Proceedings of the 1994 Winter Simulation Conference
ed. J. D. Tew, S. Manivannan, D. A. Sadowski, and A. F. Seila

SIMULATION MODEL FOR COMPETITIVE BIDDING IN CONSTRUCTION

John Seydel

Department of Management & Marketing
The University of Mississippi
University, MS 38677, U.S.A.

ABSTRACT

In this paper, bidding optimization procedures are summarized for the construction context, and a model design is proposed for use in simulating the bidding process and its complexities. Situations involving potentially large numbers of bidders are represented. The simulation model incorporates the variety typically representative of projects for which bids are submitted, as well as the tendency of bidders to respond in varying ways to that variety. Ultimately, data are to be generated by the simulation model for use in developing and testing alternative methods used in bidding optimization.

1 INTRODUCTION

In competitive bidding for construction projects, it is helpful for a given contractor to have a feel for how his/her competition is likely to bid. Of course, it is impossible to predict precisely how various competitors will approach a given bidding situation. It is, however, possible to take certain project characteristics into consideration through the use of multiple regression or neural networks. Results of these analyses allow the bidder to gain at least a little understanding of how competitors will bid for a given project. This paper addresses these results and proposes a simulation model design for generating project bid data according to specified relationships. The primary purpose of the simulation model is to generate data to support experimentation aimed at determining how well one might expect regression analyses and artificial neural networks to generate models of the relationships between project characteristics and bidder behaviors. In addition, the data generated by the model can be used in a variety of other bidding-related research, as well as for the training of personnel involved in bidding.

2 BIDDING OPTIMIZATION

The discussion in this paper refers to the general profit maximizing model based upon that which was initially proposed by Friedman (1956). According to this model, the bidder should bid an amount $\boldsymbol{A}$ so as to

$$\text{Maximize } \mathbf{E}(\boldsymbol{Profit}) = [A - \mathbf{E}(\boldsymbol{Cost})]\cdot\mathbf{P}(\boldsymbol{Win}), \quad (1)$$

where $\mathbf{P}(\boldsymbol{Win})$ is defined to be the bid acceptance probability for a given bid amount.

Let $\boldsymbol{A}$ be defined to be equal to $\boldsymbol{B}\cdot\boldsymbol{C}_e$, where $\boldsymbol{C}_e$ is designated to represent the estimated cost of the *object* (i.e., the good or service) which is to be provided. Then $\boldsymbol{B}$ represents the ratio of the bid amount to the cost estimate; hence $\boldsymbol{B}$ is referred to herein as the *bid ratio*. If actual (as opposed to estimated) costs are defined to be equal to $\boldsymbol{C}\cdot\boldsymbol{C}_e$, then $\boldsymbol{C}$ represents the ratio of actual to estimated costs for the object of interest and is referred to herein as the *cost ratio*. This value is a random variable for which the distribution may or may not be known. Dividing through Equation (1) by $\boldsymbol{C}_e$ and defining π to be equal to profit divided by estimated costs results in

$$\text{Maximize } \mathbf{E}(\pi) = (\boldsymbol{B} - 1)\cdot\mathbf{P}(\boldsymbol{Win}). \quad (2)$$

Thus, the *expected* profit margin, $\mathbf{E}(\pi)$, for a given bid is equal to the included markup multiplied by the bid acceptance probability. The bidding optimization problem is, therefore, considered to be that of determining a value for $\boldsymbol{B}^*$, the bid ratio that will maximize long run (i.e., expected) profits.

It has been recommended by Hansmann & Rivett (1959) that $\mathbf{P}(\boldsymbol{Win})$ be defined as the probability of beating the *lowest competing bid*. To understand the lowest competing bid definition, let $\boldsymbol{L}$ represent the ratio of the lowest competing bid to a given bidder's cost estimate, $\boldsymbol{C}_e$. Then, according to the lowest competing bid definition,

$$\mathbf{P}(\mathbf{\mathit{Win}}) \equiv \mathbf{P}(\mathbf{\mathit{L}} > \mathbf{\mathit{B}}) = 1 - \mathbf{F}_L(\mathbf{\mathit{B}}), \quad (3)$$

where $\mathbf{F}_L(\boldsymbol{B})$ is the cumulative distribution function (CDF) of the random variable $\boldsymbol{L}$, evaluated at $\boldsymbol{B}$. Obviously, $\mathbf{P}(\boldsymbol{Win})$ varies inversely with $\boldsymbol{B}$, and Equation (2) can be combined with Equation (3) to yield the following objective function

$$\text{Maximize } \mathbf{E}(\pi) = (\boldsymbol{B} - 1)\cdot[1 - \mathbf{F}_L(\boldsymbol{B})]. \quad (4)$$

If bidders do not adjust their strategies from project to project according to the characteristics of the projects, then $\boldsymbol{F}_L$ is static. This is unrealistic, however, and has resulted in the development of regression-based definitions and neural-network models for dealing with acceptance probabilities, as addressed below.

