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Determination of Combined Rate of Overhead and Markup in Bid Price

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Abstract

The bid price for a construction project comprises the contractor's estimated direct cost and overhead cost plus its applied markup. Contractors often use an all-in rate to lump overhead and markup together on top of direct cost for arriving at a bid price. Such a simple method is naturally prone to inaccuracy, if the applied rate is selected subjectively. Contractors often have to cut their bids to increase the chance of winning, which however also increases the risk of making a loss. Using a combined rate of overhead and markup in competitive bidding without a sound approach certainly involves a greater risk. The present research aims to develop an improved approach to determining the combined rate of overhead and markup in the bid price for a project. Four factors, i.e., direct cost, duration, type of work, and location, were used as inputs to build a regression model from cost and bid data of 182 projects for predicting the combined rate of overhead and markup in the winning bid for a project, which, together with the model error, is used to estimate the probability of winning for a bid level. Then, based on minimization of overall loss risk proposed by a previous research, the bid preventing over-cuts in price competition is determined by comparing various bid levels using the model, the probabilistic estimates of project cost, and the probability of recovering costs if losing the bid. The approach is illustrated using an example. Comparisons of the suggested bids for the cases with those from other models are made.

Keywords: bid, markup, overhead, regression; risk.

1. Introduction

The bid or contract price for a construction project comprises the contractor's estimated direct cost and overhead cost plus its applied markup, i.e. profit. The contractor's direct cost refers to all expenses for labor, equipment, materials, and subcontracts directly connected with completion of the elements of the project as required by specifications and regulations. The contractor's overhead cost consists of the site overheads for supporting a project, such as supervision, offices, utilities, and services, as well as the project's share of the home-office overheads for running the firm, such as corporate management, procurement, financing, and marketing. The profit portion of the bid price is business-oriented and a higher or lower level may be charged as deemed appropriate.

Since direct cost constitutes the greatest part of a bid, it draws most attention of contractors. The site overheads can be estimated based on a construction program, as recommended by McCaffer and Baldwin [1], Diamant [2], and CIOB [3] etc. However, such detailed estimation is time consuming and not favored by many contractors, who often exercise their experience-based judgment and use a selected rate of estimated direct cost to cover all site overheads. A project's share of the home-office overheads is usually determined simply as a fixed rate according to the ratio of the firm's annual total home-office cost to its annual total revenue. Similarly, the profit charged for a project is usually determined also as a rate based on the conditions of the project, the firm, and the market. Thus, contractors often use an all-in rate to lump overhead and profit together on top of direct cost for arriving at a bid by using Eq. (1):

$$b = \bar{d} + \bar{o} + p = \bar{d} \times \left(1 + \frac{\bar{o} + p}{\bar{d}}\right) = \bar{d} \times (1 + r) \qquad (1)$$

where b = bid price; $\bar{d}$ = estimated direct cost; $\bar{o}$ = estimated overhead cost (site overheads plus project's share of home-office overheads); p = charged profit; r = combined rate of overhead and profit applied in b.

In Eq. (1), 1+r equals the ratio of bid price to estimated direct cost ($b/\bar{d}$). Thus, with $\bar{d}$ and r established, b is obtained readily. Despite the advantage of giving a quick result, such a simple method is naturally prone to inaccuracy, if the applied rate (r) is selected subjectively. Because project owners usually award a construction contract based on the lowest bid, intense price competition is common and contractors often have to cut their bids to increase the chance of winning. However, cutting bids undoubtedly increases the risk of making a loss in completing a job, if the winning bid is exceeded by the actual total cost. Using a combined rate of overhead and markup in competitive bidding without a sound approach certainly involves a greater risk for the contractor.

Because the time available for preparing a bid usually is short, the all-in-rate method represented by Eq. (1) is widely used by contractors in bidding. To avoid suffering an unworthy loss as a result of haphazardly applying an inadequate r, they should evaluate the impact of reducing r on the increase in loss risk against the increase in the chance of winning. However, although topics on bidding and estimating in construction have attracted much research interest over the years, the question of how to select a suitable r for a project has not yet been addressed. The present research aims to develop an improved approach to determining the combined rate of overhead and markup for a project in competitive bidding. The proposed approach is built upon previous researches by Chao [4] on overhead rate estimation and Chao and Liou [5] on bid-cutting limit determination.

