Expert Systems with Applications 39 (2012) 5358–5366

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

A factor-based probabilistic cost model to support bid-price estimation

Wei-Chih Wang [a,*], Shih-Hsu Wang [b], Yu-Kun Tsui [c], Ching-Hsiang Hsu [c]

[a] Department of Civil Engineering, National Chiao Tung University, No. 1001, University Road, Hsinchu, Taiwan
[b] Department of Civil Engineering, R.O.C Military Academy, No. 1, Wei-Wu Road, Fengshan District, Kaohsiung, Taiwan
[c] Department of Civil Engineering, National Chiao Tung University, Taiwan

ARTICLE INFO

Keywords:
Factors
Probabilistic cost
Cost division
Bidding
Simulation
Residential housing project

ABSTRACT

An appropriate bid price is essential for winning a construction project contract. However, making an accurate cost estimate is both time-consuming and expensive. Thus, a method that does not take much time and can approximate a proper bid price can help a contractor in making bid-price decisions when the available bid-estimation time is insufficient. Such a method can also generate a target cost and provide a cross-check for their bid prices that were estimated using a detailed process. This study proposes a novel model for quickly making a bid-price estimation that integrates a probabilistic cost sub-model and a multi-factor evaluation sub-model. The cost sub-model, which is simulation-based, focuses on the cost divisions to save estimation time. At the same time, the multi-factor evaluation sub-model captures the specific factors affecting the cost of each cost division. The advantages of the proposed model are demonstrated by its application to three residential housing projects located in northern Taiwan. The steps for applying this model to other contractors are also provided.

1. Introduction

An accurate estimation of the bid price for a construction project is essential to securing the project contract and achieving a reasonable profit. A detailed cost estimation process is both costly and time consuming (PEH, 2008). However, in practice, the available bid-estimation time is often insufficient (Akintoye & Fitzgerald, 2000). Thus, conducting comprehensive and detailed cost estimations are not always possible. Thus, a method that does not take much time and can approximate a proper bid price can help a contractor in making bid-price decisions when the available bid-estimation time is insufficient. Such a method can also generate a target cost and provide a cross-check for their bid prices that were estimated using a detailed process.

Although many cost estimating methods (such as the average-unit-cost method, the cost-capacity factor estimation, and component ratios) can quickly compute a total project cost (Barrie & Paulson, 1992; Hendrickson & Au, 2003; Hong, Hyun, & Moon, 2011), they generally have two significant drawbacks in determining a reliable bid price. First, these methods focus on the level of total project cost (*i.e.*, they usually do not examine any details of cost divisions or cost items) and generate estimates that can vary widely in terms of accuracy. These methods are suitable for use during the early phase of a construction project, such as in the conceptual or schematic design phases, rather than during the bidding phase. Second, these methods do not explicitly capture the factors and characteristics of a construction project, such as the type of retaining walls, building complexity, number of floors, and material types, all of which influence project costs. When these project factors are not systematically evaluated in the decision-making process, bids are generally unreliable. Thus, a bid-price method that estimates costs in detail per cost division and which considers the factors that can influence project cost is preferred.

Therefore, this study developed an innovative model to compute a project bid price by integrating a probabilistic cost sub-model with a multi-factor evaluation sub-model. The simulation-based cost sub-model focuses on the cost divisions (*i.e.*, the project cost is broken down into several cost divisions) to save estimation time and reduce labor costs. In addition, the multi-factor evaluation sub-model reflects the specific factors affecting the cost of each cost division.

The remainder of this paper is organized as follows. Section 2 reviews previous research on bidding methods and parametric estimating methods. The cost divisions for residential building projects and the factors affecting these division costs are identified in Sections 3 and 4. The proposed model is described in Section 5. The experimental results from applying the model to three case projects are presented in Section 6, and the steps for applying the model to other construction companies are discussed in Section 7. Finally, we discuss the results and indicate directions for future research in Section 8.

* Corresponding author. Tel.: +886 3 5712121x54952; fax: +886 3 5716257.
E-mail addresses: weichih@mail.nctu.edu.tw (W.-C. Wang), wss.cv91g@nctu.edu.tw (S.-H. Wang), k335789@ms24.hinet.net (Y.-K. Tsui), adios0705@ctci.com.tw (C.-H. Hsu).

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doi:10.1016/j.eswa.2011.11.049

2. Previous research

2.1. Bidding methods

Most bidding research addresses the question of whether to bid (Bageis & Fortune, 2009; Han & Diekmann, 2001; Kwaku & Carleton, 1999; Lin & Chen, 2004; Oo, Drew, & Lo, 2007; Wanous, Boussabaine, & Lewis, 2000) and what bid price (or bid markup) is appropriate. This study is more focused on the second decision. Current models for determining bid markups can be classified into three types (Marzouk & Moselhi, 2003): statistical models; artificial intelligence-based models; and multi-criteria utility models. In statistical models, for instance, Carr (1983) developed a general bidding model that considers the influence of the number of bidders on markup. Additionally, Carr (1987) demonstrated how competitive bid analysis can include resource constraints and opportunity costs. Dulaima and Shan (2002) investigated the factors influencing bid markup decisions of large- and medium-size contractors in Singapore. Lowe and Parvar (2004) used a logistic regression approach to modelling contractors' decisions to bid.

