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Multicriteria Support for Construction Bidding

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Abstract—While profit maximization is one important objective in this decision domain, other objectives are important as well. This paper discusses multiple criteria and their respective objectives in construction bidding, and presents a bidding framework which recommends a pairwise comparison procedure to generate criterion weights and a linear transformation procedure to calculate relative scores for bidding alternatives. This hybrid multicriteria method is illustrated and evaluated using a set of past construction bids. The proposed bidding system is found to yield substantially improved solutions when work volume is highly important relative to expected profit. The corresponding decrease in the profit function is identified, allowing evaluation of expected profit foregone, in order that improved multiattribute functions might be attained.

Keywords—Bidding, Construction, Multicriteria analysis, Decision theory.

1. INTRODUCTION

Competitive bidding presents numerous tradeoffs to those who submit bids for work on construction projects. If a bid is relatively high, then the probability the bid will be accepted is relatively low, thus resulting in: low expected revenues, low equipment and personnel utilization, and the opportunity for a competitor to build his/her standing in the industry. However, such a bid, should it be accepted, will also result in higher profits, less chance of a loss resulting from unforeseen costs, and the ability to provide a higher level of quality to the customer. Hence, multiple criteria are affected by the determination of a bid amount, and there are serious tradeoffs that need to be considered. The purpose of the research described in this paper has been to work toward developing a workable, usable, construction-oriented *system* that provides for the

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integration of contextual factors and decision criteria and which is supported by thorough and reliable data analysis. The ultimate goal is to provide decision makers in the construction industry with effective multicriteria support for pricing the services of their firms. Working toward that goal, this paper describes, demonstrates, and evaluates a quantitative procedure for multifactor, multicriteria bidding optimization.

This research should be of interest to the many decision makers (DMs) who face these tradeoffs regularly. Nearly all public (and a substantial amount of residential) construction projects involve competitive bidding, and construction is a major industry throughout the world. In the United States, for example, construction activity accounted for nearly five percent of the country's gross national product in the 1980s according to reports of the Bureau of Census [1] and the Economic Report of the President [2]. Because of this, a large body of literature is devoted to various aspects of competitive bidding, from both descriptive and prescriptive perspectives [3]. Understandably, effectiveness in competitive bidding is crucial to the futures of many firms, as bidding too high lowers the probability of obtaining work, while bidding too low can guarantee fiscal failure. Numerous models have been proposed for supporting bidding since Friedman [4] first developed a quantitative bidding optimization model in 1957. Yet, practitioners have made relatively little use of those models, as has been pointed out by Rothkopf and Harstad [3]. They argue that the gap between theory and practice generally is a result of the need for enriched models that take context into consideration and move toward realism. Similarly, Rothkopf and Engelbrecht-Wiggans [5] have pointed out that flawed models give flawed results. It stands to reason, then, that models intended solely to maximize profit will be poorly accepted by actual bidders, who are typically concerned about numerous criteria.

1.1. Multicriteria Nature of Bidding

Multiple criteria involved in bidding have been discussed for decades. In the first known work formalizing bidding optimization, Friedman addressed the existence of multiple bidding criteria by listing objectives of profit maximization, maximizing return on investment, minimization of loss expectation, minimizing competitor profits, and maximizing operational continuity [4]. Boughton addressed these multiple objectives as well [6]. Not unexpectedly, he found, in a survey of 126 construction firms, that profit maximization was the most frequently used bidding objective, although it was by no means the only objective of importance. Carr addressed return on investment and production criteria, although profit maximization was the only objective incorporated into his model [7]. In a later study, Carr incorporated opportunity costs into a profit-based bidding approach [8]. Finally, although not mentioned explicitly in the literature, *winning the bid* is an implied objective for many contractors, including the authors and firms witnessed by the authors. This objective may or may not represent the aggregation of other objectives, such as resource utilization and maintenance of cash flows, but nevertheless is not, and should not, be neglected in actual bidding practice.

Actual *applications* of multicriteria analysis to competitive bidding are limited, however. Engelbrecht-Wiggans developed a descriptive model analyzing the simultaneous maximization of profit and minimization of two forms of regret [9]. The first general prescriptive applications of multicriteria methodology in competitive bidding are found in [10–12]. Ahmad proposed a two-stage approach, based on multiattribute utility theory (MAUT), for the decision of whether or not to bid on a project, and then the decision of what markup should be used. Unfortunately, the elicitation of utility functions, especially multiattribute functions, is complex and time consuming for DMs. The approach proposed by Seydel and Olson for determining optimal markups is based in part of the analytic hierarchy process (AHP), which was introduced by Saaty [13]. Computations are simplified, and there is less burden on the DM, although the approach relies on more restrictive assumptions than does Ahmad's multiattribute utility approach. Subsequently, Ahmad and Minkarah [14] and Hegazy *et al.* [15–17] have implemented various aspects of these multicriteria bidding approaches in computer software they have made available.

1.2. Scope of Consideration

Besides the studies indicated above, there have been numerous other studies addressing competitive bidding in a variety of applications, as discussed in an extensive survey by Engelbrecht-Wiggans [18]. To aid in the analysis of the many existing bidding applications, King and Mercer developed a classification scheme to summarize problems addressed by this body of literature [19]. According to this scheme, bidding situations are classified according to four factors: whether bidding is open (as in estate auctions) or closed (sealed bids), means of bid selection (high bid, low bid, or other), the existence of nonprice competition (all bidders meet the same specifications, or propose alternative products), and the certainty with which the value of the item being bid upon is known. The *common construction bidding situation*, which is the focus of this research, is one in which sealed bids are used, low bid price is selected, all bidders meet the same specifications, and project costs are uncertain. (Note that, although increasingly more contracts are being awarded according to factors other than price, awarding contracts to the lowest bidder is still far from having been phased out. Such things as bidder prequalification and rigid specifications, especially in public works construction, have traditionally served to represent nonprice attributes. In essence, these criteria are represented as constraints, rather than as objectives, in the bidding process. While there are many benefits to be achieved by incorporating these other criteria as objectives, doing so is reserved for future research.) This research is intended to provide an extension of the method developed by Seydel and Olson by integrating it into a general multicriteria bidding framework and by illustrating and evaluating that framework using actual construction bidding data. Note that, while auctions can be modelled either one at a time or as a sequence of auctions (see, for example, the work by Broemser [20] and Knode and Swanson [21]), this research addresses construction bidding on the basis of one project at a time. It is also assumed that screening (if any) of projects, as proposed by Ahmad [14] to avoid unfruitful estimating/bidding, has already taken place.

2. GENERAL BIDDING MODEL

Let the decision maker of concern be referred to herein as the *subject bidder*, and let bids being submitted by the subject bidder's competitors be referred to as *competing bids*. Then, for the subject bidder, the bidding decision can be modelled as an unconstrained optimization problem. This problem is stochastic in that the outcome depends upon the values of two random variables—the lowest competing bid amount, and the actual cost or value of the object for which the bid is being submitted. If a single criterion were being considered, the objective would be to optimize the outcome of the bidding process for the given criterion. The typical approach to optimization, based upon Friedman's work [4], is to seek to optimize the *expected* outcome (e.g., profit). Stated in general terms for the low bid wins situation, the objective is to determine a bid ratio $\mathbf{M}$ so as to

$$\text{Optimize } E[\mathbf{Y}(\mathbf{C},\mathbf{M}_L,\mathbf{M})] = \mathbf{A}(\mathbf{C},\mathbf{M})\Pr(\text{Win} \mid \mathbf{M}) + \mathbf{N}[1 - \Pr(\text{Win} \mid \mathbf{M})], \tag{1}$$

subject to resource limitations, where

$\mathbf{M}$	(the decision variable) is the markup ratio, of bid to bidder's estimated cost $\mathbf{C}_e$,
$\mathbf{C}$	(a random variable) is the ratio of actual to estimated cost,
$\mathbf{M}_L$	(a random variable) is the ratio of the lowest competing bid to the bidder's cost estimate,
$\mathbf{Y}(\mathbf{C},\mathbf{M}_L,\mathbf{M})$	is the outcome on the given decision criterion,
$\mathbf{A}(\mathbf{C},\mathbf{M})$	is the outcome given the bid is accepted (bidder is successful),
$\mathbf{N}$	is the outcome given the bid is not accepted (bidder is unsuccessful), and
$\Pr(\text{Win} \mid \mathbf{M})$	is the bid acceptance probability.

Both the decision space (values of $\mathbf{M}$) and the joint probability sample space (combinations of $\mathbf{M}_L$ and $\mathbf{C}$) are continuous. In practice, however, these spaces contain finite sets of positive numbers somewhere near one. The distributions of $\mathbf{M}_L$ and $\mathbf{C}$ are generally not known, but must be estimated from empirical data. Several terms are expressed as ratios rather than as absolute measures, because the only link among historical data used to generate estimates for the distribution of $\mathbf{M}_L$ is the cost estimate $\mathbf{C}_e$. Furthermore, dividing through by $\mathbf{C}_e$ results in relationships that are independent of the cost estimates. While $\mathbf{M}_L$ and $\mathbf{C}_e$ are not necessarily independent, empirical studies by Hansmann and Rivett [22] and Kuhlmann and Johnson [23] were, nevertheless, unable to establish that there is a significant relationship between $\mathbf{M}_L$ and $\mathbf{C}_e$. Therefore, relevant data should be analyzed on an *ad hoc* basis, as discussed briefly in the next section, in order to determine the extent of any such dependency.

The probability of winning, Pr(Win | $\mathbf{M}$), can be modelled as the probability of beating the lowest competing bid, following Hansmann and Rivett [22], Carr and Sandahl [24], Gunter and Swanson [25], and Mercer and Russell [26]. Required data are the bidder's estimated costs for past projects, as well as the lowest competing bids for those projects. From this information, probability distributions can be estimated. Since $\Pr(\text{Win} \mid \mathbf{M}) = \Pr(\mathbf{M}_L > \mathbf{M})$, the acceptance probability for a bid amount $\mathbf{M}$ is equal to $1 - F_L(\mathbf{M})$, and the nonacceptance probability is $F_L(\mathbf{M})$, where $F_L(\mathbf{M})$ is the cumulative distribution function of $\mathbf{M}_L$ evaluated at $\mathbf{M}$.

In most of the bidding literature, the $\mathbf{N}$ term reflecting the outcome—essentially, the cost—of an unsuccessful bid does not appear. This is likely because the firm ordinarily receives no revenue for losing a contract, and prior costs for preparing the bid are typically sunk. The nonacceptance term is incorporated here to facilitate the ability to accommodate circumstances in which it might be desirable to model nonacceptance outcomes explicitly. Such circumstances would occur when it is possible to estimate unsuccessful bid outcomes including, but not limited to: second best (i.e., Plan B) alternatives; costs associated with replacing key personnel who leave the firm during slow periods; costs of relocation; and possibly costs of dissolving the firm. In order that the procedure to be demonstrated might be more easily followed, these costs are not explicitly considered herein, except to be included in the general multicriteria model in the next section. That is, for the purposes of the demonstration, $\mathbf{N}$ is assumed to have a value of zero. Nevertheless, some nonacceptance costs, such as those associated with the loss of key personnel, are addressed, although not modelled, by the simultaneous consideration of multiple criteria, as is done below. Certainly, future research is warranted in identifying and modelling nonacceptance outcomes, as they do exist and bidders are aware of them but the bidding optimization literature generally ignores them.

