A Two-step Bidding Price Decision Algorithm under Limited Man-Hours in EPC Projects

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Abstract: In Engineering-Procurement-Construction (EPC) projects, the contractor accepts an order through a competitive bidding process. If the contractor's bidding price is set higher than that of a competitor due to cost estimation error, the contractor could fail to receive the order. Conversely, if the cost estimation error results in an underestimation of the cost, the contractor would be granted the order; however, he would eventually suffer a loss on this order. Thus, a bidding price decision in consideration of the cost estimation accuracy and the deficit order probability is essential for the contractor in EPC projects. In this paper, we develop a two-step bidding price decision algorithm. It allocates MH (Man-Hour) for cost estimation, which determines the cost estimation accuracy, to each order under the limited volume of MH, and then determines the bidding price for maximizing the expected profit under the deficit order probability constraint. Numerical examples show that the bidding price decision in consideration of the cost estimation accuracy and the deficit order probability is essential for the contractor to make a stable profit in EPC projects, and that the developed algorithm is effective for making such bidding price decision.

1 INTRODUCTION

Among various types of project contracts, the importance of Engineering, Procurement, Construction (EPC) projects (Ranjan, 2009), where contractors design and build unique products or services based on the client requirements, is widely recognized in practice in the field of construction, civil engineering, plant engineering, and so on. In EPC projects, the contractor has a single responsibility for project cost, quality, and schedule under a fixed-price that is determined before the start of the project as a lump-sum contract. Thus, a reduced project cost and shorter schedule are expected (Jinru, 2011).

Although several shortcomings, for instance, decisions on relatively detailed issues have to be made early on in the project delivery process, have been pointed out e.g., in Elfving et al. (2005), competitive bidding is widely used for selecting a contractor who carries out the project. In the competitive bidding, the client usually evaluates contractors on the basis of the multi-attribute bid evaluation criteria, such as bidding price, past experience, past performance, company reputation, and the proposed method of delivery and technical solutions (Watt et al., 2009). Then, the client basically selects the contractor who proposes the lowest price if there is not much difference in other criteria.

In EPC projects, accordingly, it is necessary for any contractor to determine the bidding price based on precise cost estimation. If the contractor's bidding price, which is obtained as a sum of the estimated cost and the target profit, is higher than that of the competitor due to cost estimation error, then the contractor could not accept the order and hence obtain no profit. In contrast, the contractor would increase the chance of accepting the order if the estimated cost is low due to cost estimation error. In this case, however, the profit could be below the contractor's expectation because of being over-budget, and he possibly suffers a loss on this order.

Namely, for stable profit from EPC projects, the contractor must determine the bidding price in consideration of cost estimation accuracy and deficit order probability. Cost estimation, however, is a highly intellectual task of predicting the costs of products or services to be provided in the future

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based on the analysis of the client's requirements and his tacit knowledge. Thus, experienced and skilled human resources, i.e., MH (Man-Hour), are required for accurate cost estimation. Those resources, however, are limited for any contractor. For these reasons, it is important to realize appropriate allocation of MH for cost estimation to each order to maximize the profits under the constraints on the volume of total MH. In addition, contractors should consider the possibility of realizing a loss due to cost estimation error and a competitive relationship with bidders. For example, the bidding price needs to be cut to some extent to accept the order successfully under a severe competitive environment; however, a low bidding price would reduce profit, or even worse, would create a large loss. Moreover, just a few deficit orders would result in the significant reduction of realized profits when the number of accepted orders is limited. (Note, in this paper, that we refer to the order creating an eventual loss as a deficit order.)

In this paper, we develop a two-step bidding price decision algorithm in consideration of the cost estimation accuracy and the deficit order probability under limited MH in EPC projects. The algorithm assumes that the costs are estimated at the same time for all orders. At the first step, the algorithm allocates MH for cost estimation to each order according to the ranking of orders under the constraints on the volume of total MH. The MH allocation determines the cost estimation accuracy of each order. At the second step, it determines the bidding price for maximizing the expected profit under the deficit order probability constraint.

We develop a mathematical model for simulating competitive bidding. Through the numerical results obtained by using this model, we show that the bidding price decision in consideration of the cost estimation accuracy and the deficit order probability is essential for the contractor to make a stable profit in EPC projects, and that our two-step bidding price decision algorithm is effective for making such bidding price decisions.