2. Review of Literature

Existing bidding models focus on bid markup determination. In conventional models such as Carr [6], the markup rate is suggested as one with the maximum expected profit, where the expected profit for a markup rate is defined as the product of it and its probability of winning. Theoretically such a markup rate will achieve the highest profit in the long term, but it tends to give too low a chance of winning for contractors in intense competition, who often sacrifice profit in order to raise the chance of winning. Ahmad and Minkarah [7] took the lead in conducting a comprehensive study of factors influencing the markup decision. Others followed, for example, Chua and Li [8] identified key factors affecting bid-reasoning sub-goals. Meanwhile, various multi-criteria markup models built upon identified factors have been proposed, e.g. the multi-attribute utility model by Dozzi et al [9], the case-based reasoning model by Chua et al [10], and the fuzzy neural network model by Chao and Liu [11]. They offered various methods for producing an optimum markup for a project, yet they did not determine how low a bid could be and provide a rational solution in line with market conditions in which bidding competitively is imperative to survive.

Chao [12] proposed a fuzzy-logic-based model for determining the minimum bid markup that incorporates the position of a decision maker in the fuzzy rules. Chao and Liou [5] developed an approach to determining the lower limit of the bid markup based on minimization of the overall loss risk defined by a probabilistic model. In contrast to conventional models based on maximization of expected profit, these two models considered the chance of winning versus the risk of making a loss in evaluating various bid levels for solving the bid-cutting limit problem. However, as markup models, they did not include the contractor's overhead in the scope of their studies and neither did they establish a connection between project attributes and a bid's probability of winning.

Means [13] presented fixed overhead rates for field supervision, office, etc. and total overhead rates for various trades of subcontractors; however, it serves only as a manual because no method is provided. A case-based reasoning model for supervision cost estimation was developed by Chen et al [14] based on collected building projects, but it did not cover other overheads. More recently, Chao [4] developed a decision support system approach using a model for estimating the overhead rate from four project attributes, but it did not cover the markup rate to be applied in a bid.

3. Description of Proposed Approach

To determine a combined rate of overhead and markup (r) to be applied in a bid for a project, the probabilities of winning for various r have to be estimated. Consider that a contractor is bidding for a project in a market. When its estimated direct cost ($\bar{d}$) for the project is established, the bid decision reduces to determining r, so that a bid b equals $\bar{d}$ ×(1+r). To obtain an estimate of the probability of winning (P_w) for an r, recent bids in the market will have to be used, as these bids are indicative of the expected competition level. There are a few estimating methods and one of them is based on assuming a normal probability distribution for the lowest or winning bid (b^*) [10]. The estimate of P_w for r applied on top of $\bar{d}$ can be made as a parallel to that of the probability of winning for a markup rate applied on top of total project cost. By collecting a sample of projects and using the sample mean and standard deviation of $b^*/\bar{d}$ as the estimated parameters of the distribution, P_w for a bid b with $b/\bar{d}$ = 1+r can be estimated, without considering influences of varying project attributes such as project size and duration.

In order to give more accurate estimates of P_w, the estimation can be connected with project attributes by a multi-input model. Chao [4] developed a model using four project attributes, namely project size, duration, location, and type of work, as inputs for estimating the overhead rate in bidding. Since factors influencing the overhead level may also influence the markup level, the same inputs are used to build a regression model establishing the relationship of the combined rate of overhead and markup in the winning bid for a project ($\bar{r}$) to the project attributes. For a project faced, $b^* / \bar{d}$ is predicted at 1+$\bar{r}$. The model can be built from the attributes, direct cost estimates, and winning bids of projects that a contractor bid for recently. Whether it has won the project or not, the perceived combined rate of overhead and markup in the winning bid b^* of a project ($\hat{r}$) is calculated as $\hat{r} = (b^* - \bar{d})/\bar{d} = b^*/\bar{d} - 1$. The root of mean squared error (*RMSE*) is used as error measure, which is defined by:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\bar{r}_i - \hat{r}_i)^2} \tag{2}$$

where n = number of projects; $\bar{r}_i$ = $\bar{r}$ from the model for project i; $\hat{r}_i$ = $\hat{r}$ for project i.