2.1. Multicriteria Model

When the above model is modified to incorporate multiple criteria, the problem can be expressed in terms of the multiple objectives

$$\begin{aligned}
\text{Optimize } E\left[\mathbf{Y}^1(\mathbf{C},\mathbf{M}_L,\mathbf{M})\right] &= \mathbf{A}^1(\mathbf{C},\mathbf{M})\Pr(\text{Win}\mid\mathbf{M}) + \mathbf{N}^1[1-\Pr(\text{Win}\mid\mathbf{M})],\\
\text{Optimize } E\left[\mathbf{Y}^2(\mathbf{C},\mathbf{M}_L,\mathbf{M})\right] &= \mathbf{A}^2(\mathbf{C},\mathbf{M})\Pr(\text{Win}\mid\mathbf{M}) + \mathbf{N}^2[1-\Pr(\text{Win}\mid\mathbf{M})],\\
&\ \ \vdots\\
\text{Optimize } E[\mathbf{Y}^m(\mathbf{C},\mathbf{M}_L,\mathbf{M})] &= \mathbf{A}^m(\mathbf{C},\mathbf{M})\Pr(\text{Win}\mid\mathbf{M}) + \mathbf{N}^m[1-\Pr(\text{Win}\mid\mathbf{M})],
\end{aligned} \tag{2}$$

subject to resource and policy limitations, where m is the number of decision criteria. This can alternatively be expressed in terms of Ω, the decision maker's multiattribute value function

$$\begin{aligned}
\text{Maximize } E[\Omega(\mathbf{C},\mathbf{M}_L,\mathbf{M})] = {} & \Omega\left(\mathbf{A}^1,\mathbf{A}^2,\dots,\mathbf{A}^m\right)\Pr(\text{Win}\mid\mathbf{M})\\
& + \Omega\left(\mathbf{N}^1,\mathbf{N}^2,\dots,\mathbf{N}^m\right)[1-\Pr(\text{Win}\mid\mathbf{M})],
\end{aligned} \tag{3}$$

for $i = 1$ to m and subject to resource and policy limitations. The $\mathbf{A}^i$ and $\mathbf{N}^i$ are defined in terms of the multiple objective formulation. If the criteria exhibit additive independence, then $E[\Omega(\mathbf{C}, \mathbf{M}_L, \mathbf{M})]$ becomes a weighted sum of the single criterion utility functions evaluated at the $\mathbf{Y}^i(\mathbf{C}, \mathbf{M}_L, \mathbf{M})$ as in [9]. In such cases, multicriteria methods such as multiattribute value (MAV) analysis, and possibly AHP, can be appropriate for solving the problem, although neither of those is without its own problems.

2.2. Criteria of Interest

As indicated above, a number of criteria have been addressed in the literature, including margin per project, return on investment, exposure to loss, competitor profits, and operational continuity [4]; opportunity costs [8]; win regret [27] and loss regret [9]; and the potential for additional work [6,28]. For the sake of simplicity, let these ten criteria be represented by the three objectives of profit maximization, volume maximization, and regret minimization.

In an actual decision situation, the DM may of course opt to consider fewer or additional criteria and may or may not wish to aggregate the criteria in the same manner as indicated here. Regardless of aggregation, no difference would be called for in the standardization and subsequent optimization procedures proposed herein. Nevertheless, there is a tradeoff to be considered in determining the level of aggregation to use. Reduced aggregation would lead to increased control over weight determination for the criteria. It could also lead, however, to greater dependencies among the criteria, possibly requiring more sophisticated means of analysis than what is being proposed here, since the assumption of additive independence would likely be violated to a greater extent.

Profit Maximization. Margin per project and return on investment generally relate to the same amount of earnings, although the two are compared against different bases. Margin per project equals project profit, $(\mathbf{M} - \mathbf{C})\mathbf{C}_e$, divided by actual costs, $\mathbf{C} \cdot \mathbf{C}_e$. Return on investment equals project profit divided by one of the measures of a given firm's investment. Hence, maximizing expected margin per project would yield the same value for the decision variable $\mathbf{M}$ as would maximizing the expectation for return on investment, because these objective functions vary only by the values of the constants used in the relationships. An optimal strategy, assuming a zero-valued nonacceptance outcome, for the profit maximization criterion would maximize

$$E[\text{Profit}(\mathbf{C}, \mathbf{M}_L, \mathbf{M})] = [(\mathbf{M} \cdot \mathbf{C}_e) - E(\text{Cost})] \Pr(\text{Win} \mid \mathbf{M}), \tag{4}$$

where $E(\text{Cost}) = E(\mathbf{C}) \cdot \mathbf{C}_e$. Note that this function has a stationary point for some positive value of $[\mathbf{M} - E(\mathbf{C})]$. That is, expected profit increases with the value of $\mathbf{M}$ up to a certain point, after which the decrease in $\Pr(\text{Win} \mid \mathbf{M})$ more than compensates for resultant increases in $\mathbf{M}$.

Volume Maximization. As values of $\mathbf{M}$ decrease, bid acceptance probabilities, $\Pr(\text{Win} \mid \mathbf{M})$, increase. Then, as the chance of bid acceptance increases, so does the expectation that operational continuity will be maintained. Furthermore, the opportunity for follow-on work (i.e., additional project related work) becomes greater with increased bid acceptance probabilities. Similarly, market share is likely to increase, and competitors' profits are likely to be restricted if the subject bidder's chances of bid acceptance increase. Finally, increased bid acceptance probabilities correspond to reduced expectations of regret from having bid too high. Hence, volume maximization might serve as a surrogate to these five criteria. Over the range of bid ratios the bidder is likely to consider, expected project revenue (volume, which equals $\mathbf{M} \cdot \mathbf{C}_e$) typically increases with decreasing values of $\mathbf{M}$, as $\Pr(\text{Win} \mid \mathbf{M})$ increases. Maximization of volume would maximize

$$E[\text{Volume}(\mathbf{M}_L, \mathbf{M})] = [\mathbf{M} \cdot \mathbf{C}_e] \Pr(\text{Win} \mid \mathbf{M}). \tag{5}$$

It might seem as though bidding as low as possible could lead to volume maximization as well as to maximizing the chance of winning the bid. If this were true, it would make the decision a trivial one and would also allow volume maximization to serve as a perfect surrogate for winning the bid (or vice versa). In fact, maximizing the chance of winning is the same as maximizing Pr(Win | $\mathbf{M}$) and does occur as $F_L(\mathbf{M})$, and hence $\mathbf{M}_L$, gets smaller (i.e., bidding as low as possible). However, the expected volume function has a stationary point, which is illustrated in Figure 1. In this fairly typical example (where $\mathbf{M}_L$ is normally distributed with a mean of 110% and a standard deviation of 5%), bidding below a markup of 10% below cost essentially guarantees winning the bid, while expected volume is maximized by bidding at cost ($\mathbf{M} = 100\%$). Pursuing a volume maximization objective corresponds, to an extent, to pursuing an objective of winning the bid. At a certain markup level, although a relatively unrealistically low one, these objectives diverge. In fact, pursuing the volume maximization objective could be viewed as pursuing winning, but with some sanity injected into the process.

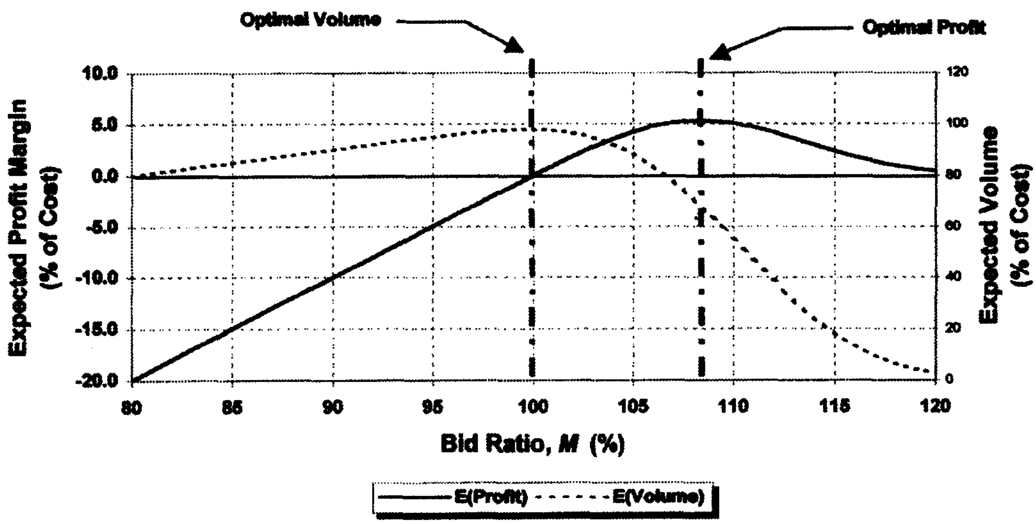

Figure 1. Comparison of expected profit and volume functions.

Both functions plotted in Figure 1 are, of course, sensitive to the distribution of $\mathbf{M}_L$, although E[Profit] will always be zero valued at $\mathbf{M} = 0$. Furthermore, in all circumstances (and not surprisingly), the optimal markup for maximizing profit will be higher than that for maximizing volume. Not uncommonly, the stationary point of the expected volume function is less than one (100%), indicating the optimal bids for such projects are at amounts below cost estimates. Certainly, this conflicts with the profit maximization objective and *should* be unlikely to be witnessed much in practice. Note that one would, however, expect to see some bids slightly below estimated costs when contractors are especially eager to keep their resources working rather than sitting idle. This is because cost estimates typically include recovery of fixed overheads such as insurance payments, equipment depreciation, administrative personnel, etc. [29]. These costs are incurred regardless of whether a bid is accepted, so, at least in the short run, it may be better to obtain a contract at less than expected total cost than to lose the contract to a competitor. Furthermore, bidding below expected total cost may be a means of access to additional work at higher rates of compensation.