2 RELATED WORK

Among the research related to the bidding price decision, there are order acceptance and project selection problems.

Order acceptance is basically the problem of making a decision to accept each order or not in Make-To-Order (MTO) manufacturing (Kolisch, 2001), and its objective is to maximize profits with capacity limitations. As literature surveys done by Slotnick and Morton (2007), Herbots et al. (2007), and Rom and Slotnick (2009) have shown, there exists a variety of related research topics. Project selection, on the other hand, is the problem of creating a mix of projects from candidate projects to help achieve an organization's goals within its resource constraints. Research and development (R&D), information technology, and capital budgeting are typical application fields of the project selection. Researchers have applied various kinds of methods to these problems (Dey, 2006; Medaglia et al., 2007; Wang et al., 2009).

Most of the literature dealing with the order acceptance and the project selection problems has assumed that the contractor can select orders or projects according to the contractor's own criteria and by the contractor's own initiative. In competitive bidding, however, the contractor basically offers a bidding price and accepts the order based on the client's decision.

A variety of studies, such as bidding theory, bidding model, and auction design, have been conducted on competitive bidding (see Ballesteros-Pérez et al., 2012 for detailed references). In particular, a number of papers regarding the competitive bidding strategy date back to Friedman (1956), who presented a method to determine an optimal bidding price based on the distribution of the ratio of the bidding price to cost estimate. However, little attention has been paid to profit volatility risk, which cannot be ignored in EPC projects. When, for instance, the number of accepted orders is limited, the realized total profit from the projects might be sharply lower than expected because the profit is significantly affected by a few deficit orders. Accordingly, the deficit order probability should be considered in the bidding price decision.

In addition to the profit volatility risk, we consider the allocation of MH for cost estimation to each order when making a decision on the bidding because certain MH is necessary to estimate cost accurately in EPC projects. Several papers have analysed the problem of allocating scarce resources in competitive bidding (see Rothkopf and Harstad, 1994 for detailed references). Among them, Kortanek et al. (1973) considered sequential bidding models where the obtained contracts require the use of restricted resources, such as production capacity, at the time of actual production. Ishii et al. (2012) develop a mathematical model where bidding prices are determined in consideration of the MH allocation for cost estimation to maximize the expected profit from the projects. Their model assumes that the contractor has no preference orders for bidding, although the contractor usually ranks the orders according to the multi-criteria, such as technical feasibility, relationship with clients, and so on, in addition to the expected profits.

Regarding cost estimation accuracy, various types of research have been performed. Oberlender and Trost (2001) studied determinants of cost estimation accuracy and developed a system for predicting cost estimation accuracy. Bertisen and Davis (2008) analysed costs of 63 projects and evaluated the accuracy of capital cost estimation statistically. In addition, several researchers have studied cost estimation methods and their accuracy. For example, Towler and Sinnott (2008) studied relations among cost estimation methods, cost estimation data, and their accuracy in the field of plant engineering. More crucially, they suggested that the cost estimation accuracy is positively correlated with the volume of MH for cost estimation.

In EPC projects, the bidding price decision affects the expected profit and the deficit order probability. Since the bidding price is determined based on the project cost estimated before starting the project, cost estimation accuracy is clearly a major factor to lead an EPC project to a successful conclusion. Nevertheless, as stated above, few studies have ever attempted to analyse the bidding price decision problem in terms of cost estimation accuracy and deficit order probability under limited MH in EPC projects.

3 FEATURES OF THE BIDDING PRICE DECISION PROBLEM IN EPC PROJECT

There are several ways to select a contractor from bidders in competitive bidding (Steel, 2004; Elfving et al., 2005; Helmus, 2008; Wang et al., 2009). In a generic competitive bidding process shown in Figure 1 (Ishii and Muraki, 2011), the client prepares a Request For Proposal (RFP) and invites several potential contractors to the bidding. The contractor first carries out the preliminary evaluation followed by the bid or no-bid decision. In the preliminary evaluation, the contractor evaluates the RFP and estimates the preliminary cost based on limited information, such as the order information provided by the RFP and the past project data of the contractor. In the bid or no-bid decision, the contractor evaluates the order from the viewpoints of profitability, technical feasibility and so on, and makes a decision whether to bid or not. If the contractor decides to place the bid, he then starts the bidding price decision process, that is, he estimates the cost more accurately and determines the bidding price. At the end of the competitive bidding, the client assesses the proposals offered by contractors and selects one contractor as a successful bidder.