Several bidding models that use techniques related to artificial neural networks have been designed to support markup decisions via a sequence of deep-reasoning steps (Li & Love, 1999; Moselhi, Hegazy, & Fazio, 1993). Furthermore, as bid-related decisions are highly unstructured and no clear rules exist for bidding decisions, Chua, Li, and Chan (2001) devised a case-based-reasoning bidding model. Liu and Ling (2003) described a fuzzy neural network based approach to estimate the markup percentage. Additionally, Liu and Ling (2005) investigated the factors considered by more successful contractors in mark-up decisions. Christodoulou (2004) presented a methodology for arriving at optimum bid markups in static competitive bidding environments using neurofuzzy systems and multidimensional risk analysis algorithms.

Several criteria or factors guide bidders in determining how to price their work in relation to estimated construction costs (Chao, 2007; Chua & Li, 2000; Dozzi, AbouRizk, & Schroeder, 1996; Dulaima & Shan, 2002; Seydel & Olson, 2001). For example, Dozzi et al. (1996) applied a multi-criteria utility theory for bid-markup decisions for construction projects. Seydel and Olson (2001) designed an approach for incorporating multiple criteria into the bidding decision. Moreover, Marzouk and Moselhi (2003) proposed a model that estimates the markup and evaluates the bid proposal using multi-attribute utility theory and the Analytical Hierarchy Process. Furthermore, Wang, Dzeng, and Lu (2007) used fuzzy integrals to develop a multi-criteria evaluation model that reflects bidder preferences regarding decision criteria. Chao (2007) adopted risk attitude of the contractor and proposed a fuzzy logic model based on determining the minimum bid markup with assessments of chance of winning and loss risk.

In summary, these statistical models have difficulty of capturing specific project characteristics (e.g., project complexity and market conditions), whereas artificial intelligence-based models require numerous training cases or rules that represent the bidding strategies of individual bidders. Notably, multi-criteria evaluations are more applicable to real-life situations than other models (Lai, Liu, & Wang, 2002; Marzouk & Moselhi, 2003). Finally, existing models typically evaluate bid markups or bid prices by focusing on the level of total bid price.

2.2. Parametric estimating methods

A parametric cost estimating method includes one or several cost estimating relationships, between the cost (the dependent variables) and the cost-governing parameters (the independent variables) (Hegazy & Ayed, 1998; PEH, 2008). Parametric cost estimating methods are often used by both contractors and government bodies in the planning and budget stages of a project (Hegazy & Ayed, 1998). This method is sometimes also used by contractors to expedite cost estimates when detailed estimating methods require inordinate amounts of time and resources and are likely to produce similar results (PEH, 2008).

Several parametric estimation methods based on regression analysis and neural networks have been suggested to improve the accuracy of conceptual cost estimates (Gunduz, Ugur, & Ozturk, 2011; Sonmez, 2008). The regression technique allows a relatively simple analysis to sort out the impact of the parameters on the cost of the project (Karshenas, 1984; Lowe, Emsley, & Harding, 2006). Neural networks based on artificial intelligence offer an alternative approach to estimate costs of building projects (Kim, Seo, & Kang, 2005) and highway projects (Hegazy & Ayed, 1998). In addition, some parametric estimating models also consider the level of uncertainty associated with project costs (PEH, 2008; Sonmez, 2008). For instance, Sonmez (2008) integrated the regression analysis and the bootstrap resampling technique to develop a probabilistic and conceptual construction cost estimate. Although most parametric estimating methods assess costs by focusing on the total project cost, Sonmez's model can be used to produce the probabilistic costs of the cost divisions. The produced cost distributions were used to indicate the range of cost expectations, but they were not used to directly support the bid-price decision, which was preferably made based on a single point estimate. Thus, for the model proposed in this study we developed a multi-factor evaluation submodel to assess the effects of various factors on the costs of the cost divisions. Afterwards we generate a single point of bid price.

3. Cost divisions

3.1. Levels of project costs

The costs of a building construction project are generally organized according to four estimates which are based on different levels of detail. Each estimate level is described as follows. The highest level is the total bid price. The second level is the bid summary level or cost division level, which summarizes the various cost divisions. Typical cost divisions include direct costs, such as site work, concrete, construction equipment, and mechanical costs, and indirect costs such as taxes, insurance, and overhead. Usually, the total cost of a second-level cost division is the sum of the costs of several third-level cost items. In this study, the total cost of a cost division is defined as the product of a unit cost (dollar/square meter) and the total floor area. (See Section 5.1.1 for further details.)

The third level is the cost item level. Each second-level cost division is subdivided into smaller third-level cost items. For instance, the cost items for the second-level site-excavation cost division are the construction of slurry walls, pilings, and finished grading. The cost of a cost item is equal to its unit cost multiplied by the quantity of that item. The fourth level is the unit cost level. A unit cost in this level is expressed as the cost required to complete a unit of work associated with a cost item, such as the cost of constructing a square meter of slurry wall. "Cost division" in this study means a second-level cost division.

3.2. Cost divisions of residential housing projects

This study focuses on residential housing projects made of reinforced concrete (RC). According to the 36 projects completed by a single contractor, ten cost divisions of construction costs for a residential housing project are as follows: (1) foundation (represented by C_1); (2) structure (C_2); (3) external finishes (C_3); (4) internal finishes (C_4); (5) doors and windows (C_5); (6) elevator (C_6); (7)

mechanical/electrical/plumbing (MEP) (C_7); (8) temporary facilities (C_8); (9) landscaping (C_9); and, (10) markup (C_{10}). Notably, in this study, the cost division of temporary facilities (C_8) includes several indirect costs such as installing a temporary water supply and electricity, field and home office overhead, insurance, inspection fees, and air-pollution control fees.

