TEACHING COMPETITIVE BIDDING USING A DSS GENERATOR

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INTRODUCTION

As Decision Support Systems (DSS) are gaining popularity (see [3, 7, 8]), the use of financial modeling languages in companies has grown rapidly. A recent survey [9] reported that 85% of the respondents were using some financial modeling language. These modeling languages, also termed 'DSS generators" by Sprague [12], are supposed to make model building much easier for a manager. Their English-like programming language, interactive mode of operation and built-in financial routines facilitate problem solving. Some of the languages also allow for risk analysis through Monte Carlo simulation, "what if" interrogation, and goal-seeking capabilities. Brightman, Harris and Thompson 13] describe some of the 60 or so commercially available languages.

The growth in the use of these languages has resulted in increased demand for students trained in modeling. Indeed, a recent advertisement in the Wall Street Journal [14] solicited candidates with modeling experience in one of the leading financial planning languages. Many business schools are introducing teaching these languages in their curricula to satisfy this market demand. This is usually made easier through the university support programs of some of the software vendors, which allow universities to lease tie software at a substantial discount. According to one survey [2], just one such financial modeling language was being leased by 110 institutions. In general, the student response also has been very positive to the teaching of a modeling language 110]. The natural language syntax of these systems enables the students/modelers to concentrate more on modeling the problem situation and less on the mechanics of programming.

Traditionally, these modeling systems have been used for financial planning, capital budgeting, planning for financial requirements, mergers and acquisitions, and lease vs. purchase analysis [9]. These analyses are facilitated by the row and column logic of most of the languages where the rows define variables and the columns represent time periods. The risk analysis and "what if" features enable the user to analyze the effects of various uncertainties.

This paper demonstrates that a different interpretation of the row and column logic can be used to develop interesting applications of such systems in areas other than financial planning. One such application of a modeling language was described in [11]. Our paper concentrates on competitive bidding decisions. It illustrates how one of these modeling languages can be used to teach risk analysis, concepts of probability and expected values as well as competitive bidding.

THE COMPETITIVE BIDDING EXERCISE

The topic of competitive bidding has received a lot of attention in recent decades. A comprehensive bibliography [13] lists almost 500 articles written on bidding models and their application. Yet, as noted by Morgenstern (in [1]), this area has not been emphasized in teaching at all. In his words,

> …omission is startling in view of the fact that so many of the most important goods and services…are allocated through a bidding or auctioning procedure….Hardly any of the leading textbooks on microeconomic theory even mention this important form of trading.

Clearly, bid prices are of vital importance to a firm. If they are too low, the firm may win contracts but achieve little or even negative profits. If too high, the firm does not win the contracts and eventually may be driven out of business. In this paper, we discuss our approach to teaching competitive bidding in a DSS class. We take tie example of a construction firm and apply a modification of the classic Friedman [4] model to determine the optimal bid. The model itself is developed using IFPS (Interactive Financial Planning System), a DSS generator marketed by Execucom Corporation, Austin, Texas.

THE BIDDING PROBLEM

Students are first introduced to the nature of competitive bidding. The specific bidding process being dealt with in our exercise involves a closed bid system. Firms regarded as competent to undertake the construction are invited to make bids, and they are supplied with the job's specifications. Once the closing date for the bids is reached, the bids are opened and the work goes to the lowest bidder. Since the type of jobs being considered in this study all involve public work, all bidders are considered equally in order to avoid political influence.

The teaching exercise reported here focuses on the development of a bidding model for one firm, Fatherly Constructors, Inc. (E.C.I). The following details are presented to students in a case format. E.C.I. is a water line construction firm based in Garden City, Kansas. Their work involves the construction of rural water projects funded by the government through the Farmers Home Administration. E.C.I. began bidding on rural water projects in 1968 and has completed construction of 25 rural water systems. The contracts which have been awarded to E.C.I. varied from a local project for approximately $60,000 to a project for nearly $12 million. Most of the projects on which E.C.I. has bid are in the $500,000-$5,000,000 range.