Regret Minimization. There is regret of losing a bid (bidding too high) and regret of winning (bidding too low). The concept of loss regret is captured in the objective of volume maximization. Win regret is by far the most commonly addressed form in the literature (see, for example, the discussions by Engelbrecht-Wiggans [9] and Gates [27]). Also known as "money left on the table," win regret is the difference between the subject bidder's bid amount and that of the lowest competing bid when $\mathbf{M} < \mathbf{M}_L$. That is, win regret is equal to $(\mathbf{M} - \mathbf{M}_L) \cdot \mathbf{C}_e$. The expectation of win regret decreases as $\mathbf{M}$ increases. Simultaneously, the bidder's exposure to potential loss via cost overruns is decreased, while expected opportunity costs resulting from foregone projects will be reduced [8]. As a result, improving performance with respect to the win regret criterion will, at the same time, affect performance with respect to the criteria of risk exposure and opportunity costs in a positive manner. Win regret minimization is obtained by minimizing

$$E[\text{Regret}(\mathbf{M}_L, \mathbf{M})] = [(E(\mathbf{M}_L) - \mathbf{M}) \cdot \mathbf{C}_e] \Pr(\text{Win} \mid \mathbf{M}), \tag{6}$$

for all values of $\mathbf{M} < E(\mathbf{M}_L)$. If $\mathbf{M} > E(\mathbf{M}_L)$, the regret expectation is 0. This function has no stationary point, although it reaches its optimum at $E(\mathbf{M}_L)$, and maintains that value for all $\mathbf{M} > E(\mathbf{M}_L)$. Hence, to optimize strictly according to the regret criterion, one would bid with a ratio equal to or greater than the expected value of $\mathbf{M}_L$.

2.3. Factors Affecting Bidder Behavior

A number of project and situational characteristics affect an individual bidder's behavior. These work through their effects on the probability distribution describing the lowest competing bid ratio, $\mathbf{M}_L$. As indicated above, if the shape and location of this distribution are known or can be estimated, then the probability of success for a particular level of $\mathbf{M}$ can be determined. The variation in the parameters for the distribution of $\mathbf{M}_L$ results from two types of uncertainty—that which is independent of cost considerations and that which reflects uncertainties resulting from the cost estimation process. Note that numerous researchers have addressed cost uncertainties in an attempt to understand a phenomenon known as the "winner's curse." (The winner's curse is the tendency for the winner in a low-bid-wins auction to be the one who underestimates his/her costs the most [30].) For example, Lederer [31] has addressed the winner's curse and developed a regression model in an attempt to overcome the tendency of bidders in high-bid-wins situations to be negatively affected by the winner's curse.

Uncertainties independent of cost considerations include the number and identities of competing bidders—the more bidders expected, the lower the acceptance probability for a given bid ratio $\mathbf{M}$ [7,23]. Addressing uncertainties relative to estimated costs ($\mathbf{C}_e$), Gordon and Welch [28] and Boughton [6] considered markups to be a function of risk and bidder attitude toward risk. Therefore, any factor introducing uncertainty is likely to increase $\mathbf{M}$. These uncertainties can arise from type of construction, proportion of labor to total estimated cost, economic conditions, level of detail in plans and specifications, resource coverage, project location, relative proportion of skilled to unskilled labor, and other factors. The more uncertainty, the greater the tendency for $\mathbf{M}_L$ to increase to compensate as bidders seek to ensure against more things going wrong.

A key part of the proposed analysis is the distribution of the lowest competitor bid ratio. This can and should be based upon historical data and should take into consideration characteristics that typically vary from project to project. These items include economic factors, the number of competitors, and other potentially relevant data. The method of Broemser [20] and Carr and Sandahl [24] uses multiple regression to control for variation in these bidding factors and provides a relatively simple yet sound technique to develop an estimate of the distribution of $\mathbf{M}_L$. This method has, therefore, been chosen to be included as part of the proposed overall bidding support system.

3. MULTICRITERIA BIDDING SUPPORT SYSTEM

The proposed bidding support system consists of a two phase procedure. The first phase applies *data analysis* to identify relevant bidding factors, followed by an *optimization* phase seeking to optimize the decision maker's multiattribute value function.

3.1. Data Analysis

Prior to any thorough bidding optimization, relevant bidding factors and their effects must be identified. These are the variables which relate the collective distribution of bid acceptance probabilities to project and situational characteristics. As indicated above, this can be done through multiple regression, a procedure which is described in a bidding context by Carr and Sandahl [24]. Independent variables can be selected on the basis of specific local conditions, and the result of the data analysis phase will be a regression model describing $\mathbf{M}_L$, the low bid ratio.

In a deviation from the Carr and Sandahl [24] method, however, a *log-normal* regression procedure, as proposed by Seydel [32], has been used here because of the ratio nature of the dependent variable. Here, $\mathbf{M}'_L$, the natural logarithm of $\mathbf{M}_L$, is the response variable, and the bidding factors are treated as predictors. When this model has been developed and tested, it is used to calculate an expected value for $\mathbf{M}'_L$ (and, subsequently, for $\mathbf{M}_L$), given any future combination of values for the bidding factors. The regression model's error mean squares constitutes an estimate of the variance of $\mathbf{M}'_L$ for a given combination of predictor variables. Hence, the standard deviation of $\mathbf{M}'_L$ is estimated as the square root of the error mean squares. Based upon these estimates for the mean and standard deviation of $\mathbf{M}'_L$, acceptance probabilities can be calculated for any given value of M through the use of the normal distribution. If regression residuals do not appear to be normally distributed, the empirical distribution can be used to estimate bid acceptance probabilities. Figure 2 demonstrates, for the profit maximization case, that the optimum bid can be dependent upon the situation (as characterized by the values of the bidding factors) involved. Here, a regression model was developed for $\mathbf{E}(\mathbf{M}_L)$, and profitability calculations for a variety of bid ratio values for two different projects were made. Profitability expectation curves for two different projects are illustrated. Given the values of the bidding factors for the project illustrated in Figure 1, $\mathbf{E}(\mathbf{M}_L)$ is 110% (with a standard deviation of 5%), while for the other project, $\mathbf{E}(\mathbf{M}_L)$ is 105% (with a standard deviation of 3%). Correspondingly, there is also a rather significant difference in their respective optimum bid ratios (i.e., M*)—108% for the project illustrated in Figure 1, and 104% for the other project.

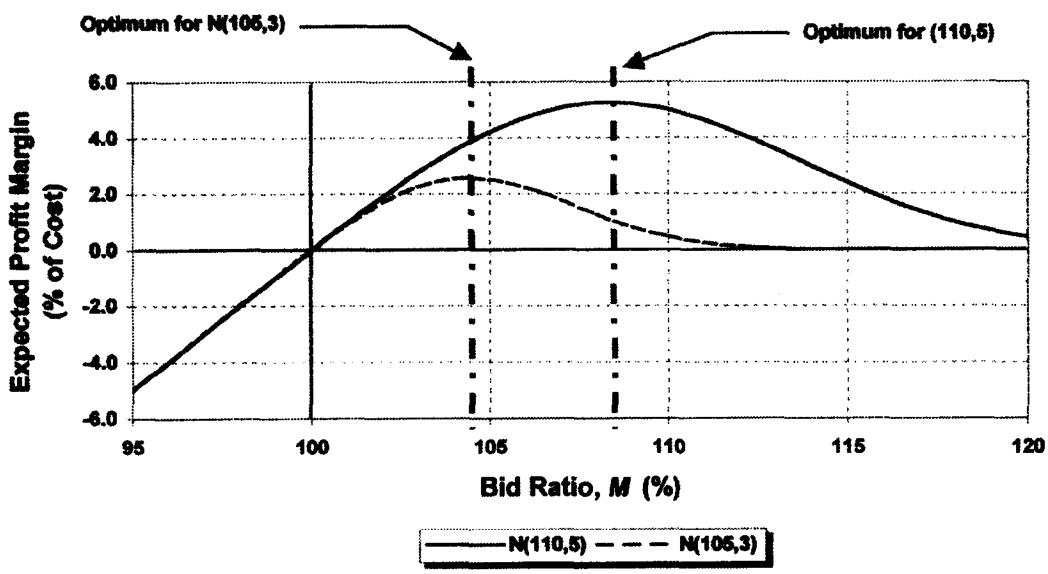

Figure 2. Profitability expectations for two different projects.

3.2. Optimization

Once the distribution of $\mathbf{M}_L$ has been estimated, the associated probabilities can be used to determine the optimal bid ratio, M*. The intent is to optimize the decision maker's multiattribute value function, indicated in equation (3). If profit is the only objective of interest, single criterion analysis is accomplished by determining which value of M maximizes expected profit, $\mathbf{M} \cdot \Pr(\text{Win} \mid \mathbf{M})$. If multiple criteria are considered, weighting and summing standardized scores for each objective will provide the value of the DM's multiattribute value function.

Let the relative weights for each objective be denoted as W_P, W_V, and W_R, for profit, volume, and regret, respectively. Although these can be obtained through a variety of multicriteria techniques, a recommended method is that typically used for criterion weighting in AHP. Under this approach, weights for each of the three criteria (profit, volume, and regret) are determined via the normalized principal eigenvector of a pairwise comparison matrix for the criteria [13]. Because of its relative simplicity, this procedure can be used by a decision maker each time she/he faces a bid decision, thus reflecting changes in preference structures as situations change (often over short time spans) for the DM.

Note that, while the relative importance for the multiple objectives can be obtained, care must be taken to assure that different scales of measure do not distort these weights. This can be done if a normalized, or *standardized*, score with a best possible value of one and a worst possible value of zero, can be developed for each criterion. For the three objectives considered (profit maximization, volume maximization, and regret minimization), estimates for the best and worst attainment levels for each criterion can be identified over the reasonable range of bid levels. Then, prior to bid opening (and, hence, *a priori*) standardized scores can then be obtained by the following general formula:

$$X' = \frac{X - X_{\text{Worst}}}{X_{\text{Best}} - X_{\text{Worst}}}, \tag{7}$$

where X' is the standardized value of X, and X_{Worst} and X_{Best} are, respectively, the least and most preferred possible value of outcome X.

Applying equation (7) to the bidding problem, let the lowest and highest values being considered for $\mathbf{M}$ be indicated by $\mathbf{M}_0$ and $\mathbf{M}_1$, respectively, and let the lowest and highest reasonable values of $\mathbf{C}$ be denoted as $\mathbf{C}_1$ and $\mathbf{C}_0$, respectively. Then, $\mathbf{P}$ can be used to represent expected profit margin, should a bid with a ratio of $\mathbf{M}$ be accepted, and would be equal to $\mathbf{M} - E(\mathbf{C})$. The standardized value for the acceptance outcome on the profit criterion would then be

$$\mathbf{P}' = \frac{[\mathbf{M} - E(\mathbf{C})] - [\mathbf{M}_0 - \mathbf{C}_0]}{[\mathbf{M}_1 - \mathbf{C}_1] - [\mathbf{M}_0 - \mathbf{C}_0]}. \tag{8a}$$

Similarly, $\mathbf{V}$ can be used to represent project volume, should a bid with a ratio equal to $\mathbf{M}$ be accepted. The volume ratio for any given bid would simply equal the bid ratio, and the minimum possible volume ratio would be zero, while the maximum value would be $\mathbf{M}_1$. Given these relationships, the standardized value for the acceptance outcome on the volume criterion would be

$$\mathbf{V}' = \frac{\mathbf{M} - \mathbf{M}_0}{\mathbf{M}_1 - \mathbf{M}_0}. \tag{8b}$$

Finally, let the lowest and highest likely values of $\mathbf{M}_L$ be denoted as $\mathbf{L}_0$ and $\mathbf{L}_1$, and let $\mathbf{R}$ represent the win regret margin resulting, given a bid with a ratio of $\mathbf{M}$ is accepted. Prior to bid opening, the expected regret margin would be equal to $E(\mathbf{L}) - \mathbf{M}$. Thus, the standardized value for the expected acceptance outcome on the regret criterion would be

$$\mathbf{R}' = \frac{[E(\mathbf{M}_L) - \mathbf{M}] - [\mathbf{L}_1 - \mathbf{M}_0]}{-[\mathbf{L}_1 - \mathbf{M}_0]}. \tag{8c}$$

If $\mathbf{M}$ is too high to be accepted (i.e., $\mathbf{M}_L \leq \mathbf{M}$), then $\mathbf{P}' = [\mathbf{M}_0 - \mathbf{C}_0]/[(\mathbf{M}_1 - \mathbf{C}_1) - (\mathbf{M}_0 - \mathbf{C}_0)]$, $\mathbf{V}' = 0$, and $\mathbf{R}' = 1$. The standardized score for profit, $\mathbf{P}'$, may be greater than zero when work is not obtained, because, while no profit is attained if no work is obtained, no losses are incurred either. Regret is zero (the best case) when no work is obtained. Thus, as the above analysis shows, when standardized values are used to represent criterion outcomes in a multicriteria model, nonacceptance outcomes are not ignored completely, even if they are not considered explicitly in the modelling.