4. Factors

Many factors affect the unit cost (or cost) of a cost division. The major factors affecting unit costs or total costs of the nine cost divisions (C_1–C_9) are identified by analyzing the 36 completed projects and interviewing two managers familiar with construction costs of these residential housing projects (Table 1).

Take the foundation cost division as an example. The unit cost of this division is dominated by four factors — ground improvement (F1.1), retaining wall (F1.2), excavation method (F1.3), and soil type (F1.4). Each factor is classified into different kinds of factor conditions. These factor conditions in the foundation cost division are as follows.

- The ground improvement factor (F1.1) indicates whether a project site requires ground improvement. Five factor conditions are identified: no ground improvement (no cost effect); improved via compaction; improved by well-point dewatering; improved by consolidation; and, improved by soil replacement (high cost effect).
- Retaining wall factor (F1.2) has three factor conditions: no retaining wall (no cost effect); sheet-pile wall; and, slurry wall (high cost effect).
- Excavation method factor (F1.3) has three factor conditions: open-cut method (low cost effect); bottom-up method; and, top-down method (high cost effect).
- Soil type factor (F1.4) has three factor conditions: gravel (low cost effect), sand, and silt (high cost effect). Excavated gravels and sand can be recycled, whereas silt must be dumped, which is costly.

Table 2 shows the three factors influencing the markup percentage in the markup cost division (C_{10}). These factors are market environment (F10.1), company conditions (F10.2), and project conditions (F10.3). The right side of Table 3 lists the sub-factors for each factor. For example, the market environment factor consists of four sub-factors: availability of future projects (F10.1.1); economic conditions (F10.1.2); market competition (F10.1.3); and, labor supply (F10.1.4). In F10.1.1, the markup will typically be low such that a company remains competitive when very few projects will be tendered in the near future. Conversely, markup may be high when many projects will be available in the future; that is, many opportunities exist. Further details regarding factors and factor conditions (Tables 1 and 2) can be found in Hsu (2004).

Table 3
Mean and standard deviation of unit costs (or costs or percentages) for each cost division in historical cost data.

Cost division	Mean of unit cost (NTD/m^2)	Standard deviation of unit cost (NTD/m^2)
1. Foundation	2235.5	1290.5
2. Structure	5312.4	1052.8
3. External finishes	1578.2	633.0
4. Internal finishes	3469.8	947.5
5. Windows	1211.9	621.6
6. MEP	3294.1	1619.0
7. Elevator	581.3	462.2
	Mean cost (NTD)	Standard deviation of cost (NTD)
8. Temporary facilities	17,614,204.6	18,129,566.3
9. Landscaping	7,626,645.1	8,006,389.0
	Mean%	Standard deviation%
10. Markup	6.51%	2.86%

5. Proposed model

Similar to many other methods (Dozzi et al., 1996; Li & Love, 1999; Marzouk & Moselhi, 2003; Wang et al., 2007), the proposed model is designed to improve the bid-price decision-making process. The total cost of a construction project is the sum of the total costs of all its cost divisions. The proposed method (Fig. 1) evaluates the unit cost (or cost or percentage) of each cost division by integrating a division-level probabilistic cost sub-model (see the right-hand side of Fig. 1) and the multi-factor evaluation sub-mod-

Table 1
Factors affecting unit costs or costs in the nine cost divisions.

Cost divisions	Factors
1. Foundation	F1.1 ground improvement; F1.2 retaining wall; F1.3 excavation method; F1.4 soil types
2. Structure	F2.1 concrete strength; F2.2 form types; F2.3 building complexity; F2.4 number of floors; F2.5 floor height; F2.6 earthquake location
3. External finishes	F3.1 number of floors; F3.2 form types; F3.3 material types of external walls, F3.4 floor height; F3.5 building complexity
4. Internal finishes	F4.1 form types; F4.2 material types of floors; F4.3 material types of internal walls; F4.4 floor height; F4.5 room area; F4.6 number of rooms in an unit
5. Windows / doors	F5.1 building complexity; F5.2 window glass; F5.3 thickness of window glass; F5.4 room area; F5.5 number of rooms in an unit; F5.6 material types of doors
6. MEP	F6.1 functions of equipment; F6.2 quality class of MEP; F6.3 room area; F6.4 number of rooms in an unit
7. Elevator	F7.1 loading capacity; F7.2 quality class of elevator; F7.3 elevator speed
8. Temporary facilities	F8.1 duration; F8.2 total floor area; F8.3 protection of nearby buildings
9. Landscaping	F9.1 sporting facilities; F9.2 entertainment facilities; F9.3 planting; F9.4 other landscaping

Table 2
Factors affecting the markup percentage in the markup cost division.