The bidding process used by E.C.I. involves a careful reading of the specifications, a detailed cost analysis, and then the bid-setting based on the estimated costs and a subjective evaluation of the competition and E.C.I.'s desire (need) for this particular contract. Obviously, a new project looks less appealing when the firm has just committed its resources to the completion of a large project. On the other hand, the firm may not want to hurt its chances of winning a future project in this geographical area by not bidding on this project.

THE MODEL

As mentioned earlier, the literature on competitive bidding is quite large and, subsequently, there are a multitude of models which one might attempt to implement. Many of these models deal with procedures that apply to bidding processes other than the ones used in the construction industry. One of the first models dealing with closed bids was that of Friedman [4]. While this model has been modified by several researchers (see Grinyer and Whittaker [5] for a review of some of those modifications), our intent was to develop as simple a bidding model as possible in order to increase the understanding of the model on the part of the students.

The two primary inputs to any bidding model are the amount of profit (bid - cost) and the probability that the given bid will be the lowest. These are combined to determine the expected profit for a bid, and that bid which yields the highest expected profit is the or final one.

The basic structure of the Friedman [4] model is as follows. Let r be the ratio of a competitor's bid to estimated cost and f(r) be the density function of r. Let x be the bid by the decision maker, and c be the cost estimate. If there are A competitors, the objective is to determine x which maximizes

$$(x-c)\ (1-f(x/c))^{\lambda} \qquad (1)$$

where

$$f(x/c) = \int_0^{x/c} f(r)dr$$

On the surface, the development of a bidding model would seem to be a simple problem. However, the determination of these basic ingredients is not simple. To be sure, the derivation of the cost estimates requires a great deal of tine and expertise. Since this was deemed to be beyond the scope of the decision support systems class, we did not investigate the estimation process. Instead, our efforts concentrated on the probability of winning.

One important input into this determination is the history of competitors' bids. Recognizing the need to relate the competitors' bids to the firm's view of the projects, the Friedman model develops a frequency distribution of the ratio of the competitors' bids to our cost estimates. A firm does not have access to the competitors' cost estimates, but their bids on past projects are available in public records. A firm does not have data on its actual costs for all of the projects unless the firm was the low bidder in every case. On the other hand, the firm does have a cost estimate for each project. It also has its bid for each project, but the bid is more susceptible to factors such as the assessment of the economic environment and the perception of the competitors' financial situation. Thus, the firm's cost estimates are used as the denominator of the ratio due to its greater expected stability. The Friedman model aggregates the past bidding data over firms to develop the frequency distribution of the competitor-bid-to-our-cost-estimate ratios (r). Thus, the distribution represents an average bidder concept. Friedman suggests that a gamma distribution will frequently provide a good fit to the frequency distribution.

A second input into the determination of the probability of winning is the number of competitors. As the number of competitors increases, the probability of winning decreases. Friedman [4] suggested the use of a Poisson distribution to model tic number of bidders. However, we present discussion in the case that indicates to the students that the number of competitors is known, as the firm is able to monitor which competitors are also seeking cost estimates from the various suppliers.

IMPLEMENTATION OF THE MODEL

The implementation of the Friedman model in the teaching exercise assumes that historic data of previous bidding patterns are valid in the case of the particular project at hand. Discussions with the president of E.C.I. are presented to indicate that bidding data back through January 1978 would (1) be pertinent to the current market and (2) provide a sufficient amount of information in order to apply and evaluate the nod- el. During the period 1978 to fall 1981, E.C.I. bid on 34 contracts against 80 competitors. A total of 191 bids were made against E.C.I. by competitors. Several competitors bid only once on a contract sought by E.C.I., while one competitor bid against E.C.I. 25 times during the time period. During this period, E.C.I. won six of the contracts.

The ratio of the competitors' bid to E.C.I.'s cost estimate is analyzed for its fit with a possible probability distribution. Information presented to the students indicated that both a gamma distribution and a log normal distribution seemed to fit the data well. A x^2-goodness of fit test and Kolmogorov-Smirnov tests confirm that either of the two could be taken as the underlying probability distribution.