For each alternative under consideration (i.e., each $\mathbf{M}$ such that $\mathbf{M}_0 \leq \mathbf{M} \leq \mathbf{M}_1$), an *a priori* multicriteria function can be evaluated for *acceptance* outcomes (i.e., where values of $\mathbf{M}$ are such that $\mathbf{M}_L > \mathbf{M}$). This function is composed of the criterion weights multiplied by the corresponding standardized scores according to each of the criteria and is equal to

$$\mathbf{MCF1} = (W_P \cdot \mathbf{P}') + (W_V \cdot \mathbf{V}') + (W_R \cdot \mathbf{R}') . \tag{9a}$$

Similarly, the function for the *nonacceptance* outcomes (i.e., when $\mathbf{L} \leq \mathbf{B}$) will be

$$\mathbf{MCF0} = \frac{W_P \cdot (\mathbf{M}_0 - \mathbf{C}_0)}{(\mathbf{M}_1 - \mathbf{C}_1) - (\mathbf{M}_0 - \mathbf{C}_0)} + W_R. \tag{9b}$$

Recall that $\Pr(\text{Win} \mid \mathbf{M}) = 1 - F_L(\mathbf{M})$, where $F_L(\mathbf{M})$ is the cumulative distribution function (CDF) for $\mathbf{M}_L$ evaluated at $\mathbf{M}$. Since the nonacceptance probability is the complement of $\Pr(\text{Win} \mid \mathbf{M})$, the value of the nonacceptance probability will simply be $F_L(\mathbf{M})$. Weighting $\mathbf{MCF1}$ by $1 - F_L(\mathbf{M})$ and $\mathbf{MCF0}$ by $F_L(\mathbf{M})$ and then summing these weighted components yields an expectation for the multicriteria function $\mathbf{MCF}$. The multicriteria decision rule, which corresponds to equation (3), would then be to choose a value of $\mathbf{M}$ so as to

$$\text{Maximize } E(\mathbf{MCF}) = \mathbf{MCF1} \cdot [1 - F_L(\mathbf{B})] + \mathbf{MCF0} \cdot F_L(\mathbf{B}). \tag{10}$$

4. EVALUATION METHODOLOGY

Whereas the previous section describes an approach to incorporating multiple criteria into the decision making process for bidding, this section is intended to address how actual outcomes might be evaluated with respect to those multiple criteria. It further seeks to establish a relationship between the two, that is, between decision making and outcome evaluation. This is necessary in order for the effectiveness of the proposed multicriteria decision making process to be examined.

4.1. Multiattribute Value Functions

Because it is extremely difficult, if not impossible, to verify a DM's value for an outcome, no *actual* DM has been used to examine the effectiveness of the multicriteria bidding approach. Instead, a general form for the DM's multiattribute value function has been assumed. This form uses two parameters per attribute or criterion, and performance of the multicriteria bidding approach is evaluated for various combinations of those parameters. Mutual and additive independence of the criteria is assumed, at least for this particular phase of the research. Thus, the multiattribute value functions used in this research have the form

$$\mathbf{Z} = \sum U_i \left[(X_i'')^{A(i)} \right], \tag{11}$$

where

$\mathbf{Z}$ = multiattribute value,

U_i = weight parameter for criterion i ($0 \leq U_i \leq 1$, $\Sigma U_i = 1$),

X_i'' = standardized score for outcome value on criterion i ($0 \leq X_i \leq 1$)

$= [X_i - X_i(\text{Worst})]/[X_i(\text{Best}) - X_i(\text{Worst})]$,

$A(i)$ = shape parameter for criterion i ($0 \leq W_i \leq 1$).

Calculating $\mathbf{Z}$ starts with determining a standardized score (X_i'') for the actual outcome on each of the criteria being considered. These scaled values are calculated in essentially the same manner as are $\mathbf{P}'$, $\mathbf{V}'$, and $\mathbf{R}'$, except that actual, rather than expected, values for the cost and low bid ratios are used. Hence, these are *a posteriori* values. If $\mathbf{P}''$ represents the scaled value for the profit criterion, its value for an acceptance outcome would be calculated as

$$\mathbf{P}'' = \frac{[\mathbf{M} - \mathbf{C}] - [\mathbf{M}_0 - \mathbf{C}_0]}{[\mathbf{M}_1 - \mathbf{C}_1] - [\mathbf{M}_0 - \mathbf{C}_0]}. \tag{12a}$$

For the volume criterion, if $\mathbf{V}''$ indicates the scaled value, the acceptance outcome would be calculated as

$$\mathbf{V}'' = \frac{\mathbf{M} - \mathbf{M}_0}{\mathbf{M}_1 - \mathbf{M}_0}. \tag{12b}$$

Finally, if $\mathbf{R}''$ represents the scaled value for the regret criterion, it would be calculated as

$$\mathbf{R}'' = \frac{[\mathbf{M}_L - \mathbf{M}] - [\mathbf{L}_1 - \mathbf{M}_0]}{-[\mathbf{L}_1 - \mathbf{M}_0]}, \tag{12c}$$

if the subject bidder's bid were less than the actual low bid. These scaled values would then be used to calculate the value of $\mathbf{Z}$ per equation (11). That is, designating the U_i values as U_P, U_V, and U_R, and designating the $A(i)$ values as $A(P)$, $A(V)$, and $A(R)$ for the profit, volume, and regret criteria, respectively, the amount of DM value for the acceptance outcome is calculated as

$$\mathbf{Z} = U_P \left[(\mathbf{P}'')^{A(P)}\right] + U_V \left[(\mathbf{V}'')^{A(V)}\right] + U_R \left[(\mathbf{R}'')^{A(R)}\right]. \tag{13a}$$

If the subject bidder's bid amount were greater than the actual low bid, then nonacceptance outcomes would be calculated, first on the profit and regret criteria, and then according to $\mathbf{Z}$. (For the volume criterion, the nonacceptance outcome is simply zero.) The nonacceptance value for $\mathbf{Z}$ is generally nonzero and is calculated in the same manner as indicated for **MCF0** in equation (9b). That is, the nonacceptance amount of DM value would be calculated as

$$\mathbf{Z} = \frac{W_P(\mathbf{M}_0 - \mathbf{C}_0)}{(\mathbf{M}_1 - \mathbf{C}_1) - (\mathbf{M}_0 - \mathbf{C}_0)} + W_R. \tag{13b}$$

4.2. Pairwise Comparison Weights and MAV Functions

Barbeau [33] demonstrated how weights generated via AHP serve as viable approximations to true (i.e., underlying) criterion weights in multicriteria modelling. In other words, a DM with a value function of the form of $\mathbf{Z}$ in equation (11) should respond to a pairwise comparison process such that the resulting criterion weights will approximate the U_i values. As the $A(i)$ values approach unity, this weight determination approach should improve in its approximations. Hence, if all $A(i)$ values were unity, the optimization procedure described in the previous section should lead to the same decision to which maximizing the expectation for $\mathbf{Z}$ would lead. Conversely, knowledge of a DM's true multiattribute value function should reveal the values for the criterion weights that would be ascertained using the pairwise comparison procedure.

Knowledge of this relationship between DM value and the proposed multicriteria method can be helpful in examining the potential effectiveness of the proposed optimization procedure. Since criterion weight determination is an *ad hoc* procedure, there is no way of verifying that multicriteria decisions based on the procedure are value maximizing [34]. Nevertheless, it is possible to specify a value function and then use its weight parameters (the U_i values) as criterion weights for evaluating the effectiveness of the proposed multicriteria bidding procedure. That is, for each value function, it is possible to determine what decision would be made using the proposed optimization procedure as well as the values of the potential outcomes from that decision to the DM.

The relationship, therefore, provides a way of comparing DM value resulting from a multicriteria decision to that resulting from a profit-based decision. Toward this end, 70 different value functions have been generated by varying both the weight and shape parameters.

Table 1 lists the sets of parameters for these value functions. The first column indicates a function's reference number, the second through fourth columns list the function's weight parameters, and the remaining columns list the function's shape parameters. Values allowed for the weight parameters in Table 1 were based upon the profit weight parameter's being 0.4, 0.6, or 0.8, as long as no criterion was weighted more highly than was profit. This should seem reasonable, given Boughton's finding [6], which showed profit maximization to be the company objective most frequently ranked. Increments of 0.1 were allowed for the weight parameters for volume and regret. These weight parameters can generally be interpreted as indicating the relative importance of the criteria, as do the criterion weights developed via pairwise comparisons, essentially. For the shape parameters, values were assigned as permutations of the values 0.2, 0.5, and 0.8. Additional functions were generated by setting all shape parameters to 0.2, 0.5, 0.8, or 1.0. Note that these shape parameters indicate decreasing levels of concavity (more of something is preferred but at a decreasing rate) for the individual attributes or criteria. With shape parameters of 1.0, the value functions are linear, which results in multiattribute value functions essentially the same as **MCF0** and **MCF1** as indicated by equations (9a) and (9b) above. There, the weights W_P, W_V, and W_R are analogous to the attribute weights (i.e., the U_i values) in equation (11). Thus, **MCF0** and **MCF1** are linear approximations to multiattribute value functions in which the criteria are mutually and additive independent.