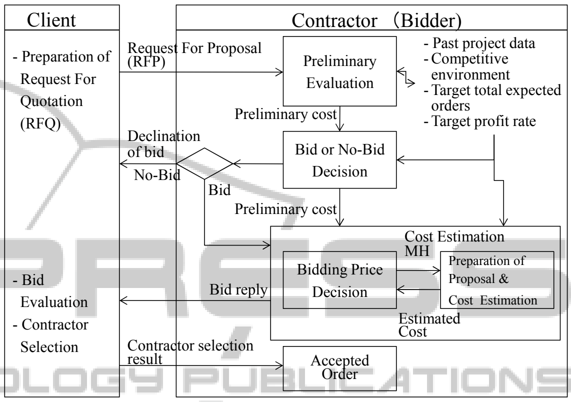

Figure 1: An overview of contractor's activities of competitive bidding.

The preliminary evaluation and bid or no-bid decision are usually made by senior managers based on the RFP, past project data, competitive environment, target profit rate, and so on.

As shown in Figure 1, the bidding price decision, for which this paper develops an algorithm in Section 4.2, is made based on order information, such as estimated cost, target profit rate, and competitive environment, so that the contractor can accept profit-making orders successfully. As Ishii et al. (2012) pointed out, since the contractor must determine the bidding price using the limited information above, he should consider the following features of the competitive bidding.

The first feature is relevant to the accuracy of cost estimation. The bidding price is basically determined by adding the target profit to the estimated cost. However, the contractor cannot estimate the precise cost in the process of determining the bidding price because of limited information and restricted time. Thus the bidding price, which is affected by estimation errors, has a probability distribution. We define the cost estimation accuracy as the standard deviation of the estimated cost or the bidding price depending on the context. A lower deviation indicates a higher accuracy.

The bidding price with the lower cost estimation accuracy is likely to be accepted as the deficit order, from which the contractor suffers an eventual loss. The bidding price with the low accuracy also has a tendency to be very high compared to the other; however, the chance of the order being accepted becomes smaller as the bidding price increases under a competitive environment where many competitors would offer low bidding prices. Based on these observations, it can be seen that consideration of the cost estimation accuracy and deficit order probability is essential for the contractor to make a stable profit in EPC projects, and the bidding price decision process needs to include all these factors.

The second feature is the MH allocation for cost estimation. Cost estimation is a series of activities where experienced engineers analyse requirements of clients, thus the MH for cost estimation affects its accuracy significantly. However, although the contractor often has more than one order at the same time, the number of MH of experienced engineers is limited. Namely, the contractor needs to allocate MH to each order effectively. Since the bidding conditions are different in each order, the contractor needs to prioritize orders and allocate more MH to the potential orders to improve the expected profits.

The third feature is the effectiveness of adjusting the bidding price. The contractor's profit increases as the bidding price rises. On the other hand, the probability of accepting the order increases as the bidding price goes down. This is because the contractor can basically accept the order when the contractor's bidding price is lower than that of the competitor. However, the contractor would accept the deficit order when the bidding price is very low. Namely, we can see that there is a bidding price that maximizes the contractor's expected profit under a competitive environment.

Based on the above observations, we introduce a parameter for adjusting the bidding price in view of the cost estimation accuracy of one's own company and that of a competitor's, as well as the deficit order probability.

4 A BIDDING PRICE DECISION PROCESS MODEL

Figure 2 shows a bidding price decision process model (Ishii et al., 2012), which represents fundamental factors and their interactive processes, to determine the bidding price in EPC projects based on the observations in the previous section. The model consists of three kinds of factors, i.e., decision processes, constraints, and given conditions.

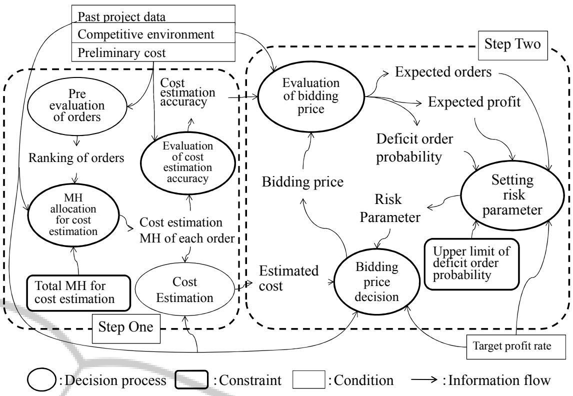

Figure 2: A bidding price decision process model in EPC projects.