Recall that our objective is to develop a simple nod el, understandable by non-mathematicians as well. A modified and simple application of the Friedman model in the bidding problem may be as follows:

(i) Set up one column for each competitor.

(ii) Having the probability distribution of the ratio of competitors' bids to our cost estimates, generate a random ratio from this distribution.

(iii) If the ratio of our bid to cost estimate is less than the competitor's ratio (which was generated from the historical probability distribution), then indicate that we have underbid that competitor.

(iv) Make the same comparison against all competitors. If we underbid all of them, we win the contract.

(v) Repeat the generation of random ratios several times in order to perform a Monte Carlo simulation.

(vi) Compute the proportion of times we won tic contract in this simulation. This is our estimate of the probability of winning.

(vii) Change our bid and repeat steps (i)-(vi).

(viii) Determine the optimal bid, the one which maximizes the expected profit (probability (bid-cost)).

The students develop their own model and perform the subsequent sensitivity analyses using the IFPS [6]. One example model is given in Figure I. The model is very similar to the description above. This is because IFPS is an English-like modeling language, with the model serving as a concise statement of the

FIGURE 1
EXAMPLE IFPS COMPETITIVE BIDDING MODEL

```
MODEL BID1 VERSION OF 08/19/82 17:31
1 COLUMNS 1-8
2 * THE NUMBER OF COLUMNS REPRESENTS THE NUMBER OF COMPETITORS PLUS 1
3 LOG OF COMPETITORS GENERATED BID TO COST RATIO=NORRANDR(0.175,0.126)
4 BID=2320000
5 COST=2300000
6 OUR BID TO COST RATIO=BID/COST
7 LOG OF OUR BID TO COST RATIO=NATLOG(OUR BID TO COST RATIO)
8 WIN=IF LOG OF OUR BID TO COST RATIO .LE. LOG OF COMPETITORS GENERATED BID TO COST RATIO THEN 1 ELSE 0
9 PROFIT=BID-COST
10 COLUMN 8 FOR PROFIT=MATRIX(PROFIT,7)
11 RWIN=0
12 EXPECTED PROFIT=PROFIT*WIN
13 COLUMN 8 FOR WIN=SUM(C1 THRU C7)
14 *IF OUR BID WON AGAINST ALL COMPETITORS THEN WE WON THE
15 * CONTRACT. RWIN FOR COLUMN 8=1 MEANS WON THE CONTRACT;OTHERWISE RWIN = 0.
16 COLUMN 8 FOR RWIN=IF MATRIX(WIN,8) .EQ. 7 THEN 1 ELSE 0
17 COLUMN 8 FOR EXPECTED PROFIT=PROFIT*MATRIX(RWIN,8)
END OF MODEL
```

problem. The model can be easily understood by a decision maker and facilitates the quick alteration of the assumptions in order to evaluate other scenarios.

One IFPS function used in the model (line 3 of Figure 1) needs some explanation. The “NORRANDR” function is used for generating pseudo-random values following a normal distribution. The ratio of the competitor’s bid to our estimated costs was assumed to follow a log normal distribution. Then the log of the ratio would follow a normal distribution. IFPS permits a user to specify a triangular, uniform or a generalized distribution. Thus, only line 3 of Figure 1 will need to be modified if historical data exhibit a different pattern.

After entering the model, tic user can either request a deterministic solution by entering ‘solve’ or a Monte Carlo simulation by entering "Monte Carlo. Figure 2 exhibits a deterministic solution of the model using information on the project with a cost estimate of $2,300,000. There are seven columns, one for each competitor. The logarithm of competitor’s bid to cost ratio is generated first. In Figure 2 it is taken as the mean of the logarithm of the historical ratios. In a stochastic case it would be generated as a pseudo random number. The logarithm of our bid to cost ratio is compared with that of a competitor. If our ratio is less than a competitor’s, we win against that competitor. The value of WIN for each column indicates whether we won against that competitor. WIN - 1 indicates that we won. We must win against all the competitors in order to win the contract.