3 PREDICTIVE MODELS FOR BIDDING

Variation in competitor behaviors in bidding situations can be considered to result from three basic premises. First, costs typically vary for the different contractors (Grinyer & Whittaker 1974). Second, the amount of markup charged by a given bidder represents a strategic decision by that bidder and will hence be kept secret from his/her competitors. Finally, projects vary from one to another with respect to their desirability, risk involved, and complexity, so markups will vary to reflect these factors (Carr & Sandahl 1978) (Gordon & Welch 1971). A bidder can compile information dealing with the third premise and can subsequently use this information to develop predictive models of collective bidding behavior.

A procedure for using regression to model bidder behaviors has been described by Carr and Sandahl (1978), Broemser (1968), and Seydel (1990). These papers propose maintaining past project information such as: the subject bidder's cost estimate; the bids submitted by competitors; and certain project characteristics and econometric data. The subject bidder would then be able to develop a regression model to predict $\boldsymbol{L}$, the lowest competing bid ratio for any upcoming project. This model would be of the form

$$L = \beta_0 + \sum_i \sum_k \beta_{ik}(X_i^P)^k + \sum_j \sum_l \beta_{jl}(X_j^E)^l + \epsilon, \quad (5)$$

where: the β values are regression coefficients; the X_i^P indicate project-related factors; the X_j^E indicate economy-related factors; and the ϵ term indicates a random component.

Because of its stochastic nature, as indicated by the ϵ term, the regression model is primarily useful for determining the parameters of the probability distribution for $\boldsymbol{L}$. Regression-based procedures therefore result in the use of probability distributions which are *conditional* upon the values of the bidding factors for the situations being considered. Thus, a more precise set of estimates for $\mathbf{P}(\boldsymbol{Win})$ should be available for determining profit expectations associated with various markup levels. The results reported by Broemser (1968) and Seydel (1990) indicate potentially improved results for bidders applying the regression-based method, but, unfortunately, the improvement is far from overwhelming.

Methodologies for applying artificial neural networks (ANNs) to construction bidding problems have been developed by Caporaletti *et al* (1992) and by Moselhi *et al* (1992). In addition, the methodology proposed by Moselhi has been incorporated into the software architecture proposed by Moselhi *et al* (1993). In a manner that is both similar to and different from the regression-based approach, the approach of Caporaletti *et al* is used to generate estimates of bid acceptance probabilities and, subsequently, optimal bid ratios. The similarity of this approach to the regression-based approach is that, for upcoming bids, predictions for $\boldsymbol{L}$ are made based upon models derived from historical data. These models incorporate a variety of bidding factors, just as do regression models. The difference is that, in the case of ANNs, no model is specified by the decision maker. It is, instead, represented implicitly by the training of the artificial neuronal structure. In addition, given a prediction for $\boldsymbol{L}$, probabilities are not calculated from a normal distribution or any other theoretical distribution. Instead, probability estimates result from an analysis of the empirical, or cumulative relative frequency (CRF), distribution of the residuals observed during the training of the network. The overall process consists of training a network on historical data, performing a residual analysis to ascertain information about the CRF used to estimate $\mathbf{P}(\boldsymbol{Win})$, and calculating profit expectations for varying values of $\boldsymbol{B}$. As with regression, however, empirical results have not been especially encouraging.

4 BIDDING SIMULATION DESIGN

Obviously, it should be possible for the model developer to achieve better results on the simulated data than on real data, since he/she knows the dependent/independent variable relationships. Thus, performing regression and/or neural network analyses on the simulated data should provide a reasonable pattern for the analysis of actual data, as well an upper limit that could be expected of the fit that might be obtained for a predictive model.

4.1 Simulation Experiment Structure

The experiments for which the simulation model to be described has been designed center around a hypothetical subject bidder. Historical data are to be generated for a variety of circumstances likely to have been represented in the past ten years of the bidder's commercial life. These data will then be partitioned into two smaller data sets -- an analysis sample and a holdout sample. The analysis sample will consist of all projects in the first five years of the time period under consideration and will be used to develop regression and neural network models on $\boldsymbol{L}$. The remainder of the data will then be used to test those models. The same simulation process will be used to generate the data in both sets, so all data will represent observations from the same population.

4.2 Simulation Overview

All data will be generated by first creating an array of projects on which the hypothetical firm has bid over the given time period. Once the project data have been created, a set of competitors who have also bid on projects for which the subject bidder has submitted bids will be simulated. This will be done by considering each competitor individually with respect to size and the manner in which he/she responds to the bidding factors. Finally, project data will be merged with competitor data to determine bidding distributions for the projects in the data sets.