The model enables us to evaluate the expected orders, the expected profits, and the deficit order probability, based on the bidding price, the cost estimation accuracy, and the information on competitive environment. The bidding price is determined based on the estimated cost, the target profit rate, and the risk parameter for adjusting the bidding price. The estimated cost and the cost estimation accuracy are both determined depending on the MH allocated to each order for cost estimation. The MH allocation is determined according to the ranking of orders provided by the pre-evaluation of orders processed under the total MH constraint as shown in Figure 2.

4.1 A Mathematical Model on Bidding Price Decision

4.1.1 Evaluation of Cost Estimation Accuracy

Since cost estimation requires a detailed analysis conducted by experienced engineers, it can be seen that the MH for cost estimation significantly affects the cost estimation accuracy. In fact, Towler and Sinnott (2008) suggest that the cost estimation accuracy is positively correlated with the volume of MH for cost estimation. It is also clear that the marginal rate of cost estimation accuracy approaches zero according to the increase of the volume of MH. Thus, in this paper, we define the cost estimation accuracy (σ) as the function of the MH for cost estimation per order (*PMH*) based on the logistic curve (Ishii and Muraki, 2011) as follows:

$$\sigma(PMH) = \sigma_{\min} \cdot \sigma_{\max} / \{\sigma_{\max} + (\sigma_{\min} - \sigma_{\max}) \cdot e^{-C \cdot PMH}\} \quad (PMH > 0.0) \qquad (1)$$

where σ_{min} and σ_{max} are the minimum and the maximum value of the standard deviation of the bidding price, and C is a parameter of the logistic curve. In practice, the contractor could determine these parameters from past project data.

4.1.2 Evaluation of Bidding Price

In the model, we consider n contractors ($k=1,2,\ldots,n$) and the bidding for L orders ($i=1,2,\ldots,L$). Particularly, $k=1$ represents one's own company, and $k>=2$ are its competitors. In the model, based on standard order cost (*STD*), each contractor (k) sets a tentative bidding price (*TBP*) of the order (i) in consideration of the relative cost difference from *STD* (*RC*) and target profit rate (*e_profit*) as follows:

$$TBP_k^i = STD_i \cdot (1 + RC_k^i) \cdot (1 + e\_profit_k^i) \cdot rp_k^i \qquad (2)$$

where *TBP* can be adjusted by changing the value of risk parameter (*rp*). If there is no difference in cost-competitiveness among contractors, *RC* is set to *0*.

The expected volume of order (i) in one's own company ($k=1$) is as follows:

$$\int_0^{+\infty} x_1^i \cdot p_1(x_1^i, TBP_1^i, \sigma_1^i) \cdot \prod_{k=2}^{n} \int_{x_1^i}^{+\infty} p_k(x_k^i, TBP_k^i, \sigma_k^i) dx_k^i \cdot dx_1^i \qquad (3)$$

where $p_k(x_k^i, TBP_k^i, \sigma_k^i)$ is the probability density function of the bidding price (x_k^i) of the contractor (k) for order (i), and its average value and standard deviation are TBP_k^i and σ_k^i, respectively. As shown in Eq. (3), the expected order is the average value of one's own bidding price falling below those of all other contractors ($k>=2$).

As shown in Eq. (4), the expected profit is the average excess of the bidding price over the standard order cost with the relative cost difference (*STDR*) as defined in Eq. (5).

$$\int_0^{+\infty} (x_1^i - STDR_1^i) \cdot p_1(x_1^i, TBP_1^i, \sigma_1^i) \cdot \prod_{k=2}^{n} \int_{x_1^i}^{+\infty} p_k(x_k^i, TBP_k^i, \sigma_k^i) dx_k^i \cdot dx_1^i \qquad (4)$$

$$STDR_k^i = STD_i \cdot (1 + RC_k^i) \qquad (5)$$

In addition, as shown in Eq. (6), the deficit order probability is the probability of accepting the order whose bidding price is lower than *STDR*.