Figure 3 exhibits a sample Monte Carlo run and associated output. We win the contract when RWIN - 1. Fran the frequency table, Prob(RWIN 1) - 0.50. This is also verified frau the sample statistics printout. The average value of RWIN is 0.515. Thus in a simulation of 100 events with a given bid, E.C.I. won the contract 51.5 percent of the time. The profit associated with our bid is $20,000. Thus the expected profit is $10,300.

Using the “WHAT IF command of IFPS, the decision maker can evaluate another bid. This is also illustrated in Figure 3. The ability to get an immediate feedback on a possible alternative makes the system very useful. A user can not only determine the attractiveness of another bid interactively, but can also examine the effects of changes in other assumptions of the model. For instance, the cost estimate may be different or the pattern of historical bid to cost ratio may be different. Similarly, the student can investigate the impact of having more or fewer competitors by changing the number of columns in the

FIGURE 2
OUTPUT FROM MODEL IN FIGURE 1

```
INPUT: SOLVE
MODEL BID1  VERSION OF  08/19/82  17:31 -- 8 COLUMNS 9 VARIABLES
ENTER SOLVE OPTIONS
INPUT: WIDTH 132 50 8
INPUT: ALL
```

	1	2	3	4	5	6	7	8
THE NUMBER OF COLUMNS REPRESENTS THE NUMBER OF COMPETITORS PLUS 1								
LOG OF COMPETITORS GENERATED BID TO COST RATIO	.1750	.1750	.1750	.1750	.1750	.1750	.1750	
BID	2320000	2320000	2320000	2320000	2320000	2320000	2320000	
COST	2300000	2300000	2300000	2300000	2300000	2300000	2300000	
OUR BID TO COST RATIO	1.009	1.009	1.009	1.009	1.009	1.009	1.009	
LOG OF OUR BID TO COST RATIO	.0087	.0087	.0087	.0087	.0087	.0087	.0087	
WIN	1	1	1	1	1	1	1	7
PROFIT	20000	20000	20000	20000	20000	20000	20000	20000
RWIN	0	0	0	0	0	0	0	1
EXPECTED PROFIT	20000	20000	20000	20000	20000	20000	20000	20000

IF OUR BID WON AGAINST ALL COMPETITORS THEN WE WON THE
CONTRACT. RWIN FOR COLUMN 8=1 MEANS WON THE CONTRACT;OTHERWISE RWIN = 0.

FIGURE 3
OUTPUT SHOWING MONTE CARLO AND WHAT-IF OPTIONS

```
ENTER SOLVE OPTIONS
INPUT: MONTE CARLO 200
ENTER MONTE CARLO OPTIONS
INPUT: FREQ,RWIN,FREQ,EXPECTED PROFIT,NONE

                         FREQUENCY TABLE

PROBABILITY OF VALUE BEING GREATER THAN INDICATED

        90     80     70     60     50     40     30     20     10

RWIN
   R  .000   .000   .000   .000  1.000  1.000  1.000  1.000  1.000

EXPECTED PROFIT
   R    0      0      0      0  20000  20000  20000  20000  20000

                        SAMPLE STATISTICS

        MEAN    STD DEV SKEWNESS KURTOSIS  10PC CONF MEAN  90PC

RWIN
   R    .5150   .5010     -.1      1.0      .4697     .5603

EXPECTED PROFIT
   R    10300   10021     -.1      1.0      9393      11207
ENTER SOLVE OR MODELING LANGUAGE COMMAND
INPUT: WHAT IF
WHAT IF CASE 1
ENTER STATEMENTS
INPUT: BID=2200000
INPUT: MONTE CARLO 200
ENTER MONTE CARLO OPTIONS
INPUT: FREQ,RWIN,FREQ,EXPECTED PROFIT,NONE

***** WHAT IF CASE 1 *****

                         FREQUENCY TABLE

          PROBABILITY OF VALUE BEING GREATER THAN INDICATED

        90     80     70     60     50     40     30     20     10

RWIN
   R  .000   .000  1.000  1.000  1.000  1.000  1.000  1.000  1.000

EXPECTED PROFIT
   R-100000-100000-100000-100000-100000-100000-100000    0      0

                        SAMPLE STATISTICS

           MEAN   STD DEV SKEWNESS KURTOSIS  10PC CONF MEAN  90PC

RWIN
   R       .7450   .4370    -1.1      2.3      .7055      .7845

EXPECTED PROFIT
   R      -74500   43695     1.1      2.3     -78455     -70545
```