Factors	Sub-factors
F10.1 Market environment	F10.1.1 availability of future projects; F10.1.2 economic conditions; F10.1.3 market competition; F10.1.4 labor supply
F10.2 Company conditions	F10.2.1 capital availability; F10.2.2 current workload; F10.2.3 technology capability
F10.3 Project conditions	F10.3.1 relationship with project client; F10.3.2 project risk; F10.3.3 project complexity; F10.3.4 completeness of tendering information

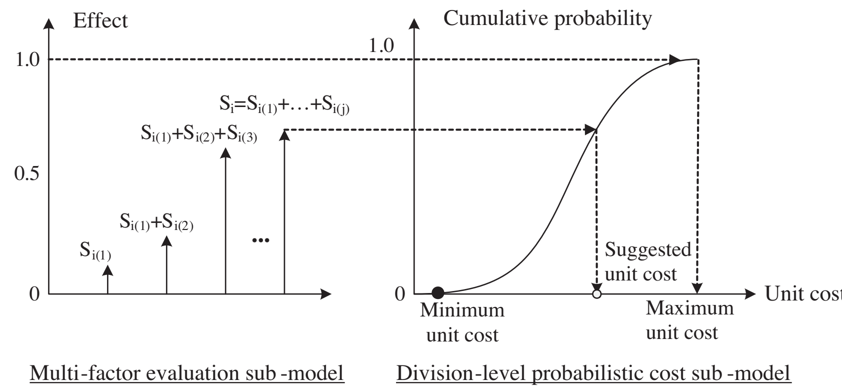

Fig. 1. Proposed model of each cost division.

el (left-hand side of Fig. 1). The division-level probabilistic cost sub-model uses a cumulative distribution to represent the possible range of unit cost (or cost or percentage) for a particular cost division. This type of distribution is used in order to take into consideration the level of uncertainties when it comes to cost estimates, and it is derived based on historical data from similar residential housing construction projects. In addition, the minimum distribution value indicates the minimum unit cost (or cost or percentage) of a particular cost division under best case scenario condition, and vice versa for the maximum distribution value.

The multi-factor evaluation sub-model is then applied to reflect the specific factor conditions. The factor conditions guide bidders in determining how to price their work above the minimum unit cost (or cost or percentage) for a cost division. After the unit cost (or cost or percentage) of each cost division is assessed, total construction costs can be calculated.

5.1. Division-level probabilistic cost sub-model

5.1.1. Total construction cost

In this investigation, total cost, C_{Tot} of a project is derived by

$$\begin{aligned} C_{Tot} &= [\text{construction cost} \times (1+\text{markup})] \times (1+tax) \\ &= [(C_1+\cdots+C_i+C_8+C_9)\times(1+C_{10})]\times(1+t) \end{aligned} \quad (1)$$

where C_1–C, are the costs of cost divisions (1)–(9), respectively. Notably, C_{10} is the markup and is expressed as a percentage of total construction cost. The value t is tax, which is a percentage (constant value, usually 5% in Taiwan) of the sum of total construction cost plus markup.

In assessing the costs of cost divisions (1)–(7) (*i.e.*, C_1–C_7), the cost of a cost division equals its unit cost (*i.e.*, the cost required to complete a unit of work associated with a cost division) multiplied by total floor area. That is,

$$C_i = U_i \times Q \text{ for } i = 1 \sim 7 \quad (2)$$

where U_i is unit cost of cost division i, and Q is total floor area. Thus, for instance, the cost of division (1) (*i.e.*, C_1) equals $U_1 \times Q$.

By integrating Eq. (2) into Eq. (1), Eq. (1) can be rewritten as

$$C_{Tot} = \{[(U_1Q+\cdots+U_7Q)+C_8+C_9]\times(1+C_{10})\}\times(1+t) \quad (3)$$

Notably, the costs of temporary facilities (C_8) and landscaping (C_9) are usually uncorrelated with total floor area and are highly dependent on owner needs in individual projects. Thus, C_8 and C_9 in Eq. (3) are analyzed directly in terms of cost rather than unit cost.

Finally, Eq. (3) is rewritten as follows to reflect the effect of inflation on total construction costs:

$$C_{Tot} = \left\{[(U_1Q+\cdots+U_7Q)+C_8+C_9]\left(\frac{\mathrm{CCI_{year}}}{\mathrm{CCI_{ave}}}\right)\times(1+C_{10})\right\} \times (1+t) \quad (4)$$

where $\mathrm{CCI_{year}}$ is the construction cost index of the analysis year for a new project, and $\mathrm{CCI_{ave}}$ is the average construction cost index of the years when historical projects were completed. In this study, $\mathrm{CCI_{ave}}$ is 76.4 for 1994–2003 — the historical projects were finished in that period. Notably, we assume the markup percentage (C_{10}) is not affected by inflation.

5.1.2. Historical cost data

The 36 residential housing projects located in northern Taiwan are used as a historical database. All projects were completed by one general contractor. As mentioned, all projects were all completed during 1994–2003. Some major characteristics of these projects are summarized as follows: (1) all were reinforced concrete (RC) structures; (2) average total actual cost (including markup) was about NT $ 295,464,995 (roughly US $8.9 million; US $1 ≅ NT $33); (3) average number of floors, 12; (4) average number of underground floors, 2; and (5) average total floor area, 16,093 m^2. Table 3 lists the means and standard deviations of unit cost (or cost or percentage) for the ten cost divisions of these projects.

5.1.3. Probabilistic cost distribution

U_is ($i = 1 \sim 7$), C_8 and C_9 are variables in unit costs or costs. Additionally, C_{10} is a variable in percentage. In the proposed division-level cost model, each variable follows a Normal distribution according to the calculated mean and standard deviation of unit cost (or cost percentage). A simulation is conducted to generate a

Table 4
Simulated minimum and maximum unit costs (or costs or percentages) for each cost division.