$$\int_0^{STDR_1^i} p_1(x_1^i, TBP_1^i, \sigma_1^i) \cdot \prod_{k=2}^{n} \int_{x_1^i}^{+\infty} p_k(x_k^i, TBP_k^i, \sigma_k^i) dx_k^i \cdot dx_1^i \qquad (6)$$

We also assume that the data used in the above equations, such as the number of competitors (*n-1*), standard order cost (*STD*), relative cost difference over *STD* (*RC*), probability density function of bidding price (p_k), and so on, can be provided from RFP, past project data, several departments of the contractor, and published data. For example, *STD* can be specified in reference to the preliminary cost, which is estimated by scaling it from the cost data of past projects, which used similar technology (Kerzner, 2009). Although a project is a temporary endeavour undertaken to create a unique product, similar parts can be found in functional units of past projects. Accordingly, even if the cost data of similar projects are not available, the preliminary cost estimate can be made by breaking down the project into functional units, and adding up the cost data of similar functional units in past projects. The cost data, the number of competitors, and so on, can also be estimated based on published data in many industries. For example, magazines related to the EPC business, such as Chemical Engineering, Hydrocarbon Processing, publish plant cost indexes, cost engineering data, EPC project news and surveys, periodically.

4.2 A Two-step Bidding Price Decision Algorithm

In this section, we develop a two-step algorithm for bidding price decision. As shown in Figure 2, this algorithm determines the allocation of MH for cost estimation according to the ranking of orders at the first step, and searches the value of *rp* for maximizing the expected profit of each order under the deficit order probability constraint at the second step.

4.2.1 Step One: Ranking of Orders and MH Allocation

There are several procedures to rank orders. For example, pair-wise comparisons, scoring models, and analytical hierarchy process (AHP) are commonly used (Martino, 1995).

In this paper, we shall rank orders based only on the expected profit so as to assess the effectiveness of our algorithm from the perspective of profits. Specifically, we define the ranking score (*Score*) of the order (i) as the expected profit based on the tentative bidding price (*TBPF*) estimated for the ranking at *rp* =1 as follows:

$$Score_i = TBPF_1^i \cdot \prod_{k=2}^{n} \int_{TBPF_1^i}^{+\infty} p_k(x_k^i, TBPF_k^i, \sigma_k^i) dx_k^i \qquad (7)$$

$$TBPF_k^i = STD_i \cdot (1 + RC_k^i) \cdot (1 + e\_profit_k^i) \qquad (8)$$

Note that we can modify the ranking score in consideration of multiple criteria besides the expected profit, such as technical feasibility, relationship with clients, and so on.

In the following MH allocation procedure, the order with the high *Score* is ranked high because such an order is expected to generate a large profit.

As described in the procedure below, we consider three grades of accuracy, A (high accuracy), B (average), and C (low accuracy), and we assign one of them to each order. The expected profit increases according to the increase of cost estimation accuracy, and hence, the following procedure results in the grade of high accuracy to high-ranking orders, and the grade of low accuracy to low-ranking orders in view of the allowable total MH.

MH Allocation Procedure

Step 0 [Parameter Setting]: Set the range of allowable total MH for cost estimation, and set the accuracy level from ($\sigma_{\min}$, $\sigma_{\max}$) to each grade; A (high accuracy), B (average), and C (low accuracy).

Step 1 [Initial MH Allocation]: Set all the orders to grade B, and allocate the corresponding MH for cost estimation to each order based on Eq. (1).

Step 2 [Termination Condition]: Calculate the total MH required (*TMR*) by summing up all the MH allocated to each order. If *TMR* is within the range of allowable total MH, stop the procedure with the current MH allocation. If *TMR* is above the allowable range, go to Step 3. If *TMR* is below the allowable range, go to Step 4.

Step 3 [Downgrading]: Choose the lowest-ranked one from grade B orders, and set it to grade C. If the grades of orders are all C, stop the procedure with the current MH allocation. Otherwise, go to Step 5.

Step 4 [Upgrading]: Choose the highest-ranked one from grade B orders, and set it to grade A. If the grades of orders are all A, stop the procedure with the current MH allocation. Otherwise, go to Step 5.

Step 5 [MH Reallocation]: According to the given grades, reallocate the MH for cost estimation to each order based on Eq. (1). Return to Step 2.