Then, the model output $\bar{r}$ for the project is used to estimate the mean of $b^* / \bar{d}$ as 1+$\bar{r}$. Next, assuming that $\hat{r}$ is normally distributed around $\bar{r}$ and since the variance of $\hat{r}$ is equivalent to that of 1+$\hat{r}$, the standard deviation of $b^* / \bar{d}$ is estimated using the *RMSE* of the model. Therefore, P_w for a bid with $b / \bar{d}$ = 1+r can be estimated using the Excel function below.

$$P_w = 1 - \text{NORMDIST}(1+r, 1+\bar{r}, RMSE, \text{TRUE}) \tag{3}$$

Chao and Liou [5] developed an approach to determining the bid that prevents over-cuts in bidding for a project. First, set the timeframe for analysis within the duration of a project (D) a contractor is bidding for. If the contractor wins with a bid b, there is a probability that the contractor completes the project without making a loss (P_n) because the actual project cost is lower than b. If the contractor does not win the project, the contractor will continue seeking other jobs and there is a probability that the firm wins other contracts during D and is able to recover its costs without making a loss (P_o). At the time of bidding, the expected probability of not making a loss ($\bar{P}$) is defined by P_n and P_o, the two consequences of bidding, weighted by P_w and 1-P_w, respectively, as:

$$\bar{P} = P_w \times P_n + (1 - P_w)P_o \tag{4}$$

The approach is to evaluate $\bar{P}$ for various b in order to find out a bid $b^\#$ with a combined rate of overhead and markup ($r^\#$) that maximizes $\bar{P}$, i.e. has the highest overall probability of not making a loss. The bid $b^\# = \bar{d} \times (1 + r^\#)$ is taken as the suggested bid. To evaluate P_n for a bid b, we start by estimating project cost ($\bar{c}$) using Eq. (5):

$$\bar{c} = \bar{d} + \bar{o} = \bar{d} \times (1 + \frac{\bar{o}}{\bar{d}}) = \bar{d} \times (1 + \bar{r}_o) \tag{5}$$

where $\bar{d}$ = estimated direct cost; $\bar{o}$ = estimated overhead cost; $\bar{r}_o$ = estimated overhead rate.

In Eq. (5), $\bar{r}_0$ is to be produced from the model in Chao [4] that maps overhead rates from project attributes, so as to obtain $\bar{c}$. Consider the actual direct cost (d) and the actual overhead rate (r_o) for a project as random numbers with the following relations to the actual overhead cost (o) and the actual project cost (c):

$$c = d + o = d \times (1 + \frac{o}{d}) = d \times (1 + r_o) \tag{6}$$

To obtain a probability distribution for c in Eq. (6), probabilistic estimating methods such as Diekmann [15] are used. The probability distribution for d is aggregated from the distributions for all work items. As a project comprises many items in various trades, the central limit theorem applies generally, the distribution of d is approximately normal, and so are that of c. The mean of c (μ_c) can be estimated using $\bar{c} = \bar{d} \times (1 + \bar{r}_o)$ from Eq. (5). Since d and r_o in Eq. (6) usually are not linearly correlated, σ_c^2 as the variance of $c = d \times (1 + r_o)$ can be obtained using Eq. (7).

$$\sigma_c{}^2 = \mu_d{}^2 \sigma_{1+r_o}{}^2 + \mu_{1+r_o}{}^2 \sigma_d{}^2 + \sigma_d{}^2 \sigma_{1+r_o}{}^2 = \mu_d{}^2 \sigma_{r_o}{}^2 + (1 + \mu_{r_o})^2 \sigma_d{}^2 + \sigma_d{}^2 \sigma_{r_o}{}^2 \tag{7}$$

where μ_d = mean of d; $\sigma_{r_o}^2$ = variance of r_o; μ_{r_o} = mean of r_o; σ_d^2 = variance of d.