Cost division	Minimum unit cost (NTD/m^2)	Maximum unit cost (NTD/m^2)
1. Foundation	179.7	7165.2
2. Structure	2369.3	9291.0
3. External finishes	567.9	3846.7
4. Internal finishes	2160.7	6931.2
5. Windows	715.8	3492.5
6. MEP	993.7	9376.1
7. Elevator	0.0	2368.5
	Minimum cost (NTD)	Maximum cost(NTD)
8. Temporary facilities	7,398,300	91,964,500
9. Landscaping	0.0000	37,155,300
	Minimum%	Maximum%
10. Markup	0%	17.26%

cumulative distribution of unit cost (or cost or percentage) of each cost division. A common simulation program, @Risk4.5, is used to execute the simulation algorithm. This algorithm was implemented on a Pentium 3 personal computer running Windows XP. Generating each distribution 5000 times took approximately 3 minutes. Table 4 shows the simulated minimum and maximum unit costs (or costs or percentages) of each cost division. Notably, other methods can be used to produce such a cumulative distribution. For example, in simulating each cost division, a Beta statistical distribution may be assumed based on the optimistic, most likely, and pessimistic unit costs (or costs or percentages) generated from historical cost data. Additionally, when simulation is unavailable, a cumulative distribution can be generated using readily available statistical tables with an assumed normal distribution (Moder, Phillips, & Davis, 1983).

5.2. Multi-factor evaluation sub- model

The multi-factor evaluation model must identify all factors in each cost division. Notably, the proposed method does not limit the number of factors involved. As we assume the factors in a cost division i are independent, the importance of each factor j is pair-wisely compared with other factors to obtain the weight ($W_{i(j)}$) of each factor j. The evaluation result of a factor j for a given cost division i is a qualitative or quantitative value (e.g., factor condition) that is mapped to a corresponding effect value ($E_{i(j)}$) to represent the effect of a factor on unit cost (or cost or percentage) of a cost division i. Multiplying the effect value ($E_{i(j)}$) by its weight ($W_{i(j)}$) obtains a weighted effect value ($S_{i(j)} = W_{i(j)} \times E_{i(j)}$) of a cost division i. The sum of all weighted effect values of factors is the expected effect value ($S_i = \Sigma S_{i(j)}$) of a cost division i. This process is repeated for each cost division. The following subsections describe $W_{i(j)}$, $E_{i(j)}$ and S_i in detail.

5.2.1. Factor weights

The factors in each cost division are pair-wisely compared to determine their importance or preferences. The scale of 1–9 is used to rate the relative importance of pair-wise comparisons (Saaty, 1978). Scale values are as follows: 1, equally important; 3, slightly more important; 5, strongly more important; 7, demonstratedly more important; and, 9, absolutely more important. Scale values 2, 4, 6, and 8 denote the degree of importance between values 1 and 3, 3 and 5, 5 and 7, and 7 and 9, respectively. The matrix of preferences is processed to determine the eigenvector corresponding to the maximum eigenvalue of a matrix (Saaty, 1978). The sum of weights in each cost division must equal 1.

Take the foundation cost division as an example. The preferences of the four factors (*i.e.*, F1.1, F1.2, F1.3, and F1.4) are pair-wisely compared (Fig. 2). The eigenvector of the matrix (Fig. 2) is (0.0632, 0.6005, 0.2731, 0.0632) using the maximum eigenvalue of 4.0498. That is, the weights of factors F1.1, F1.2, F1.3, and F1.4 are 0.0632, 0.6005, 0.2731, and 0.0632, respectively.

5.2.2. Effect values of factors

Again, the foundation cost division is used as an example. Table 5 summarizes the effect values ($E_{i(j)}$) corresponding to the factor conditions of factors F1.1, F1.2, F1.3 and F1.4. For instance, the factor conditions in the ground improvement factor (F1.1) are no ground improvement, improved via compaction, improved by well-point dewatering, improved by consolidation, and improved by soil replacement. The corresponding effect values of these factor conditions are 0, 0.2, 0.5, 0.8, and 1, respectively. For example, when no ground improvement is needed, no cost is added; restated, the effect value is zero. Similarly, the cost is highest when good soil (improved weight-bearing strength) is purchased to replace the poor foundation soil. Thus, the effect value will be highest (*i.e.*, 1).

	F1.1	F1.2	F1.3	F1.4
F1.1	1	1/8	1/5	1
F1.2	8	1	3	8
F1.3	5	1/3	1	5
F1.4	1	1/8	1/5	1

Fig. 2. Pairwise weighting matrix of factors in the foundation cost division.

Table 5
Effect values corresponding to various factor conditions in the foundation cost division.

Factors	Factor conditions	Effect value ($E_{i(j)}$)
Ground improvement (F1.1)	No ground improvement	0
	Improved via compaction	0.2
	Improved by well-point dewatering	0.5
	Improved by consolidation	0.8
	Improved by soil replacement	1
Retaining wall (F1.2)	No retaining wall	0
	Sheet-pile wall	0.5
	Slurry wall	1
Excavation method (F1.3)	Open-cut method	0
	Bottom-up method	0.5
	Top-down method	1
Soil type (F1.4)	Gravel	0
	Sand	0.5
	Silt	1

5.2.3. Weighted effect values of factors

Take the same foundation cost division as an example. In a given project, suppose the factor conditions of "no ground improvement," "slurry wall," "bottom-up method," and "silt" are selected in factors F1.1, F1.2, F1.3, and F1.4, respectively. The effect values ($E_{i(j)}$) of F1.1, F1.2, F1.3, and F1.4 will be 0, 1, 0.5, and 1, respectively. The weighted effect values ($S_{i(j)} = W_{i(j)} \times E_{i(j)}$) corresponding to factors F1.1, F1.2, F1.3, and F1.4 will be 0 (=0 × 6.32%), 0.6005 (=1 × 60.05%), 0.1365 (=0.5 × 27.31%), and 0.0632 (=1 × 6.32%), respectively. Thus, the expected effect value ($S_i = \Sigma S_{i(j)}$) for the foundation cost division will be 0.8002 (=0 + 0.6005 + 0.1365 + 0.0632).