4.3. Construction Project Data

Construction data for a large university system were used for evaluating the relative effectiveness of the proposed multicriteria bidding approach. In addition, these data provided information for developing probability distributions for $\mathbf{M}_L$, the ratio of lowest bids to estimated costs. Of 1,100 major building projects built over 25 years, 83 projects had adequate information recorded to support the regression-based determination of distribution parameters described above. This set of 83 projects was subsequently partitioned into two sets: an analysis set, used to estimate parameters for the regression equation for specifying probability distributions, and a holdout sample, used to evaluate the multicriteria bidding approach. The analysis set had 55 observations, while the holdout sample contained 28 observations. To use these data, the best available architect's estimate for each project (developed similarly to those generated by actual contractors) was used as the estimated cost (i.e., $\mathbf{C}_e$) of the project for a mythical subject bidder.

A limitation concerning the use of the data in the evaluation of the proposed optimization procedure was the simulation of values to represent actual project costs. (Note, however, that this is a limitation *not* on the use of the proposed multicriteria bidding system but on the evaluation of the system's effectiveness.) Only the actual builder will know his/her true project costs. Even for that builder, it is difficult to isolate costs associated with the project as it was bid, since change orders often cause the constructed project to be substantially different. Furthermore, only the most sophisticated of builders have cost reporting that is sufficiently accurate for this sort of analysis [6]. Determination of actual costs from data available to the university was, therefore, essentially impossible. In order that some variation of actual costs from estimated costs might be incorporated into the evaluation, a cost ratio ($\mathbf{C}$) for each project was simulated from a triangular $(0.9, 1.0, 1.2)$ distribution. This seemed reasonable to the authors based upon their experience with construction project accounting. As a result, the holdout data set used in the analysis is a hybrid of actual and simulated data.

This hybrid data set contains observations on project reference number, estimated costs ($\mathbf{C}_e$), simulated cost ratios ($\mathbf{C}$), lowest bid ratio ($\mathbf{M}_L$), and the regression model variables (number of bidders, interest rates, and proportional makeup) for each of the projects included. One might argue that the *number of bidders* is not necessarily known prior to the submission of bids. In such a case, a regression model using this information as a predictor variable would be of no use in supporting the bidding decision. To a certain extent it is true that the number of bidders is

Table 1. Value function parameters.

	Weight Parameters			Shape Parameters				Weight Parameters			Shape Parameters		
	U_P	U_V	U_R	$A(P)$	$A(V)$	$A(R)$		U_P	U_V	U_R	$A(P)$	$A(V)$	$A(R)$
Function	Profit	Vol.	Regret	Profit	Vol.	Regret	Function	Profit	Vol.	Regret	Profit	Vol.	Regret
1	0.4	0.2	0.4	0.2	0.5	0.8	36	0.6	0.1	0.3	0.8	0.5	0.2
2	0.4	0.2	0.4	0.2	0.8	0.5	37	0.6	0.1	0.3	0.2	0.2	0.2
3	0.4	0.2	0.4	0.5	0.2	0.8	38	0.6	0.1	0.3	0.5	0.5	0.5
4	0.4	0.2	0.4	0.5	0.8	0.2	39	0.6	0.1	0.3	0.8	0.8	0.8
5	0.4	0.2	0.4	0.8	0.2	0.5	40	0.6	0.1	0.3	1.0	1.0	1.0
6	0.4	0.2	0.4	0.8	0.5	0.2	41	0.6	0.2	0.2	0.2	0.5	0.8
7	0.4	0.2	0.4	0.2	0.2	0.2	42	0.6	0.2	0.2	0.2	0.8	0.5
8	0.4	0.2	0.4	0.5	0.5	0.5	43	0.6	0.2	0.2	0.5	0.2	0.8
9	0.4	0.2	0.4	0.8	0.8	0.8	44	0.6	0.2	0.2	0.5	0.8	0.2
10	0.4	0.2	0.4	1.0	1.0	1.0	45	0.6	0.2	0.2	0.8	0.2	0.5
11	0.4	0.3	0.3	0.2	0.5	0.8	46	0.6	0.2	0.2	0.8	0.5	0.2
12	0.4	0.3	0.3	0.2	0.8	0.5	47	0.6	0.2	0.2	0.2	0.2	0.2
13	0.4	0.3	0.3	0.5	0.2	0.8	48	0.6	0.2	0.2	0.5	0.5	0.5
14	0.4	0.3	0.3	0.5	0.8	0.2	49	0.6	0.2	0.2	0.8	0.8	0.8
15	0.4	0.3	0.3	0.8	0.2	0.5	50	0.6	0.2	0.2	1.0	1.0	1.0
16	0.4	0.3	0.3	0.8	0.5	0.2	51	0.6	0.3	0.1	0.2	0.5	0.8
17	0.4	0.3	0.3	0.2	0.2	0.2	52	0.6	0.3	0.1	0.2	0.8	0.5
18	0.4	0.3	0.3	0.5	0.5	0.5	53	0.6	0.3	0.1	0.5	0.2	0.8
19	0.4	0.3	0.3	0.8	0.8	0.8	54	0.6	0.3	0.1	0.5	0.8	0.2
20	0.4	0.3	0.3	1.0	1.0	1.0	55	0.6	0.3	0.1	0.8	0.2	0.5
21	0.4	0.4	0.2	0.2	0.5	0.8	56	0.6	0.3	0.1	0.8	0.5	0.2
22	0.4	0.4	0.2	0.2	0.8	0.5	57	0.6	0.3	0.1	0.2	0.2	0.2
23	0.4	0.4	0.2	0.5	0.2	0.8	58	0.6	0.3	0.1	0.5	0.5	0.5
24	0.4	0.4	0.2	0.5	0.8	0.2	59	0.6	0.3	0.1	0.8	0.8	0.8
25	0.4	0.4	0.2	0.8	0.2	0.5	60	0.6	0.3	0.1	1.0	1.0	1.0
26	0.4	0.4	0.2	0.8	0.5	0.2	61	0.8	0.1	0.1	0.2	0.5	0.8
27	0.4	0.4	0.2	0.2	0.2	0.2	62	0.8	0.1	0.1	0.2	0.8	0.5
28	0.4	0.4	0.2	0.5	0.5	0.5	63	0.8	0.1	0.1	0.5	0.2	0.8
29	0.4	0.4	0.2	0.8	0.8	0.8	64	0.8	0.1	0.1	0.5	0.8	0.2
30	0.4	0.4	0.2	1.0	1.0	1.0	65	0.8	0.1	0.1	0.8	0.2	0.5
31	0.6	0.1	0.3	0.2	0.5	0.8	66	0.8	0.1	0.1	0.8	0.5	0.2
32	0.6	0.1	0.3	0.2	0.8	0.5	67	0.8	0.1	0.1	0.2	0.2	0.2
33	0.6	0.1	0.3	0.5	0.2	0.8	68	0.8	0.1	0.1	0.5	0.5	0.5
34	0.6	0.1	0.3	0.5	0.8	0.2	69	0.8	0.1	0.1	0.8	0.8	0.8
35	0.6	0.1	0.3	0.8	0.2	0.5	70	0.8	0.1	0.1	1.0	1.0	1.0

unknown prior to bidding, but often a bidder can know, or at least estimate, how many other firms are interested in bidding. In situations involving bidding for public works projects, plan deposit fees are typically required, and the number of bidders can thus be estimated according to the amount of plan sets acquired. In other situations, the authors' own experiences have shown that often the number, as well as identities, of the competing bidders is typically well known among those submitting bids. Nevertheless, should reasonable estimates not be feasible for the number of bidders, a revised regression model not including that factor among the independent variables could be developed and used to estimate the distribution of $\mathbf{M}_L$.

Regression on $\mathbf{M}'_L$ (the natural logarithm of $\mathbf{M}_L$) was used to estimate the variance of $\mathbf{M}'_L$ and the expected low bid ratio for each of the projects. It was also found, via a chi-square goodness-of-fit test on the residuals for the data in the analysis sample, that it was not reasonable to reject the null hypothesis of normality of those residuals (observed significance level was 33%). Therefore, the appropriate Pr(Win | **M**) values were determined to be the complementary cumulative values from a lognormal distribution of $\mathbf{M}_L$, with a mean and variance as estimated according to the regression model. Table 2 lists the data in the holdout sample and includes each project's expected low bid ratio, $E(\mathbf{M}_L)$, as calculated according to the regression model developed from the analysis data set. In addition, the regression model is indicated at the bottom of the table.

5. COMPARING THE MULTICRITERIA AND PROFIT-BASED APPROACHES

One goal of this research has been to compare the performance of a multicriteria bidding method with that of a profit-based method. This comparison is not intended to show that DM value improves through the use of a multicriteria approach, since that should be a trivial exposition. That is, any approach that considers additional relevant criteria will naturally result in a performance with an improvement that varies directly (although not necessarily linearly) with the relative importance of the additional criteria [34]. Rather, the primary intention is to examine *how much* DM value improves, as well as to determine under what value functions there is a *substantial* improvement in value by adopting the multicriteria procedure. A secondary intention has been to determine whether there will be a substantial worsening of profits as DMs incorporate multiple criteria into their analyses. Hence, a statistical analysis is not appropriate, but a quantitative analysis of the results is, nevertheless, both possible and helpful.

5.1. General Comparison—Evaluating the Methodology

Comparisons of results for the two bidding decision rules started with the assumption of a value function. Then, data for one of the projects in the holdout sample were examined. For that project, an expected cost ratio, $E(\mathbf{C})$, and an expected low bid ratio, $E(\mathbf{M}_L)$, were calculated. These are indicated in Table 2. For each value of **M** corresponding to a percentage point on the CDF for $\mathbf{M}_L$, values of $\mathbf{P}'$, $\mathbf{V}'$, and $\mathbf{R}'$ were calculated for the project, according to equations (8a)–(8c). From these standardized values, multiattribute functions were calculated for both acceptance and nonacceptance outcomes (**MCF1** and **MCF0**, respectively) according to equations (9a) and (9b). In order to do this, values for W_P, W_V, and W_R (the criterion weights that would have been obtained via pairwise comparisons or some other procedure) were needed. As discussed above, these criterion weights can be considered to be estimates for the weight parameters (i.e., the U_i values) in **Z**, the decision maker's MAV function as indicated in equation (11). Hence, the U_i values were used as if they had been estimated via some elicitation process. From the multiattribute functions, a value of $E(\mathbf{MCF})$, as indicated in equation (10), was then calculated for each value of **M** being considered. As discussed above, the Pr(Win | **M**) values (i.e., the bid acceptance probabilities) used for that calculation were based upon the CDF of $\mathbf{M}_L$, the low bid ratio. The value of **M** corresponding to the largest $E(\mathbf{MCF})$ was designated the value optimum, or **MV**, for the project. In a similar manner, values of E(Profit) were calculated per equation (4) for each value of **M** under consideration. The value of **M** corresponding to the largest value of E(Profit) was then designated the profit optimum, or **MP**, for the project.

For one of the projects in the holdout sample, Table 3 illustrates and tabulates these calculations of value and profit expectations for each bid ratio considered between $\mathbf{M} = 1.053$ and $\mathbf{M} = 1.245$. Although not shown in the table, underbidding was allowed down to 90% of expected cost, reflecting an environment where volume might be at a premium. The single asterisk (*) indicates the expected profit corresponding to **MP**, which corresponds to bidding 19.8% above estimated costs, while the doubled asterisk (**) indicates the **MCF** expectation for **MV**, which corresponds to bidding only 7.2% above estimated costs. Note that the multicriteria approach resulted here in a substantially higher probability of winning (46%) than did the profit-based

Table 2. Construction project data (holdout sample).

