, the neural network model was able to estimate similar results using all 18 variables in the estimation, while regression utilized only 5 variables. They concluded that ANNs are more suitable for issues involving high levels of uncertainty and in situations where some decision support approach is needed. Skitmore and Ng (2003) then developed standard regression and cross-validation regression analysis models for actual construction duration estimates when client sector, contractor selection method, contractual arrangement, project type, contract period, and a contract sum were known. A set of 93 Australian construction projects was used to develop the model.

Separately, Li et al. (2005) used the data of 30 completed office building projects to study the relationship between a number of independent variables (average floor area, total floor area, average story height, total building height, number of stories above ground, number of basements, and types of construction) and the construction cost. They developed a regression-cost model for reinforced concrete (RC) and steel office buildings, finding the total floor area and total building height account for over 96% of the accuracy of the model. For steel office buildings, the total floor area, average floor area and total building height account for over 95% of the accuracy.

Two years later An et al. (2007) proposed a case-based reasoning cost estimation model that incorporated experience employing an analytic hierarchy process (AHP). They used the data of 580 residential buildings built by general contractors between 1997 and 2002 in South Korea. They selected nine variables (gross floor area, number of stories, total unit, unit area, location, roof types, foundation types, usage of basement, and finish grades) as the input variables for the case-based reasoning model based on the interviews of cost engineers in Korean construction companies. They applied three different weighting approaches, and found that the analytical hierarchical process (AHP) was more accurate, reliable, and explanatory than other approaches. It might be argued, however, that AHP depends on expert experience and judgment. Therefore, this method contains both uncertainty and imprecision due to the need for human intervention and may not provide optimal solutions.

Eleven variables was selected by Kim et al. (2005) in their study comparing the two estimating methods (CBR and ANN) of construction costs (location, total area, number of stories, roof types, total unit, unit per story, average area of unit, foundation types, usage of basement, finishing grades, and duration). In the CBR method, they applied the Gradient Descent Method (GDM) and regression analysis method to evaluate the weights of the variables. Regression was more accurate than GDM. They found that the number of stories, units per story, and finishing grades are insignificant factors.

In America, the regression analysis and the bootstrap-resampling technique were integrated to develop conceptual cost estimating (Sonmez 2008). Data was compiled from 20 U.S. building projects with the data of 20 factors. These involved time and location of project, project duration, project characteristics such as total gross building area and number of stories, site conditions, structural frame and exterior finish types.

In the Middle East, Arafa and Alqedra (2011) developed an artificial neural network model to estimate the cost of the structure system of the building at early stage. They used the data of 71 building projects in the Gaza Strip. Seven significant parameters were identified for the structural skeleton cost of the project and used as input variables of the model: the ground floor area, typical floor area, number of stories, number of columns, type of footing, number of elevators, and number of rooms. They applied sensitively analysis and found that the ground floor area, number of stories, type of foundation, and number of elevators in the buildings are the most important factors affecting the early estimates of building cost.

Similarity, neural networks with bootstrap-prediction intervals were integrated to develop conceptual cost estimating (Sonmez 2011). This time, data were compiled from 20 U.S. building projects built over a 13-year time frame at 10 different locations, along with the data of 21 factors. The factors were related to building, as well as site and project characteristics such as total gross building area and number of stories.

Jin et al. (2012) proposed an improved CBR model using multiple regression analysis in case revision for improving performance of cost prediction. Ten parameters were used. The multiple regression analysis illustrated seven parameters most influenced, the cost prediction, namely: site area, underground area, ground area, building area, number of underground floors, number of floors, and landscape area .

Neural networks were also examined by Elkassas et al. (2009) who conducted a study to predict the financial cost for construction projects using ANN models. They created three back-propagation ANN to estimate the financial cost of three types of construction projects: pipeline projects, industrial projects and building projects. 35 samples of pipeline projects, 115 samples of industrial project, and 65 samples of building project were used to develop, train, and test the models. The input layer in all models includes fifteen variables which are project type, project duration, estimation contract value, advance payment, time lag, interest rate, mark-up, time unit first payment, retention, project location, weather conditions, safety conditions, possibility increment in project duration, owner payment delay, and inflation. The study concluded that ANN models gave a good accurate estimation.

3 DISCUSSION

The studies outlined above are similar in that they all attempt to identify relationships between non-cost factors and total cost to devise the most suitable path for accuracy. However, disparity arises in the attempt to define these key variables. A number of opinions exist as to which variables are most influential in estimating total cost.

The work above identified a total of 64 variables influencing cost estimation. Of these, 10 variables were mentioned by a significant number of researchers, and are therefore seen as most greatly influencing the total cost estimation. Table 1 was developed as a result of the secondary research methodology adopted in this research, clarifiing these key variables for future use (Alqahtani and Whyte 2013).

Table 1. Most significant non-cost factor.

1) Number of stories	**2) Type of building**
3) Gross floor area	**4) Project duration**
5) Project duration	**6) Location**
7) Roof types	**8) Foundation types**
9) Number of elevators	**10) Inflation rate**

It must be recognized that each of these factors separately or in combination can affect the accuracy of estimation costs. Variations in these non-cost factors from one project to another would cause varieties in the cost, mostly when differently configured.

4 CONCLUSION

Life Cycle Cost (LCC) estimation is one of the most crucial functions in decision making at the early phase of a project life-cycle. Identifying the main factors that affect the LCC in construction projects is an important step to achieve an accurate estimate of LCC. This study attempted to critically review and identify the applicability of previous research on determining the full range of factors affecting the value of LCC at all phases of construction project life-cycle. Based on the literature review, 10 factors were identified to most greatly influence LCC (see Table 1). These factors must be considered when formulating input variables for the neural network model to be utilized for building and testing model in this research. Future studies shall develop these ideas.

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