In Eq. (7), μ_d can be estimated at $\bar{d}$ using the sum of mean direct costs for all work items and σ_d^2 can be estimated using the sum of variances of direct cost for all items (SV). For each item, the minimum, most likely, and maximum estimates can be used to form a triangular distribution, from which its mean and variance can be solved. Next, μ_{r_o} can be estimated at $\bar{r}_o$ from the overhead rate model and $\sigma_{r_o}^2$ can be estimated using the mean squared error of it (MSE_o). By standardizing c against $\bar{d}$, P_n for a bid with $b/\bar{d}$ = 1+r can be estimated using the Excel function below:

$$P_n = \text{NORMDIST}(1+r,\ 1+\bar{r}_o,\ (\frac{\bar{d}\text{^}2*MSE_o+(1+\bar{r}_o)\text{^}2*SV+SV*MSE_o}{\bar{d}\text{^}2})\text{^}0.5,\ \text{TRUE}) \qquad (8)$$

The last term in Eq. (4), P_o, the probability of recovering the contractor's costs from other contracts won within D, given losing the current bid, represents the firm's prospect in the near future. P_o close to 0 means poor prospect, i.e. few jobs and very low winning bids, whereas P_o close to 1 represents the opposite, excellent prospect, i.e. plenty of jobs and winning bids getting steadily high. The details on assessing P_o are given in Chao and Liou [5].

4. Illustrative Example

To illustrate the proposed approach, 210 recent public projects in Taiwan were collected from a contractor who bid for the projects in order to build a regression model for estimating $\bar{r}$ as the dependent variable. Four project attributes are used as model inputs or independent variables, i.e. project size represented by estimated direct cost ($\bar{d}$), duration (D), location, and type of work. With respect to location as well as type of work, a classification scheme was developed and binary representation was used. Whether the firm won or not, the winning bid (b^*) of a project was used along with its $\bar{d}$ to calculate the combined rate of overhead and markup in b^*, i.e. $\hat{r}=(b^*-\bar{d})/\bar{d}=b^*/\bar{d}-1$, for use as the target output. Next, a regression analysis was carried out on the 210 projects and the obtained R^2 of 0.158 shows poor explanation of variation of $\hat{r}$. An examination of the model errors reveals 26 projects with very large deviations from target outputs, indicating existence of other factors unique to them, and so they were discarded, resulting in a sample of 184 usable projects. Then, statistical analyses were carried out on the 184 projects, including descriptive statistics and correlations among the variables, whose results are shown in Tables 1, 2, 3, and 4.

Table 1. Statistics of $\bar{d}$, D, and $\hat{r}$ for the usable 184 projects (note: NT\$1≈US\$0.03)

	Minimum	Maximum	Mean	Standard deviation
$\bar{d}$ (NT\$ million)	7.5	1253.3	154.8	188.7
D (day)	36	1095	457	191
$\hat{r}$	0.053	0.321	0.121	0.086

Table 2. Statistics of $\hat{r}$ by location

Location	Number of projects	Mean	Standard deviation
Taipei area (*TP*)	15	0.085	0.072
Other cities (*CT*)	88	0.124	0.082
Remote areas (*RMT*)	81	0.125	0.091

Table 3. Statistics of $\hat{r}$ by type of work

Type of work	Number of projects	Mean	Standard deviation
Pipelines (*PP*)	76	0.095	0.023
Site works (*ST*)	51	0.117	0.086
Roads (*RD*)	18	0.140	0.081
Bridges (*BRD*)	25	0.159	0.089
Buildings (*BLD*)	9	0.170	0.105
Ports (*PRT*)	5	0.216	0.099

Table 4. Coefficients of correlation among quantifiable project attributes

	$\bar{d}$	Duration	$\hat{r}$
$\bar{d}$	1		
D	0.593	1	
$\hat{r}$	-0.183	-0.065	1

The statistics in Tables 1, 2, and 3 show that the projects vary widely in size, duration, and $\hat{r}$ with large standard deviations and the mean of $\hat{r}$ increases with increasing project remoteness and complexity vis-à-vis location and type of work, respectively. In Table 4, $\bar{d}$ and duration are positively correlated, while $\hat{r}$ correlates with $\bar{d}$ and D negatively albeit weakly. The above appear reasonable from the viewpoint of construction management and economics principles, indicating suitability of the data for model building.