4.2.2 Step Two: Searching Risk Parameter Value for Profit Maximization

Given the MH allocation determined by the procedure described above, we search the value of *rp* by solving the following optimization problem:

Maximize

$$\sum_{i=1}^{L}\int_{0}^{+\infty}(x_1^i - STDR_1^i)\cdot p_1(x_1^i, TBP_1^i, \sigma_1^i)\cdot\prod_{k=2}^{n}\int_{x_1^i}^{+\infty}p_k(x_k^i, TBP_k^i, \sigma_k^i)dx_k^i\cdot dx_1^i \qquad (9)$$

subject to

$$TBP_k^i = STD_i\cdot(1+RC_k^i)\cdot(1+e\_profit_k^i)\cdot rp_k^i \qquad (10)$$
$$(i=1,2,\ldots,L;\ k=1,2,\ldots,n)$$

$$\int_{0}^{STDR_1^i}p_1(x_1^i, TBP_1^i, \sigma_1^i)\cdot\prod_{k=2}^{n}\int_{x_1^i}^{+\infty}p_k(x_k^i, TBP_k^i, \sigma_k^i)dx_k^i\cdot dx_1^i \le rprob_i \qquad (11)$$
$$i=1,2,\ldots.L)$$

where $rprob_i$ is the upper limit of the deficit order probability of the order (i).

In the above optimization problem, the objective is to maximize the total expected profit from orders. Eq. (10) defines *TBP*, and Eq. (11) is the upper limit constraint of the deficit order probability. Note that Eq. (10) can be eliminated from the problem by substituting Eq. (10) into Eq. (9) and (11). Moreover, the problem can be separated into *L* problems ($i=1,2,\ldots,L$). As a result, *rp* of one's own company ($k=1$) is the single decision variable of each problem. In this paper, we use a simple iterative algorithm to search for a solution by gradually eliminating search space.

Given the MH allocation for cost estimation and the value of *rp*, the final bidding price is determined as follows:

$$NET_i\cdot(1+e\_profit_1^i)\cdot rp_1^i \qquad (12)$$

where *NET*, as shown in Figure 2, is the estimated cost that is calculated by the allocated MH after the bid or no-bid decision.

5 NUMERICAL EXAMPLES

In this section, we analyse and discuss the performance of the two-step bidding price decision algorithm in EPC projects based on the numerical examples from the following perspectives: relations between cost estimation accuracy and expected profit, effectiveness of bidding price adjustment, and effect of the upper limit constraint of the deficit order probability.

5.1 Problem Setting

5.1.1 Setting of Cases

In this paper, we use the cases shown in Table 1 for numerical examples. Cases 0 and 1 are set to show the effectiveness of bidding price adjustment by the risk parameter. Cases 2 and 3 are set to show the effects of the competitors' cost estimation accuracy on the expected profit and deficit order probability of one's own company. The competitors' cost estimation accuracy σ_k^i (k>=2) in Table 1 are set based on the expected accuracy for bidding (Oberlender, 2000).

Table 1: Cases for numerical examples.

Case	rp_1^i	σ_k^i (k>=2)
Case 0	1.0	8% of STD_i
Case 1	To be searched	8% of STD_i
Case 2	To be searched	6% of STD_i
Case 3	To be searched	10% of STD_i

Table 2: Conditions of orders. (*NBR*: number of bidders).

Order id (i)	1	2	3	4	5	6	7	8
STD_i		100.0			200.0		300.0	
NBR (n)	2	3	4	2	3	4	2	3
Order id (i)	9	10	11	12	13	14	15	16
STD_i			400.0		500.0		600.0	
NBR (n)	4	2	3	4	3	4	3	4

We set other parameter values through all the cases as follows: $rp_k^i = 1.0$ (k >= 2), $RC_k^i = 0.0$ (k >= 1), $rprob_i$=1.0, and $e\_profit_k^i = 0.1$. We set $rprob_i$ to 1.0 (100%) to maximize the expected profit without the upper limit constraint of the deficit order probability. The effect of the constraint is shown in section 5.2.4.

Note that the value of σ_1^i is determined by Eq. (1) and the allocated MH. We suppose that the bidding price follows a normal distribution. Furthermore, we consider four conditions for the range of allowable total MH for cost estimation, i.e., (A) 70-80, (B) 80-90, (C) 90-100, and (D) 100-110 [M MH].