Subject Bidder -- Consider the hypothetical subject bidder for the simulation: FBK Builders is a firm that specializes in custom residential construction, primarily wood frame. As a rule, FBK obtains work through the competitive bidding process, where bids represent fixed priced offers for all work specified. Although there are 50 competitors against which FBK has bid in the past five years, the number of opponents FBK encounters on any particular project varies. The most opponents FBK has encountered has been 12, the least has been one, and the average number of competitors FBK has bid is five. The company is based in Boise, Idaho, and operates almost strictly within 20 miles of its home office. FBK maintains crews and equipment to perform all carpentry, both rough and finish, but usually relies upon subcontractors for other work, such as concrete, drywall, roofing, etc. With respect to other residential contractors, FBK is a medium-sized firm, with a bonding capacity of about $1,000,000, while their competitors have bonding capacities of between $100,000 and $10,000,000.

Project Data -- Each project is to represent a record in a file of 250 projects. Generating project data starts by assigning timing for a project according to the cumulative relative frequency distribution for the timing of building permits on a national basis. After that, several variables are assigned values, some of which are based upon values of previous variables. For example, ***remodel-proportion*** is assigned a value of zero for projects which have been assigned values of "true" for ***new-construction***, but for other projects, it is assigned a value from a Uniform (0.1,0.9) distribution.

There will exist a file of time series data for three economy-related measures: real ***GNP-growth***; national ***unemployment-rate***; and ***interest-rate*** (three-month Treasury bill rate). In a merge step, a value for each of these measures is to be assigned from the economic data file to each project record according to the project's ***bid-date***. The values assigned will reflect one-month lags for each of the three economy-related variables.

The variables chosen for inclusion in the simulation have generally been suggested and/or otherwise discussed in the bidding literature, in particular in (Boughton 1987), (Broemser 1968), (Carr & Sandahl 1978), (Gordon & Welch 1971), (Seydel 1990), and (Walker 1970). In addition, the specification of the distributional characteristics of those variables has come from both quantitative and qualitative discussions found in that literature, not to mention the actual bidding experience of this author.

Competitor Data -- In the project data set, there are to be values for a number of variables, or factors, as discussed in the subsection above. The competitor data set is intended to incorporate information with respect to how each competitor responds to those factors. Bid markups are considered to be a function of project risk (i.e., uncertainty) and bidders' attitudes toward this risk (Boughton 1987) (Gordon & Welch 1971). Any factor which introduces or increases uncertainty is likely to have a direct relationship with the markup, and hence the bid ratio, $\boldsymbol{B}$, chosen by any given bidder for a project. Bounds for relationships between bidding factors and each competitor's bidding *systematic* behavior have been established. Rates from within these bounds will then be used to generate the deterministic component of the competitors' bids.

There will also be a *stochastic* component introduced into the bids. This will be done by randomly specifying for each competitor a set of parameters for a triangular distribution to describe the random component of the competitor's bid on any given project. That is, if the random component for competitor i's bid ratios is denoted by $\boldsymbol{V}_i$, then

$$V_i \sim Triangular(l_i, m_i, u_i) \quad (6)$$

where: l_i, the lower parameter is generated randomly on the interval [-0.05,-0.03]; the mode parameter, m_i, is randomly generated on the interval [-0.02,0.02]; and u_i, the upper parameter, is determined so that $E(V_i)=0$. A competitor's bid ratio will then be the deterministic component defined by his/her unique set of rate values plus a randomly generated value of V_i.

Low Bid Distribution -- The low bid distribution is to be created by a sort of merger of the data in the two data sets described above -- the project data set and the competitor data set, both of which are incomplete until bid values have been determined and incorporated. Execution of this step determines those bid values and hence completes the simulation of data required for subsequent data analysis via regression. That is, upon completion of this step, each project record will have a set of characteristics describing the project, including both project-related and economy-related factors. Among the project-related factors for a given record will be the ***low-bid*** amount, the primary outcome of this step of the simulation.

The merging process takes place a project at a time. It begins with the determination of the identities of competitors bidding on a given project. A quantity of unique integers are generated randomly on the interval [1,50]. Once bidder identities have been determined, a bid is to be generated for each of the identified bidders according to his/her bidding parameters and the values of the particular project's bidding factors. In this manner, an array of bids will be generated for each project. From the array, which is ***number-of-bidders*** in length, the minimum is to be chosen and designated as the project's ***low-bid*** amount. This value divided by FBK's ***cost-estimate*** for the project would then correspond to L. Recall that it is from the distribution of L that **P(*Win*)** values are determined, whether unconditionally or through some sort of predictive model such as regression analysis as described above.

5 CONCLUDING REMARKS

Only information concerning distributional forms is to be hard coded, so that all variables and parameters will be capable of being varied. While the proposed simulation is not intended to benefit the decision making process directly, it is expected to provide several indirect contributions. These should lead to a better understanding of the bidding process, as well as to improvements in procedures which do directly support the decision making process for competitive bidding.

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AUTHOR BIOGRAPHY

JOHN SEYDEL is an assistant professor of management science at the The University of Mississippi. He received his Ph.D. degree in business analysis from Texas A&M University in 1991. His research interests include multicriteria decision making, total quality management, simulation applications, neural networks, and competitive bidding. He is an active member of **DSI**, **TIMS**, **POMS**, and **SME**.