Project	C_e	C	M_L	X_1	X_2	X_3	$E(M_L)$
11984	$ 5,963,108	1.11451	1.0797	−3.78	0.901	12	1.15496
12024	14,577,435	1.03831	0.7088	7.08	0.759	11	0.85651
12180	14,307,030	0.97581	0.8462	−14.91	0.777	6	1.40322
12237	16,194,944	1.01853	0.9138	−0.50	0.761	6	1.07067
12327	3,955,542	0.98431	0.9670	7.08	0.886	13	0.92347
12380	10,554,266	1.03124	0.6290	−1.05	0.661	8	0.95791
12392	669,439	0.94347	0.9010	7.08	0.881	8	1.00251
12414	15,750,000	1.03051	0.7810	2.51	0.783	15	0.88523
12431	2,152,638	1.00871	1.0380	−1.05	0.868	9	1.12611
12465	4,320,000	0.97652	0.8760	6.61	0.747	6	0.93197
12490	1,626,295	0.99909	1.1020	5.88	0.802	10	0.92400
12514	16,797,114	0.96613	1.0070	0.64	0.845	10	1.05283
12526	11,246,631	1.15284	0.7210	4.34	0.897	11	1.01336
12550	4,327,000	0.98213	0.5520	4.03	0.752	17	0.81028
12620	6,132,841	1.13859	1.0436	3.04	0.904	5	1.15745
32400	1,529,145	0.98921	0.9140	7.08	0.866	13	0.90763
32454	836,057	0.95061	1.1071	6.55	0.830	14	0.87292
32485	4,338,668	0.95915	1.2107	2.72	0.717	5	0.99021
32583	2,350,620	1.11683	0.9090	3.06	0.758	13	0.88804
42395	580,753	1.11249	1.7341	3.30	0.797	5	1.05026
42436	6,592,188	0.93257	1.2246	5.88	0.732	6	0.93200
42503	14,251,735	1.09398	0.7990	2.85	0.760	11	0.92432
42571	2,200,975	1.09340	0.9010	1.60	0.781	5	1.06766
52351	913,368	1.08691	0.9080	10.94	0.797	7	0.88549
52403	253,930	1.10138	0.9500	−4.29	0.747	6	1.13165
52406	818,278	1.03740	0.7800	4.22	0.884	9	1.03951
92114	79,041	1.01953	1.2168	−5.11	0.901	4	1.35808
92575	239,735	1.00063	1.1950	−0.96	0.867	9	1.12333

Variables:

C_e ... Estimated project costs

C ... Simulated ratio of actual costs to estimated costs

M_L ... Ratio of lowest competitor bid to C_e

X_1 ... Three-month treasury bill percentage yields (less inflation)

X_2 ... Proportion of estimated costs designated to be actual construction

X_3 ... Number of competitors bidding on project

Regression Model:

$M'_L = -0.51186 - 0.0178X_1 + 0.86500X_2 - 0.01729X_3$

SE = Model standard error = 0.1828

$R^2 = 31\%$

Model significance = 0.003

Estimate for $E(\mathbf{L}) = \exp(\mathbf{L}' + \mathbf{SE}^2/2)$

Goodness-of-Fit:

H_0: Error terms ~ Normal(0,SE)

Degrees of freedom = 8

$\chi^2 = 9.18$

Observed significance = 0.326

Table 3. Decision analysis for project #12237. (Value function #1.)

M	Markup	P′	V′	R′	MCF1	MCF0	Pr(Win | B)	E(MCF)	E(Profit)
1.053	$ 316,801	0.36	0.70	0.98	0.68	0.53	0.50	0.6046	$158,401
1.058	395,217	0.36	0.71	0.99	0.68	0.53	0.49	0.6055	193,656
1.063	474,001	0.37	0.71	0.99	0.69	0.53	0.48	0.6062	227,520
1.067	553,169	0.37	0.71	1.00	0.69	0.53	0.47	0.6068	259,989
1.072	632,689	0.38	0.71	1.00	0.69	0.53	0.46	0.6071**	291,037
1.077	713,217	0.38	0.72	1.00	0.70	0.53	0.45	0.6068	320,948
1.082	794,017	0.39	0.72	1.00	0.70	0.53	0.44	0.6064	349,367
1.087	875,617	0.39	0.72	1.00	0.70	0.53	0.43	0.6060	376,515
1.092	957,969	0.40	0.73	1.00	0.71	0.53	0.42	0.6056	402,347
1.098	1,041,137	0.40	0.73	1.00	0.71	0.53	0.41	0.6051	426,866
1.103	1,125,217	0.41	0.74	1.00	0.71	0.53	0.40	0.6045	450,087
1.108	1,210,225	0.42	0.74	1.00	0.71	0.53	0.39	0.6039	471,988
1.113	1,296,273	0.42	0.74	1.00	0.72	0.53	0.38	0.6033	492,584
1.119	1,383,409	0.43	0.75	1.00	0.72	0.53	0.37	0.6026	511,861
1.124	1,471,777	0.43	0.75	1.00	0.72	0.53	0.36	0.6018	529,840
1.130	1,561,409	0.44	0.75	1.00	0.73	0.53	0.35	0.6011	546,493
1.135	1,652,417	0.45	0.76	1.00	0.73	0.53	0.34	0.6002	561,822
1.141	1,744,929	0.45	0.76	1.00	0.73	0.53	0.33	0.5993	575,827
1.147	1,839,073	0.46	0.76	1.00	0.74	0.53	0.32	0.5984	588,503
1.153	1,934,913	0.47	0.77	1.00	0.74	0.53	0.31	0.5974	599,823
1.159	2,032,625	0.47	0.77	1.00	0.74	0.53	0.30	0.5964	609,788
1.165	2,132,337	0.48	0.78	1.00	0.75	0.53	0.29	0.5954	618,378
1.171	2,234,241	0.49	0.78	1.00	0.75	0.53	0.28	0.5942	625,587
1.178	2,338,465	0.49	0.79	1.00	0.75	0.53	0.27	0.5931	631,386
1.184	2,445,265	0.50	0.79	1.00	0.76	0.53	0.26	0.5918	635,769
1.191	2,554,785	0.51	0.79	1.00	0.76	0.53	0.25	0.5906	638,696
1.198	2,667,297	0.52	0.80	1.00	0.77	0.53	0.24	0.5892	640,151*
1.205	2,783,089	0.52	0.80	1.00	0.77	0.53	0.23	0.5879	640,111
1.213	2,902,433	0.53	0.81	1.00	0.77	0.53	0.22	0.5864	638,535
1.220	3,025,713	0.54	0.81	1.00	0.78	0.53	0.21	0.5849	635,400
1.228	3,153,313	0.55	0.82	1.00	0.78	0.53	0.20	0.5834	630,663
1.236	3,285,665	0.56	0.82	1.00	0.79	0.53	0.19	0.5818	624,276
1.245	3,423,297	0.57	0.83	1.00	0.79	0.53	0.18	0.5801	616,193

Weight Parameters: $U_P = 0.4$, $U_V = 0.2$, $U_R = 0.4$

Shape Parameters: $A(P) = 0.2$, $A(V) = 0.5$, $A(R) = 0.8$

approach (acceptance probability of 24%). For the strategy corresponding to $\mathbf{M} = \mathbf{MV}$, volume was obviously improved, but at the expense of a great deal of profit, relative to the profit maximizing strategy.

The multicriteria decision rule for a project was to bid an amount of $\mathbf{MV} \cdot \mathbf{C}_e$, while the profit-based decision rule was to bid $\mathbf{MP} \cdot \mathbf{C}_e$. These two amounts were treated as bids by the mythical subject bidder, thus resulting in two different decision outcomes from any given project for a specified MAV function. For each of the two hypothetical bids, a simulated profit amount ($\mathbf{P}$) was calculated as

$$\mathbf{P} = (\mathbf{M} - \mathbf{C}) \cdot \mathbf{C}_e, \tag{14}$$

if $\mathbf{M} < \mathbf{M}_L$ (otherwise $\mathbf{P} = 0$), and a simulated amount for DM value ($\mathbf{Z}$) was calculated per equations (13a) and (13b). Both outcomes were calculated as if done upon completion of the project, so actual (i.e., simulated) costs were incorporated into the calculations. (Obviously, calculations involving actual costs could not be done in practice, since such costs are typically known only by the successful bidder, if anyone. However, the purpose here is not to recommend an evaluation methodology for practical application, but to examine the effects that might be evaluated, if costs could somehow be known. If an actual DM were interested in assessing the impact of the multicriteria approach, he/she could conduct analysis by replacing $\mathbf{C}$ with $\mathbf{C}_e$.)

For a given MAV function, upon completion of these calculations of the profit and DM value for a project, the process was repeated for another project. This was done for all 28 projects in the holdout sample. Two values for the DM value outcome (one according the multicriteria decision rule and the other according to the profit-based decision rule) and two values for the profit outcome (one according the profit-based decision rule and the other according to the multicriteria decision rule) were thus obtained for each project. These values, along with the associated optima (**MV** and **MP**), are tabulated by project in Table 4 for one of the sets of value function parameters ($U_P = U_R = 0.4$, $U_V = 0.2$, $A(P) = 0.2$, $A(V) = 0.5$, and $A(R) = 0.8$). There it can be seen that, across the 28 projects in the holdout sample, using the multicriteria approach resulted in improving DM value by 1.3% (i.e., from 20.616 to 20.883) over that which occurred when the profit-based approach was used. At the same time, volume increased by 32.8%, while profit decreased by 88.7% and regret increased by over 275%! Obviously, any sizable weight on volume (here, only 0.2, as compared with 0.4 for the other two criteria) will result in a substantial worsening of profit and regret outcomes over time. While DM value theoretically increased, as addressed in Section 6, the poor performance on the regret criterion certainly served as a limiting factor. However, note that, if winning the bid had been a serious objective, the multicriteria approach for this set of criterion weights would have improved the proportion of bids won by 100%. While this would have come at cost of $2,201,922 in foregone profits, the bidder might have felt this worthwhile in order to maintain a competent work force and/or to remain a viable business entity. Of general concern is the comparatively large amount of money left on the table (i.e., regret) resulting from the use of the multicriteria approach, in spite of a criterion weight for regret equal to that for profit and double that for volume. This tended to occur regardless of the combination of criterion weights used, possibly because the value for U_R was never allowed to exceed 0.4. Apparently, the procedure is extremely sensitive to the weight for volume and relatively insensitive to that for regret. Further, research needs to be directed toward determining what are reasonable values for these parameters among actual DMs. Note that, of the eleven projects for which winning bids could have resulted in profitable outcomes (i.e., $\mathbf{M}_L > 1.000$), five would have been won with the multicriteria approach summarized in Table 4, and three would have been won if the profit maximization approach had been used. Certainly, a means of screening projects prior to estimating and bidding for them, in order to identify those that are potentially profitable, is called for, and Ahmad [11] has proposed such.