5.1.2 Setting of Orders

In this paper, we assume a midsize EPC contractor in the chemical plant engineering business, and consider the conditions of 16 orders in each case as shown in Table 2.

Regarding the cost estimation accuracy of one's own company (see Eq. (1)), we set C to 0.25*100/STD_i, and σ_{min} and σ_{max} to 0.5% and 30% of STD_i, respectively. In addition, we set the cost estimation accuracy level to 5% of STD_i for grade A, 8% of STD_i for grade B, and 15% of STD_i for grade C when performing the MH allocation procedure.

5.2 Results of Numerical Calculations

5.2.1 Cost Estimation Accuracy and Expected Profit

As shown in Table 3, the significant difference in the total expected profits is caused by the total MH for cost estimation for all the cases. For example, the expected profits in Case 0.A (70-80 [M MH]), Case 0.B (80-90 [M MH]), Case 0.C (90-100 [M MH]), and Case 0.D (100-110 [M MH]) are 28.6, 46.3, 51.7, and 61.5 [MM$], respectively.

Since the cost estimation accuracy depends on the MH for cost estimation as shown in Eq. (1), the results indicate that the cost estimation accuracy affects the expected profit significantly. Namely, the contractor can expect a higher profit by increasing the cost estimation accuracy in EPC projects. However, there is usually a limit to the available MH for cost estimation. Thus we can conclude that an effective mechanism to allocate the MH for cost estimation to each order under the constraint of the volume of total MH is necessary in the bidding price decision process.

5.2.2 Effectiveness of Bidding Price Adjustment by Risk Parameter

Based on the results of Case 0 and Case 1, we analyse the effect of the bidding price adjustment on the expected profit. The bidding price is adjusted by *rp* to attain the maximum expected profits in Case 1, and the value of *rp* is fixed in Case 0.

As shown in Table 3, there is a significant difference in the expected profits between Case 0 and Case 1. For example, the total expected profits in Case 0.A and Case 1.A are 28.6 and 53.3 [MM$], respectively. The bidding price adjustment also affects the expected orders and profit rate. In Case 0.A, for instance, the expected orders and profits are 1858.2 and 28.6; therefore the expected profit rate is 1.54%. In contrast, in Case 1.A, the expected orders and profits are 1141.6 and 53.3; therefore the expected profit rate is 4.67%, which is about three times as high as that in Case 0.A.

Table 3: Expected orders (*EO*; Eq. (3)) and Expected profits (*EP*; Eq. (4)).

	The Range of Allowable Total MH for Cost Estimation [M MH]			
[MM$]	70-80	80-90	90-100	100-110
Case 0	Case 0.A	Case 0.B	Case 0.C	Case 0.D
EO	1858.2	1817.9	1823.3	1809.0
EP	28.6	46.3	51.7	61.5
Case 1	Case 1.A	Case 1.B	Case 1.C	Case 1.D
EO	1141.6	1238.1	1269.5	1357.2
EP	53.3	56.4	60.9	69.1
Case 2	Case 2.A	Case 2.B	Case 2.C	Case 2.D
EO	1275.2	1395.2	1437.6	1547.3
EP	48.0	51.3	56.3	65.5
Case 3	Case 3.A	Case 3.B	Case 3.C	Case 3.D
EO	1061.6	1143.7	1168.1	1236.6
EP	60.2	63.5	67.5	74.8

The deficit order probability is significantly decreased by the adjustment of the bidding price as shown in Table 4. For example, the range of deficit order probability in the orders is between 11.0% and 25.8% in Case 0.A, and between 0.777% and 5.81% in Case 1.A. In Case 0.A, the MH allocation procedure results in the low cost estimation accuracy level (grade C) to the orders 2, 3, 6, and 9, and these orders result in negative earnings as shown in Table 5. However, in Case 1.A, the bidding price adjustment decreases the deficit order probabilities of these orders and improves the expected profits.

Table 6 shows the effects of the competitors' cost estimation accuracy on the value of *rp*, the expected profit, and the deficit order probability of each order. Note that the competitors' cost estimation accuracy of Case 2.B, Case 1.B, and Case 3.B is 6%, 8%, and 10% of STD_i, respectively. As shown in Table 6, as the competitors' cost estimation accuracy increases, the value of *rp* searched for by the algorithm decreases and the deficit order probability of each order increases. This is because the high accuracy of the competitors' cost estimation reduces the chance of accepting the orders at high prices, and consequently, a small *rp* is chosen to accept such orders.