5.3. Integration of two sub-models

After evaluating the expected effect values (S_i) of multiple factors for each cost division i, the method yields a suggested unit cost (or cost or percentage) from the cumulative distribution for a cost division i (right side of Fig. 1). After repeating the same process to

Table 6
General descriptions of three case projects.

Major characteristics	Case project I	Case project II	Case project III
Completion time	Aug. 1999	Nov. 2000	Dec. 2004
Construction cost index	77.06	76.69	92.60
Construction duration (months)	20	20	23
Total floor area (m^2)	7363	4490	14,518
Number of floors	14	13	14
Floor height (m)	3.6	3.2	3.6
Room area (m^2)	163.6	171.0	272.7
Number of rooms in an unit	4	4	4
Concrete strength	4000 psi	4000 psi	5000 psi
Retaining wall	Slurry wall	Slurry wall	Slurry wall
Excavation method	Bottom up	Bottom up	Bottom up
Soil type	Silt	Silt	Silt

Table 7
$W_{i(j)}$, $E_{i(j)}$, $S_{i(j)}$ and S_i for the nine cost divisions in case project I.

Cost division	Factor	Weight ($W_{i(j)}$)	Effect value ($E_{i(j)}$)	Weighted effect value ($S_{i(j)} = E_{i(j)} * W_{i(j)}$)	Expected effect value($S_i = \Sigma S_{i(j)}$)
1. Foundation	F1.1	6.32%	0.0	0.0000	0.8002
	F1.2	60.05%	1.0	0.6005	
	F1.3	27.31%	0.5	0.1365	
	F1.4	6.32%	1.0	0.0632	
2. Structure	F2.1	6.91%	0.5	0.0346	0.6618
	F2.2	6.91%	1.0	0.0691	
	F2.3	3.08%	0.5	0.0154	
	F2.4	15.84%	0.6	0.0885	
	F2.5	23.59%	1.0	0.2359	
	F2.6	43.67%	0.5	0.2183	
3. External finishes	F3.1	3.46%	0.6	0.0194	0.6290
	F3.2	6.66%	0.0	0	
	F3.3	54.87%	0.6	0.3292	
	F3.4	21.08%	1.0	0.2108	
	F3.5	13.93%	0.5	0.0696	
4. Internal finishes	F4.1	9.60%	0.0	0	0.5956
	F4.2	44.89%	0.6	0.2693	
	F4.3	24.99%	0.6	0.1499	
	F4.4	14.06%	1.0	0.1406	
	F4.5	2.85%	0.3	0.0087	
	F4.6	3.62%	0.8	0.0271	
5. Windows	F5.1	7.77%	0.5	0.0138	0.4454
	F5.2	17.36%	0.9	0.0593	
	F5.3	14.18%	0.5	0.0214	
	F5.4	4.76%	0.3	0.0331	
	F5.5	4.89%	0.8	0.1437	
	F5.6	51.05%	0.3	0.1741	
6. MEP	F6.1	59.78%	0.5	0.2989	0.5142
	F6.2	26.04%	0.5	0.1302	
	F6.3	4.79%	0.3	0.0146	
	F6.4	9.40%	0.8	0.0705	
7. Elevator	F7.1	10.47%	0.5	0.0524	0.5001
	F7.2	63.70%	0.5	0.3185	
	F7.3	25.83%	0.5	0.1292	
8. Temporary facilities	F8.1	46.29%	0.6	0.2671	0.5122
	F8.2	48.15%	0.5	0.2173	
	F8.3	5.56%	0.5	0.0278	
9. Landscaping	F9.1	5.14%	0.5	0.0257	0.4465
	F9.2	7.93%	0.5	0.0396	
	F9.3	69.11%	0.5	0.3456	
	F9.4	17.82%	0.2	0.0356	

Table 8
$W_{i(j)}$, $E_{i(j)}$, $S_{i(j)}$ and S_i for the markup division in case project I.

Factor	Weight ($W_{i(j)}$) (%)	Effect value ($E_{i(j)}$)	Weighted effect value ($S_{i(j)}$)	Expected effect value (S_i)
F10.1 Market environment	63.70	0.6	0.3900	0.6300
F10.1.1	26.22	1.0	0.2622	
F10.1.2	56.50	0.3	0.1695	
F10.1.3	11.75	1.0	0.1175	
F10.1.4	5.53	1.0	0.0553	
F10.2 Company conditions	10.47	0.9	0.1000	
F10.2.1	19.98	1.0	0.1998	
F10.2.2	68.33	1.0	0.6833	
F10.2.3	11.69	0.5	0.0584	
F10.3 Project conditions	25.83	0.5	0.1400	
F10.3.1	8.86	1.0	0.0886	
F10.3.2	23.89	0.5	0.1194	
F10.3.3	23.89	0.5	0.1194	
F10.3.4	43.37	0.5	0.2168	

obtain the unit cost (or cost or percentage) of each cost division, Eq. (4) is then applied to compute project total bid price.

