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Determining bid markup and resources allocated to cost estimation in competitive bidding

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ABSTRACT

To win a project contract through competitive bidding, contractors submit a bid price that is determined by putting a markup on the estimated project cost. The success of the bid is therefore heavily dependent on the accuracy of that estimate, meaning that sufficient resources should be allocated to the estimation process. This paper develops a novel optimization model for simultaneously determining the bid markup and the resources that should be allocated to cost estimation. We begin by deriving optimality conditions for this simultaneous optimization model and illustrating them with numerical examples, for which purpose only we assume a single competitor and uniformly distributed estimation errors. To analyze a more realistic situation, we then examine computational solutions to our model. Through these two approaches, we investigate the effects of the bid-markup decision and resource allocation on the contractor's expected profit, and we highlight the significance in competitive bidding of the markup and allocation.

1. Introduction

1.1. Background

Competitive bidding is widely used to choose contractors. A client who needs a contractor to carry out a certain project invites potential contractors to submit bid prices that are not revealed to competing contractors. The lowest bid tends to determine the winning contractor, who is then paid the bid price and executes the project as specified by the client. In this process, the contractor's profit is highly dependent on its bidding strategy.

Because the contractor determines its bid price by putting a markup on its estimated project cost, the bid price is markedly affected by the accuracy of that estimation. Nevertheless, it is very difficult to estimate the cost of a project accurately, especially for construction projects. Indeed, the average growth in the costs of very large civilian projects from the beginning of detailed engineering has been measured as 88% [28]. For transport infrastructure projects, the average cost escalation has been assessed as 28%; this figure appears to be valid globally according to data from 20 countries [13]. Consequently, traditional cost–benefit analysis will give misleading results because of such inaccurate cost estimates. To make matters worse, the risks due to misleading cost estimates are typically either underplayed or ignored altogether in infrastructure decision making [13].

The motivation behind this research is to highlight the significance in competitive bidding of the bid-markup decision and the resources allocated to cost estimation, which we do through effective use of mathematical modeling and analysis. By making certain assumptions, this approach allows us to have universal consequences that are independent of project type and contractor. Moreover, appropriate markup and resource allocation can be determined based on computational solutions to the mathematical model, while simultaneously allowing the quantitative impact of those decisions on expected contractor profit to be clarified. This marks a positive contrast with various existing methods of qualitative analysis. As such, our mathematical approach has the potential to play a critical role in the decision-making process of contractors.

1.2. Literature review

Since the seminal work by Friedman [14], a considerable number of studies have pursued effective models of the determination of bid markups (or bid prices) [11,23,30,33]. These models are divided into three main categories [27]: statistical models, artificial-intelligence-

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based models, and multi-criteria utility models. Statistical models determine the optimal markup according to the statistical bidding behavior of each competitor [24,29,34]. Recently, an entropy metric [6] and Monte Carlo simulation [18] were used effectively in such statistical models. Artificial-intelligence-based models estimate an appropriate markup by using case-based reasoning [8,9] and artificial neural networks [17,25,26]. Multi-criteria utility models include many practical factors in the bid-markup estimation [3,4,7,10,38]. However, such models do not deal with the allocation of resources for cost estimation.

Project resource/budget allocation is a subject of active research [1,12,15,16,31]. However, to the best of our knowledge, only two studies have addressed the problem of allocating resources for estimating project costs in competitive bidding. Ishii et al. [21] implemented a two-step heuristic algorithm that involves allocating resources preferentially to estimate the cost of a profit-making project and then determining an appropriate bid price. Takano et al. [35] built a multi-period resource allocation model for cost estimation in a sequential competitive bidding situation. Nevertheless, it is noteworthy that both the aforementioned studies consider resource allocation separately from the bid-markup decision. No previous study on competitive bidding has investigated the interaction between the bid-markup decision and the allocation of resources for cost estimation.

Jackson [22] conducted a questionnaire survey that revealed that more complete design information (e.g., about existing site conditions and design definitions) leads to more accurate cost estimates. The survey results also highlighted the importance of a qualified and experienced design/construction team. Moreover, the accuracy of a cost estimate has been shown to be positively correlated with the number of man-hours (MHs) spent making the estimate [19,36], and there is a clear relationship between the accuracy of the estimate and the amount of preparation [5,37]. These studies indicate that cost can be estimated more accurately by increasing the amount of resources allocated to its estimation. An appropriate markup should depend on the accuracy of the contractor's cost estimate [24,29,34]. As a result, in order for contractors to improve their profits, it is essential to determine the bid markup and the resources allocated to cost estimation simultaneously.