5.2. Project Specific Comparison—Aiding the Decision Maker

The purpose of comparing the outcomes of the multicriteria and profit-based approaches has been to identify the proposed methodology's effectiveness with respect to improvement in DM value and the corresponding cost in terms of profit. Hence, the purpose of the comparisons has not been to assist the DM in determining whether to use the multicriteria approach for any given instance. Nevertheless, some of the information generated by the procedure could be useful to the DM on a project-by-project basis by allowing him/her to be aware of the tradeoffs involved.

For any given project about to be bid, the procedure can identify both the optimal bid amount according to the profit maximization objective and the optimal bid amount according to the multicriteria approach. The actual profit ramifications, should the bid be accepted, will be

Table 4. Summary of results for value function #1.

Project	M_L	MV	MP	Z | MV	Z | MP	Profit | MV	Profit | MP	
11984	1.080	1.151	1.237	0.721	0.721	0	0	
12024	0.709	0.937	1.138	0.721	0.721	0	0	
12180	0.846	1.361	1.361	0.721	0.721	0	0	
12237	0.914	1.072	1.198	0.721	0.721	0	0	
12327	0.967	0.965	1.148	0.877	0.721	−76,588	0	
12380	0.629	0.982	1.157	0.721	0.721	0	0	
12392	0.901	1.009	1.174	0.721	0.721	0	0	
12414	0.781	0.948	1.140	0.721	0.721	0	0	
12431	1.038	1.128	1.225	0.721	0.721	0	0	
12465	0.876	0.969	1.159	0.721	0.721	0	0	
12490	1.102	0.966	1.149	0.834	0.721	−54,603	0	
12514	1.007	1.055	1.192	0.721	0.721	0	0	
12526	0.721	1.015	1.178	0.721	0.721	0	0	
12550	0.552	0.918	1.124	0.721	0.721	0	0	
12620	1.044	1.154	1.240	0.721	0.721	0	0	
32400	0.914	0.958	1.154	0.721	0.721	0	0	
32454	1.107	0.945	1.141	0.831	0.721	−4,850	0	
32485	1.211	1.001	1.177	0.831	0.925	181,784	945,044	
32583	0.909	0.951	1.144	0.721	0.721	0	0	
42395	1.734	1.052	1.197	0.659	0.750	−35,141	49,040	
42436	1.225	0.969	1.159	0.813	0.916	241,471	1,489,759	
42503	0.799	0.966	1.149	0.721	0.721	0	0	
42571	0.901	1.069	1.202	0.721	0.721	0	0	
52351	0.908	0.949	1.141	0.721	0.721	0	0	
52403	0.950	1.133	1.225	0.721	0.721	0	0	
52406	0.780	1.041	1.192	0.721	0.721	0	0	
92114	1.217	1.323	1.336	0.721	0.721	0	0	
92575	1.195	1.125	1.222	0.897	0.721	29,848	0	
		Totals:		20.883	20.616	$ 281,921	$ 2,483,843	
						17,789,664	13,442,120	(Volume sums)
						3,359,329	894,464	(Regret sums)

Legend:

MV... Optimum bid ratio per multicriteria method.
MP... Optimum bid ratio per profit-based method.
Z | MV... DM value of outcome using multicriteria method.
Z | MP... DM value of outcome using profit-based method.
Profit | **MV**... Profit resulting from use of multicriteria method.
Profit | **MP**... Profit resulting from use of profit-based method.

obvious. However, the corresponding expected profits can also be indicated, along with the acceptance probabilities corresponding to each of the two bid amounts. In addition, the expected regret for each bid amount can be identified, along with the expected DM value associated with each bid amount. Expected regret would simply be the difference between the expected low bid (determined via the regression model) and the given bid amount.

Consider, for example, Project #12237, for which the decision analysis is summarized above in Table 3. The optimal bids are $17,367,456 (for maximizing DM value) and $19,402,064 (for maximizing profit), with acceptance probabilities of 46% and 24%, respectively. Since, the expected low bid ratio, $E(M_L)$, is 1.07 and the expected cost (C_e) is $16,194,944, the expected low bid is $17,339,441 and expected win regret is 0 for either bid amount. Expected DM value $E(\mathbf{MCF})$ at the lower bid amount is 0.61 (where ideal would be 1.00), and that associated with the higher amount is 0.59. It would be up to the DM to determine whether the doubled chance of winning and/or the 3% improvement in preopening optimism (i.e., expected DM value) is worth the $2,034,608 difference in possible profit. Of course, that profit difference is only a possibility, and the DM may be capable of understanding that it is only a $349,114 difference in terms of expected (or long run per project) profit.

6. RESULTS AND CONCLUSIONS

The procedure described above and illustrated in Table 4 was followed for each of the 70 MAV functions indicated in Table 1. For each MAV function, four primary sums were calculated, as indicated on the totals line of Table 4. These sums are the DM value totals for either of the decision rules (maximize expected DM value and maximize expected profit) and the profit totals for either of the decision rules. A look at these measures allows one to develop a feel for the *tradeoffs* involved when criteria besides profit are considered in the bidding problem. Subsequently, when the bidding totals are compared across MAV functions, it can be seen under which circumstances the multicriteria approach will make a substantial contribution and when the contribution is of relatively little value. In addition, one can begin to identify the effects of nonlinear MAV functions on the outcomes of the proposed multicriteria approach.

Summarized in Table 5 are the DM value and profit results for each of the 70 MAV functions. Essentially, the table indicates the *effectiveness* of the multicriteria approach, as measured by the percentage improvement in DM value that resulted from using the multicriteria approach rather than the profit based approach. Furthermore, the percentage worsening of profit total corresponding to the improvement in DM value is shown for each MAV function. Note that improvement in DM value ranged between 1% and 7%, while profit totals worsened between 82% and 127%.

If the DM value outcome corresponding to a given MAV function showed an improvement of more than 5%, then the multicriteria approach was considered to have had a *substantial* effect on DM value. As can be seen in the table, this occurred for MAV function numbers 24 through 45. For these functions, although not only for these functions, profit has weights of 0.4 and 0.6. The most improvement in DM value occurred with MAV function 30, which is linear and where profit and volume are equally weighted. The least improvement in value occurred with MAV function 2, where profit and regret are equally weighted. In general, it appears that noteworthy improvements in DM value occur when volume is the most important criterion and/or when profit is more important than any other criterion. Apparently, the regret criterion tends to confound the results as it becomes increasingly important, and improvements become relatively inconsequential.

Table 5 shows that, for a given set of weight parameters, the effectiveness of the proposed multicriteria bidding approach varied somewhat according to the shape parameters of the MAV functions. Recall that the optimization approach essentially relies upon the use of linear approximations to DM value assessments. Hence, it would be expected that the effectiveness of the approach would improve as the underlying MAV functions approach linearity, and this improvement generally did occur. However, for the most part, this improvement in effectiveness was relatively small, with the greatest improvement having been from a 4.10% improvement in DM value to a 7.03% improvement. On an absolute scale, this is not especially noteworthy. In fact, for two sets of weight parameters, the effectiveness of the multicriteria approach was actually *worse* for linear underlying MAV functions than it was for nonlinear functions. (This anomaly occurred for functions where profit is weighted at 0.6 and where volume is weighted no more highly than is regret.) As a result, it appears that the proposed approach is relatively robust to nonlinearities in the DM's underlying MAV function.

Table 5. Summary of effects of multicriteria bidding approach.

	Weight Parameters			Shape Parameters			% Improvement	% Worsening
Function	U_P	U_V	U_R	$A(P)$	$A(V)$	$A(R)$	DM Value	Profit
1	0.4	0.2	0.4	0.2	0.5	0.8	1.29	88.65
2	0.4	0.2	0.4	0.2	0.8	0.5	1.27	88.65
3	0.4	0.2	0.4	0.5	0.2	0.8	1.39	88.65
4	0.4	0.2	0.4	0.5	0.8	0.2	1.43	88.65
5	0.4	0.2	0.4	0.8	0.2	0.5	1.55	88.65
6	0.4	0.2	0.4	0.8	0.5	0.2	1.64	88.65
7	0.4	0.2	0.4	0.2	0.2	0.2	1.80	88.65
8	0.4	0.2	0.4	0.5	0.5	0.5	1.77	88.65
9	0.4	0.2	0.4	0.8	0.8	0.8	1.64	88.65
10	0.4	0.2	0.4	1.0	1.0	1.0	1.47	88.65
11	0.4	0.3	0.3	0.2	0.5	0.8	1.87	93.63
12	0.4	0.3	0.3	0.2	0.8	0.5	2.13	97.78
13	0.4	0.3	0.3	0.5	0.2	0.8	2.48	101.29
14	0.4	0.3	0.3	0.5	0.8	0.2	2.65	104.30
15	0.4	0.3	0.3	0.8	0.2	0.5	2.96	106.91
16	0.4	0.3	0.3	0.8	0.5	0.2	3.18	109.19
17	0.4	0.3	0.3	0.2	0.2	0.2	3.50	111.21
18	0.4	0.3	0.3	0.5	0.5	0.5	3.63	113.00
19	0.4	0.3	0.3	0.8	0.8	0.8	3.65	114.60
20	0.4	0.3	0.3	1.0	1.0	1.0	3.63	116.04
21	0.4	0.4	0.2	0.2	0.5	0.8	4.10	117.54
22	0.4	0.4	0.2	0.2	0.8	0.5	4.44	118.90
23	0.4	0.4	0.2	0.5	0.2	0.8	4.94	120.14
24	0.4	0.4	0.2	0.5	0.8	0.2	5.21	121.29
25	0.4	0.4	0.2	0.8	0.2	0.5	5.68	122.33
26	0.4	0.4	0.2	0.8	0.5	0.2	6.03	123.30
27	0.4	0.4	0.2	0.2	0.2	0.2	6.47	124.20
28	0.4	0.4	0.2	0.5	0.5	0.5	6.74	125.03
29	0.4	0.4	0.2	0.8	0.8	0.8	6.91	125.81
30	0.4	0.4	0.2	1.0	1.0	1.0	7.03	126.53
31	0.6	0.1	0.3	0.2	0.5	0.8	6.75	123.31
32	0.6	0.1	0.3	0.2	0.8	0.5	6.50	120.30
33	0.6	0.1	0.3	0.5	0.2	0.8	6.33	117.46
34	0.6	0.1	0.3	0.5	0.8	0.2	6.16	114.79
35	0.6	0.1	0.3	0.8	0.2	0.5	6.04	112.28
36	0.6	0.1	0.3	0.8	0.5	0.2	5.93	109.91
37	0.6	0.1	0.3	0.2	0.2	0.2	5.76	107.66
38	0.6	0.1	0.3	0.5	0.5	0.5	5.63	105.53
39	0.6	0.1	0.3	0.8	0.8	0.8	5.52	103.51
40	0.6	0.1	0.3	1.0	1.0	1.0	5.43	101.59
41	0.6	0.2	0.2	0.2	0.5	0.8	5.32	100.56
42	0.6	0.2	0.2	0.2	0.8	0.5	5.21	99.57
43	0.6	0.2	0.2	0.5	0.2	0.8	5.14	98.63
44	0.6	0.2	0.2	0.5	0.8	0.2	5.06	97.73
45	0.6	0.2	0.2	0.8	0.2	0.5	5.02	96.87

Table 5. (cont.)