6. Case studies

6.1. Description of case projects

The proposed method is applied to three residential housing projects — projects I, II, and III) — all of which were located in northern Taiwan. These case projects and the aforementioned 36 projects were all completed by the same contractor. Table 6 lists the major characteristics of the three case projects. For example, project I is made of RC, has 14 floors and 3 underground floors, and a total floor area of roughly 7363 m^2. Project I, which was completed in mid-1999; took about 20 months to complete. A cost manager who was fully involved in the bidding process for these three projects provided input for application of the proposed method. The following subsections examine evaluation results.

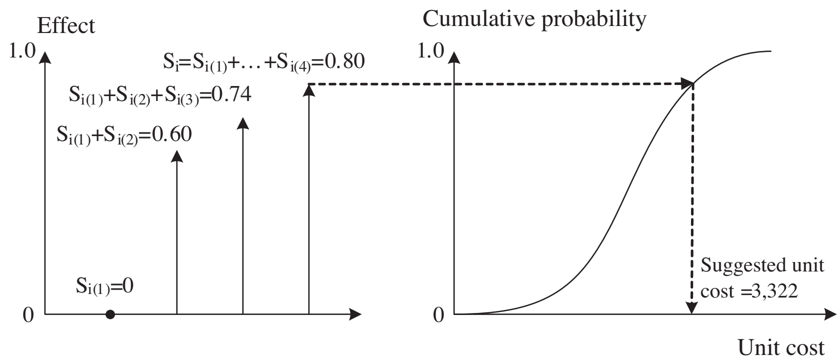

Fig. 3. Unit cost suggested for the foundation cost division in case project I.

Table 9
Suggested unit cost (or cost or percentage) of each cost division in case project I.

Cost division	Expected effect value (S_i)	Suggested unit cost (NTD/m^2)	Suggested cost (NTD)	Suggested cost considering CCI (NTD)
1. Foundation	0.8002	3322.3	24,461,430	24,674,361
2. Structure	0.6618	5751.3	42,345,672	42,714,280
3. External finishes	0.6290	1786.3	13,152,170	13,266,656
4. Internal finishes	0.5956	3698.9	27,234,261	27,471,329
5. Windows	0.4454	1126.8	8,296,403	8,368,621
6. MEP	0.5142	3351.5	24,676,424	24,891,227
7. Elevator	0.5001	581.3	4,279,996	4,317,252
8. Temporary facilities	0.5122		18,166,354	18,324,488
9. Landscaping	0.4465		6,552,430	6,609,467
			Suggested%	Suggested%
10. Markup	0.6300		7.43%	7.43%

Note: CCI is construction cost index; Average CCI is 76.4 for 1994–2003; CCI is 77.06 in 1999.

6.2. Evaluation results for project I

Tables 7 and 8 present the calculated weights, effect values, weighted effect values and expected effect values for each cost division by applying the proposed multi-factor evaluation model. For instance, the expected effect value (S_i) for the foundation cost division is 0.8002 (Table 7), and the expected effect value for the markup division is 0.63 (Table 8).

The expected effect value (S_i) of each cost division i is then utilized to determine a suggested unit cost (or cost or percentage) from the cumulative distribution i. For instance, the suggested unit cost of the foundation cost division is NT \$3322.30/m^2 based on the expected effect value of 0.8002 (S_i) (Fig. 3). Similarly, the unit costs (or costs or percentages) for the other cost divisions can be determined (left side of Table 9). The details of the evaluation results can be found in Hsu (2004).

The suggested cost of each division can be computed by multiplying unit cost by total floor area (7362.8 m^2). The right side of Table 9 summarizes the suggested cost considering the construction cost index for each cost division. Finally, based on the suggested costs of divisions (1)–(9) and the suggested percentage for the markup division, the suggested total cost using Eq. (4) is NT \$192,481,864. Actual bid price (including costs and markup) for project I was NT \$186,492,943. Thus, total bid price approximated by the proposed model is roughly 3.21% (=192,481,864−186,492,943/186,492,943) higher than actual project bid price.

6.3. Evaluations of case projects II and III

The proposed method was also applied to projects II and III. The right side of Table 10 shows the computational results for the two projects. The suggested total bid prices are around 1.00% and 1.08% higher than the actual bid prices of projects II and III, respectively.

Table 10
Evaluation results of three case studies.

	Case project I	Case project II	Case project III
Actual bid price (a)	\$186,493,993	112,570,700	455,501,682
Suggested bid price (b)	\$192,481,864	113,701,379	460,398,206
Difference ((b) − (a))	\$5,987,871	1,130,679	4,896,525
Difference in% ((b) − (a)/(a))	3.21%	1.00%	1.08%

7. Steps in applying the model to other companies

Fig. 4 presents the steps in applying the proposed model to other construction companies for estimating a bid price for a particular project type. These steps are as follows. First, a company must prepare a cost sub-model; that is, a cost database of a particular project type (e.g., warehouse projects) must be established (Step 1.1). In Step 1.2, the mean and standard deviation of the unit cost (or cost or percentage) of each cost division must be identified. In Step 1.3, the cumulative distribution of unit cost (or cost or percentage) of each cost division must be determined using @Risk simulation or a statistical table of Normal distribution.