1.3. Our approach

The purpose of this paper is to devise a novel optimization model for simultaneously determining the bid markup and the resources allocated to cost estimation. Specifically, we revise the model developed by King and Mercer [24] so that it incorporates a relationship between the accuracy of the cost estimate and the amount of resources invested in making the estimate.

We adopt two approaches to our simultaneous optimization model. The first approach is to derive optimality conditions for our model. For that purpose alone, we assume that only one competitor participates in the competitive bidding and that the estimation errors are uniformly distributed. After differentiating our model partially, we obtain its optimality conditions based on those assumptions and illustrate the conditions with numerical examples.

The second approach is to examine computational solutions to our simultaneous optimization model. In contrast to the first approach, this one requires no strong assumptions. To analyze a realistic situation, this approach deals with multiple competitors and estimation errors that follow triangular distributions. We use the computational solutions to examine the contractor's expected profit closely with respect to the bid markup and resource allocation. We also evaluate the sensitivity of the solutions in relation to the bidding behavior of the competitors.

The remainder of this paper is organized as follows. Section 2 presents our simultaneous optimization model for determining the bid markup and the resources allocated to cost estimation. Section 3 shows analytical results based on the aforementioned first approach, and Section 4 reports computational results based on the second approach. Section 5 concludes the paper with a brief summary of our work and a discussion of future research directions.

2. Competitive bidding models

This section begins by describing the competitive bidding model formulated by King and Mercer [24] and then describes our simultaneous optimization model.

2.1. King–Mercer model

To win a project contract through competitive bidding, a contractor begins by estimating the cost of completing the project. Because that estimated cost is subject to unavoidable error, it is reasonable to treat it as a random variable. Therefore, we denote the estimated cost as $(1 + e) C$, where C is the true project cost and e is a random estimation error. The contractor determines its bid price by putting a markup m on the estimated cost. Accordingly, the bid price is given as

$$B(m, e) := (1 + m)(1 + e) C. \tag{1}$$

Let $P(b)$ be the probability of winning the contract when the bid price is b. If the contractor wins the contract, the eventual profit will be the difference between the bid price and the true project cost, that is, $B(m, e) - C$. Consequently, King and Mercer [24] formulated the contractor's expected profit as

$$R(m) := \int (B(m, e) - C)\, P(B(m, e))\, \phi(e)\, \mathrm{d}e, \tag{2}$$

where $\phi(e)$ is the probability density function (PDF) of the estimation error e.

If the estimated cost contains no estimation error (i.e., $e = 0$), it follows that $B(m, e) = (1 + m) C$ and therefore that contractor's expected profit is

$$R(m) = m\, C\, P((1 + m) C).$$

As pointed out by King and Mercer [24], this model is equivalent to Friedman's well-known model [14]. Hence, we see that Friedman's model ignores the effect of an inaccurate cost estimate on the contractor's expected profit.

2.2. Simultaneous optimization model

In the King–Mercer model (2), the probability distribution of the estimation error is fixed. However, as we mentioned in Section 1, the accuracy of the estimated cost can be controlled by adjusting the amount of resources used for cost estimation. Thus, we assume that the variation of estimation error depends on the amount of resources used for that estimation. More precisely, the PDF of the estimation error is defined as $\phi(e \mid w)$, where w is the amount of resources used to estimate the cost. This definition implies that the estimation-error variance can be decreased by allocating more resources to cost estimation.

Following previous studies [5,37], we represent the amount w of resources as a percentage of the project cost C. Accordingly, for the example of $C = 100$ and $w = 0.5\%$, the estimation cost is calculated as $C\ w = 100 \times 0.005 = 0.5$. Our simultaneous optimization model determines the decision variables m and w simultaneously in such a way that the expected profit is maximized. Consequently, our model is posed as follows:

$$\text{maximize} \quad R(m, w) := \int (B(m, e) - C)\, P(B(m, e))\, \phi(e \mid w)\, \mathrm{d}e - C\, w. \tag{3}$$

For the sake of completeness, we define the winning probability