Two of the 184 projects, called Project A and Project B, were set aside for simulation of bidding. The remaining 182 projects were used to build a regression model of $\bar{r}$. The obtained model achieves a higher R^2 of 0.283 and an $RMSE$ of 0.07265, which is lower than the sample standard deviation of 0.086 in Table 1. It is shown below.

$$\bar{r} = 0.247 - 0.0002\bar{d} + 0.0001D - 0.0288TP + 0.0284CT - 0.1964PP - 0.1391ST - 0.1146RD - 0.0915BRD - 0.0756BLD \quad (9)$$

Using Eq. (9) and the attributes in Table 5, $\bar{r}$ is estimated at 0.145 and 0.109 for Projects A and B, respectively. Then, for each project, P_w for various levels of r are estimated using Eq. (3). Next, the standard deviation of direct cost is estimated at $0.05\bar{d}$ for Project A and at $0.04\bar{d}$ for project B, so the SV for the two projects are $(0.05\bar{d})^2$ and $(0.05\bar{d})^2$. The overhead rates for each project are estimated using the following regression model in Chao [4] that is parsimonious in inputs with an MSE_o of 0.00116. The obtained $\bar{r}_o$ are shown in Table 5.

$$\bar{r}_o = 0.18 - 0.023TP - 0.021CT - 0.1PP - 0.1ST - 0.093RD - 0.089BRD \quad (10)$$

Table 5. Attributes of projects A and B and cost estimates for them

	Project A	Project B
$\bar{d}$ (NT$ million)	153.64	82.73
D (day)	540	500
Location	TP	CT
Type of work	BRD	PP
SV	$(0.05\bar{d})^2$	$(0.04\bar{d})^2$
$\bar{r}_o$	0.068	0.059

With all needed parameters established for each project, P_n for various levels of r are estimated using Eq. (8). Then, for each project with poor prospect (P_o=0.25) and with average prospect (P_o=0.5), $\bar{P}$ for various level of r are assessed using Eq. (4) and the combined rates of overhead and markup achieving maximum $\bar{P}$ are determined as the suggested $r^{\#}$. The $\hat{r}$ perceived in the actual lowest bids, $\bar{r}$ estimated by Eq. (9), $\bar{r}$ estimated using the sample mean of $\hat{r}$, $r^{\#}$ suggested by the proposed approach with each prospect, and $r^{\#}$ suggested by the conventional model are compared in Table 6.

Table 6. Combined rates of overhead and markup for projects A and B

	Project A	Project B
$\hat{r}$ perceived in actual lowest bid	0.162	0.080
$\bar{r}$ estimated by Eq. (9)	0.145	0.109
$\bar{r}$ estimated using sample mean of $\hat{r}$	0.121	0.121
$r^{\#}$ suggested by proposed approach with poor prospect	0.120	0.102
$r^{\#}$ suggested by proposed approach with average prospect	0.136	0.116
$r^{\#}$ suggested by conventional model	0.151	0.146

For both projects, $\bar{r}$ estimated by Eq. (9) are closer to $\hat{r}$ in the actual lowest bids than those estimated using the sample mean of $\hat{r}$, so better accuracy in estimating P_w for a bid can be attained. The suggested $r^{\#}$ from the proposed approach are lower than those suggested by the conventional model that is based on maximization of expected profit, showing that it gives more competitive bids. However, no excessive loss risk is involved in applying the suggested $r^{\#}$ since the proposed approach is based on minimization of overall loss risk. Note that the suggested $r^{\#}$ are lower for both projects with poor prospect because of the effect of smaller P_o, which makes the project being bid for more important as discussed in Chao and Liou [5]. Note also that $\hat{r}$ in the actual lowest bid for Project A being higher is due to the random nature of bids received.

5. Conclusions

Contractors often apply an all-in rate of overhead and markup on top of the estimated direct cost for arriving at a bid, but this practice involves a greater risk if the rate is selected subjectively without a sound basis, especially so when price competition is intense. The proposed approach in the present research is based on building a model for estimating the combined rate of overhead and profit in the winning bid for a project from four project attributes as well as determining the optimum rate in a bid for the project in order to achieve minimum overall loss risk while keeping competitiveness. The proposed approach can help prevent over-cuts in bids under intense price competition and help enhance the construction industry's performance by reducing contractor failures. The approach's practicality will be studied further in the future in order to provide suggestions for practitioners when using it.

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