Second, a company must generate a multi-factor evaluation sub-model of that particular project type. In Step 2.1, the factors and factor conditions affecting the unit cost (or cost or percentage) of each cost division must be identified. In Step 2.2, the effect values of factor conditions must be specified. In Step 2.3, the factor weights of each cost division should be given based on pairwise comparisons between factors.

Finally, with the cost sub-model and multi-factor evaluation sub-model established, a company can estimate the bid price of a new project via Steps 3.1–3.5 (Fig. 4). This model can be imple-

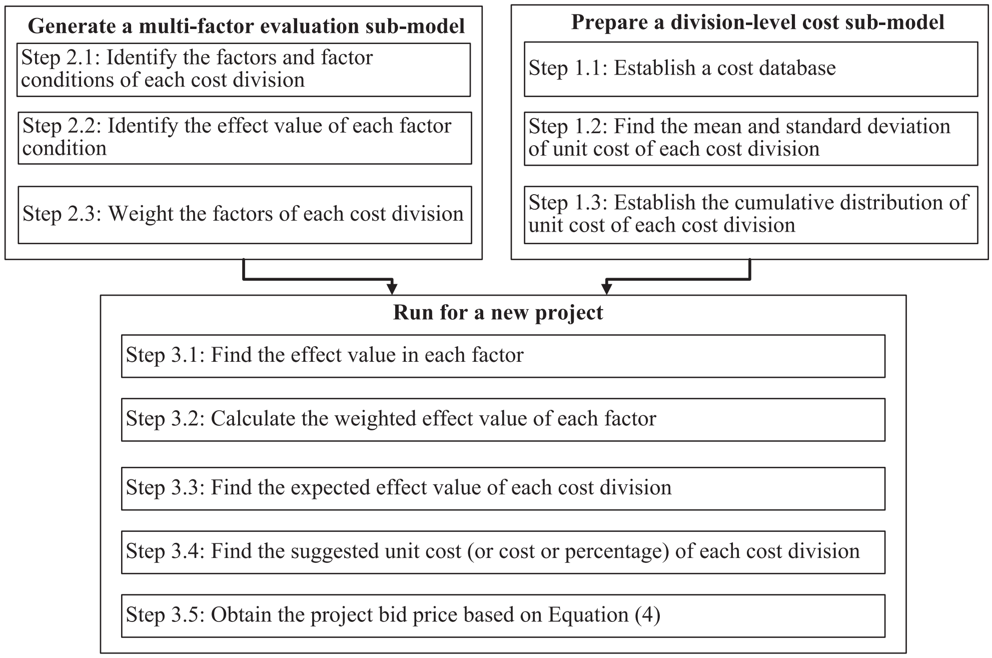

Fig. 4. Steps in applying the proposed model to other construction companies.

mented easily in a computerized environment using such tools as spreadsheets. In such a computerized environment, obtaining the bid price of a new project requires only a few hours. However, a company must establish several models (with a different cost database, factors, and factor conditions) to deal with different project types.

8. Conclusions

The proposed model generates reliable results that are 3.21%, 1%, and 1.08% different from the actual bid prices of projects I, II and II, respectively. This model is innovative in two significant ways. First, the cost sub-model is focused on the level of the cost divisions rather than on the level of the total bid price. In addition, since the project costs are usually uncertain (*i.e.*, represented by a cumulative distribution of project costs), the proposed cost sub-model fits real-world practices more closely than the existing models (Wang et al., 2007). Second, incorporating the effects of various factors on the cost of the cost divisions can systematically capture the bid-price decision-making process. In general, the model can suggest an approximate bid price in a rather short period of time, allowing contractors to quickly make a bid-price decision, especially when sufficient estimation time is not available, or to cross-check their bid price based on a detailed estimation process. This model can also be easily applied to other types of projects and be implemented by most construction companies.

The evaluation results of the three case studies were presented to two cost-estimating managers of the contractor who provided the historical cost data for this study. Overall, they appreciated the evaluation results and the strengths of our proposed model. They believe that the model will assist contractors with verifying the accuracy of their bid price calculated according to the conventional detailed estimating process. They also agreed that the model was helpful for approximating the project value and to decide whether or not to bid for a given project. However, they also indicated that they would be reluctant to use the bid price obtained by our proposed model directly for submission because they were not familiar with probabilistic estimating techniques. The contractor's comment regarding their unfamiliarity with probabilistic estimating techniques is consistent with the study conducted by Akintoye and Fitzgerald (2000). Their comment suggests that academic researchers need to promote the advantage of probabilistic estimating by reporting much more real-world case studies and gain the confidence of the contractors.

Subsequent research projects are as follows. First, like several other bidding models (Carr, 1987; Chua et al., 2001), the proposed model should be extended to derive a bid price that maximizes the probability of being awarded the contract. Second, computerization will markedly reduce the time needed to execute the model. Third, the model can be applied to other projects for further refinement (e.g., refining the effect values shown in Table 5). Fourth, the parametric range estimating of cost distribution suggested by Sonmez (2008) may be applied and substitute the probabilistic cost sub-model used in this study.

Acknowledgements

The authors would like to thank the National Science Council of Taiwan (under Contract No. NSC96-2211-E-009-151) and the Ministry of Education of Taiwan (via the Aim for the Top University program) for financially supporting this research. Mr. Y. H. Lu is also appreciated for providing valuable data and sharing his experience.

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