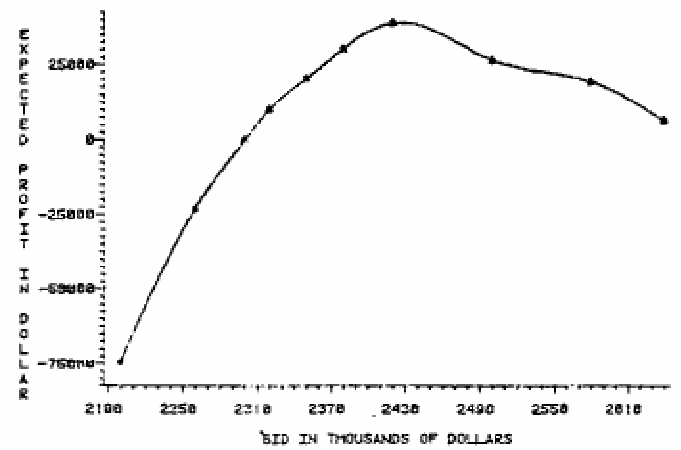
problem structure. The interactive system enables a user to try out many combinations and analyze their impact. The natural language syntax makes it relatively easy for the user to modify the assumptions.

TABLE 1
BID, PROBABILITY OF WINNING AND EXPECTED PROFIT FOR A CONTRACT WITH ESTIMATED COST OF $2,300,000

Bid	Probability of Winning	Profit	Expected Profit
$2,200,000	0.745	-$100,000	-$74,500
2,260,000	0.575	-40,000	-23,000
2,300,000	0.520	-0-	-0-
2,320,000	0.515	20,000	10,300
2,350,000	0.415	50,000	20,750
2,380,000	0.385	80,000	30,800
2,420,000	0.330	120,000	39,600
2,500,000	0.135	200,000	27,000
2,580,000	0.070	280,000	19,600
2,640,000	0.020	340,000	6,800
2,700,000	0.020	400,000	8,000

As illustrated in Figure 3, a series of bids was tested using the "WHAT IF" command if IFPS. A summary of alternative bids, their estimated probability of winning and associated profits is given in Table 1. It appears that a bid of approximately $2,420,000 yields the largest expected profit. Figure 4 presents the observed relationship between bid and expected profit.

FIGURE 4
EXPECTED PROFIT VS. BID FOR A CONTRACT



ADVANTAGES OF THE TEACHING EXERCISE

This exercise is a simplification of a real problem. However, it illustrates how a financial modeling language can be used to transcribe a problem into a computer model. Moreover, it is an example of how the language can be used with problems that are not strictly of a financial planning nature. While many students in a decision support systems class like a financial analyst orientation, many do not.

The English-like language allows a modeler/student to concentrate more on the characteristics of tic problem and less on the mechanics of running a computer program. Students can be asked to modify the model to take into account other possible probability distributions, the value the contract has for the company, other intangible costs, and the like.

The approach can also be used to introduce Monte Carlo simulation. A command in IFPS allows the user to print all of the randomly generated values. The ability to generate pseudo-random values from other distributions with a minor change in the model enables the instructor to exemplify effects of assumptions about underlying distributions. The output generated by IFPS is used to discuss the analysis of simulated values.

The mean value of RWIN was interpreted as the probability of winning. This figure multiplied by the profit estimate was the expected profit. This can be used as an example of expected values. The probabilities and associated payoffs matrix can also be used in teaching various other decision making under risk criteria, e.g. minimax, maximize the probability of winning and others.

Thus this exercise not only introduces competitive bidding, it also can be used as a case example in teaching decision analysis, Monte Carlo simulation, and the use of probability distributions.

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