Function	Weight Parameters U_P	U_V	U_R	Shape Parameters $A(P)$	$A(V)$	$A(R)$	% Improvement DM Value	% Worsening Profit
46	0.6	0.2	0.2	0.8	0.5	0.2	4.97	96.05
47	0.6	0.2	0.2	0.2	0.2	0.2	4.91	95.26
48	0.6	0.2	0.2	0.5	0.5	0.5	4.84	94.50
49	0.6	0.2	0.2	0.8	0.8	0.8	4.79	93.78
50	0.6	0.2	0.2	1.0	1.0	1.0	4.73	93.09
51	0.6	0.3	0.1	0.2	0.5	0.8	4.72	93.01
52	0.6	0.3	0.1	0.2	0.8	0.5	4.69	92.93
53	0.6	0.3	0.1	0.5	0.2	0.8	4.71	92.86
54	0.6	0.3	0.1	0:5	0.8	0.2	4.69	92.79
55	0.6	0.3	0.1	0.8	0.2	0.5	4.71	92.72
56	0.6	0.3	0.1	0.8	0.5	0.2	4.72	92.66
57	0.6	0.3	0.1	0.2	0.2	0.2	4.73	92.60
58	0.6	0.3	0.1	0.5	0.5	0.5	4.73	92.54
59	0.6	0.3	0.1	0.8	0.8	0.8	4.72	92.48
60	0.6	0.3	0.1	1.0	1.0	1.0	4.70	92.42
61	0.8	0.1	0.1	0.2	0.5	0.8	4.63	91.21
62	0.8	0.1	0.1	0.2	0.8	0.5	4.56	90.03
63	0.8	0.1	0.1	0.5	0.2	0.8	4.53	88.90
64	0.8	0.1	0.1	0.5	0.8	0.2	4.49	87.80
65	0.8	0.1	0.1	0.8	0.2	0.5	4.48	86.73
66	0.8	0.1	0.1	0.8	0.5	0.2	4.47	85.69
67	0.8	0.1	0.1	0.2	0.2	0.2	4.41	84.69
68	0.8	0.1	0.1	0.5	0.5	0.5	4.38	83.71
69	0.8	0.1	0.1	0.8	0.8	0.8	4.36	82.77
70	0.8	0.1	0.1	1.0	1.0	1.0	4.35	81.85

Examination of the profitability results in Table 5 reveals that improvements in DM value are not gained without a considerable worsening on the profit dimension. In fact, for nearly half of the MAV functions considered, there was more than a 100% worsening, which could easily be considered as a *drastic* effect. That is, a worsening of 100% would indicate a contractor operating with zero profit, while a worsening of more than 100% would indicate a contractor *operating at a loss*. Across the 70 MAV functions, the minimum worsening on the profit criterion corresponds to a linear MAV function with profit weighted at 0.8. That is, profit is weighted quite heavily, while volume and regret are only minimally weighted. One would, of course, expect that functions with high profit weights would lead to relatively little compromise on profit outcomes. However, an 82% reduction in profit is still severe, indicating that the proposed multicriteria approach is quite sensitive to variation in the importance of criteria other than profit. The most notable worsenings of profit outcomes occurred where the profit weight was the lowest considered and volume was equally important, while regret was slightly less important (MAV functions 21 through 30). This also seems reasonable, since bidding for optimal volumes typically results in bids farther below cost than profit maximization results in bids above cost. Furthermore, acceptance probabilities are higher with volume maximization since bids are lower. Hence, any time volume is weighted on a par with profit, negative total profits are likely to result.

It should be noted that, for any project on which both decision rules resulted in acceptance of the bid (see, for example, outcomes for projects 32485, 42395, and 42436 in Table 4), DM value resulting from the multicriteria method was worse than that from the profit-based method. This is an interesting and perhaps initially distressing occurrence. Nevertheless, this is a reasonable result. A bid considering volume as a criterion will always be lower than one considering only profit. As a result, if a bid based solely on profit maximization were to be accepted, so would a bid based in part on volume. Because the latter is lower in amount, actual profits will be lower, regret will be higher, and, paradoxically, volume will be lower for a specific job. Hence, in such cases, the multicriteria approach has as its primary advantage that more projects will be won, and subsequently there will be more nonzero attainments on the volume criterion. Nevertheless, as this criterion carries progressively higher relative weights, the multicriteria bidding approach based upon this MAV function model should be of increasing worth to the DM. This is borne out by the fact that the greatest DM value improvements, as indicated in Table 5, occurred with MAV functions characterized by the maximum weight considered for volume.

In general, it appears that the proposed multicriteria bidding approach could prove beneficial to a relatively wide range of decision makers. Those who value volume quite highly will likely find their overall satisfaction with the outcomes (as reflected by their MAV functions) improved substantially (i.e., at least 5%) with the proposed approach. In addition, those who value profit highly yet wish to bring other criteria into consideration are likely to benefit substantially or nearly substantially. Of course, as the importance of volume increases, the DM will pay a severe price in terms of profitability. This could be especially difficult to tolerate, as profitability is often the only tangible measure on which DMs are evaluated. As a result, any determination of importance measures for the criteria should take into consideration how the DM will ultimately be evaluated. More importantly, it should be the appropriate person (or persons) whose preference information is to be incorporated into the bidding optimization process. This is the person who is ultimately affected by the decision, generally the owner or CEO, and not a lower level manager, of the firm. Furthermore, as situations change, so do the preference structures of the DMs. For example, when a firm has developed a sizeable backlog of work, the volume criterion is not likely to have a high importance attached to it for future bidding opportunities, but when work is short in supply, the opposite holds. Hence, not only should the appropriate DM be taken into consideration, but the current situation of the firm is also relevant in assessing preference information.

7. SUMMARY

While numerous works have addressed bidding optimization over the past 40 years, industry practitioners generally continue to ignore those works and, instead, use rules of thumb and other arbitrary approaches for determining prices [6,19]. This likely results, at least in part, from the fact that existing optimization methods tend to produce unsatisfactory results, as they are incapable of incorporating tradeoffs among multiple criteria. Furthermore, in order to be successfully adopted by industry practitioners, bidding optimization, whether multicriteria or not, must take place as part of a system. Such a system is necessarily comprised of at least two components: an analysis component for generating the probability information required in the evaluation of various bidding alternatives, and an optimization component for determining which alternative is best, given the tradeoffs involved. Although the analysis component has been discussed briefly in this paper and in detail in other work [5,24,32], the optimization component has been the focus of this paper. Its success depends upon the reliability of the analysis component, which begins with good record keeping and is followed by the implementation of sound statistical procedures.

This system's perspective has guided the research and the discussion that has been presented here. Based upon actual data, a probability model has been developed to take into consideration major factors which affect bidder behavior. Then, based upon that model, a multicriteria optimization approach was presented and evaluated for effectiveness. That approach employs an elicitation procedure (preferably based on pairwise comparisons) to generate estimates of the weights for the DM's multicriteria objective function. In the evaluation of the proposed bidding optimization approach, a wide range of preference structures (as indicated by MAV functions) were considered. For a good portion of the preference structures considered, the multicriteria approach, when compared to the profit-based approach, led to substantial or nearly substantial improvement in DM value outcomes. On the other hand, for a few preference structures, there was little improvement when the additional criteria were considered. Essentially, in situations where there was relatively little concern about regret ("money left on the table") and related criteria, the proposed multicriteria optimization approach proved beneficial.

An extension of this research would consider the automation of the process, and hence, address a third component for the bidding system: an information processing capability which would make it possible to acquire, maintain, and manipulate the data required by bidding optimization. One such system is already operational and is described by Hegazy and Moselhi [15] and Moselhi *et al.* [17]. In addition, somewhat different architectures have been proposed by Ahmad and Minkarah [14] and Seydel [35], and Ward and Chapman [36] have provided some general guidelines for bidding information systems. Other extensions to the research include a more detailed look at the criteria contractors actually consider, as well as an empirical study of the relationship between criterion weights determined via pairwise comparisons and those determined through other procedures.

Another extension of this research must address how to modify the proposed system, if possible, to deal with situations in which bid takers (i.e., potential customers) are awarding contracts according to criteria beyond price (i.e., lowest bid). Increasingly, firms are seeking to implement Deming's fourth point: "end the practice of awarding business on price tag alone" [37]. Customers are looking at ways to choose trade partners on the basis of product quality, provider reputation, delivery speed, service beyond the sale, etc. Such an extension will need to incorporate a considerably broader competitive analysis addressing the subject bidder's relative strengths and weaknesses according to the criteria indicated by the potential customer. At present, the literature does address the problem from the bid taker perspective, but no work has been found addressing this from the bidder's perspective. However, the product/service design tool, QFD (quality function deployment, as discussed by Zangwill [38], for example) may provide some inspiration for modelling the supplier/customer joint multicriteria selection problem in a bidding context. After all, a bid taker considering multiple criteria is essentially looking for the product (i.e., bidder) with the best combination of values for factors that are important to the bid taker. It then is up to the bidder to design a package (price, quality, timing, etc.) that will appeal to the customer. Of course, for any given bid, essentially the only factor under the bidder's control is price. The acceptance probability associated with a given price will then be dependent upon how well the subject bidder measures up competitively to the other bidders with respect to the customer's criteria. It is here that QFD might furnish some guidance for organizing the extensive data resulting from the necessary competitive analysis and then utilizing those data to provide estimates of acceptance probabilities for various markup levels. Alternatively, a game theoretic approach might be useful in formulating a descriptive analysis. Nevertheless, because of the complexities inherent to game theory, it is not likely to be of much help in developing prescriptive analyses of this problem.

In summary, this paper has proposed an approach for incorporating multiple criteria into the bidding decision and has considered that approach as part of an overall bidding system. In the process, a method for evaluating the effectiveness of the proposed approach has been developed and demonstrated. Furthermore, the evaluation provides a look at the tradeoffs involved in moving away from the traditional single criterion approach. The construction bidding context was addressed, but the approach should be generalizable to other one-item-at-a-time auctions in which a moderate level of uncertainty exists and in which the low bidder wins. Of course, context-specific data would always need to be used. Competitive bidding is an interesting area in which little has been done with respect to *using* operations research techniques to improve results. This is because bidding is a complex problem, and no particular method will remove the complexity. However, the development and implementation of methods such as those proposed here are likely to lead to greater acceptance by practitioners and to improved results by those who are willing to use those methods.

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