Figure 3 depicts the relation of the expected order and profit of the order id 10 with the value of *rp* in Case 1.B. In addition, Figure 4 depicts the relation of the expected profits of the order id 10 with the value of *rp* in Case 1.B and Case 1.C, each of which corresponds to a different range of allowable total MH. Figure 3 shows that the expected order decreases as the value of *rp* increases. However, it is found from Figures 3 and 4 that there is a value of *rp* that attains the maximum expected profit. Furthermore, Figure 4 tells us the higher cost estimation accuracy, i.e., more MH for cost estimation, makes the maximum expected profit higher.

Table 4: Range of deficit order probability (Eq. (6)) [%].

	The range of allowable total MH for cost estimation [M MH]			
	70-80	80-90	90-100	100-110
Case 0	Case 0.A	Case 0.B	Case 0.C	Case 0.D
	11.0-25.8	11.0-12.1	3.20-12.1	2.98-12.1
Case 1	Case 1.A	Case 1.B	Case 1.C	Case 1.D
	0.777-5.81	4.33-5.81	1.77-5.81	1.77-5.81

Table 5: Effectiveness of bidding price adjustment by risk parameter. (*EP*: Expected Profit, *DOP*: Deficit Order Probability).

Order	Case 0.A			Case 1.A		
id (i)	rp_1^i	*EP* [MM$]	*DOP* [%]	rp_1^i	*EP* [MM$]	*DOP* [%]
2	1.0	-1.92	25.8	1.20	0.155	2.32
3	1.0	-2.25	25.2	1.26	0.0290	0.777
6	1.0	-4.50	25.2	1.26	0.0581	0.777
9	1.0	-6.75	25.2	1.26	0.0871	0.777

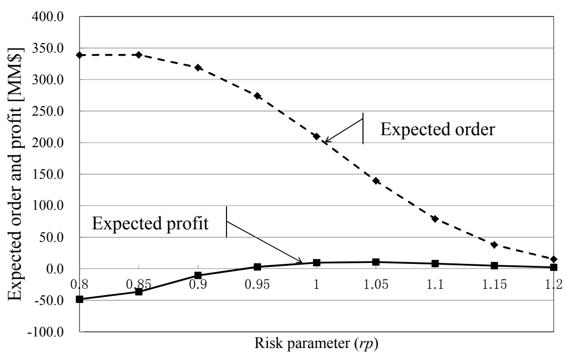

Figure 3: Relations among expected order, expected profit, and risk parameter. (Case 1.B; Order id = 10).

We can see that the higher cost estimation accuracy reduces the chance of accepting orders at very low price and thus increases the expected profit. However, the higher cost estimation accuracy also reduces chance of accepting profitable orders when the value of *rp* is high. In Figure 4, for instance, the expected profit in Case 1.C is lower than that in Case 1.B when *rp* is 1.15 or more.

Table 6: Bidding price adjustment with different competitors' accuracy (80-90 [M MH]). (EP: Expected Profit, DOP: Deficit Order Probability).

Order *id* (*i*)	Case 2.B			Case 1.B			Case 3.B		
	rp_1^i	*EP* [MM$]	*DOP* [%]	rp_1^i	*EP* [MM$]	*DOP* [%]	rp_1^i	*EP* [MM$]	*DOP* [%]
1	1.026	2.27	7.12	1.035	2.70	5.44	1.045	3.14	4.09
2	1.026	0.916	6.99	1.030	0.983	5.81	1.035	1.09	4.73
3	1.035	0.444	5.44	1.040	0.418	4.32	1.042	0.436	3.63
4	1.026	4.54	7.12	1.035	5.40	5.44	1.045	6.29	4.09
5	1.026	1.83	6.99	1.030	1.97	5.81	1.035	2.18	4.73
6	1.035	0.888	5.44	1.040	0.836	4.32	1.042	0.872	3.63
7	1.026	6.81	7.12	1.035	8.11	5.44	1.045	9.43	4.09
8	1.026	2.75	6.99	1.030	2.95	5.81	1.035	3.27	4.73
9	1.035	1.33	5.44	1.040	1.25	4.32	1.042	1.31	3.63
10	1.026	9.08	7.06	1.035	10.8	5.54	1.044	12.6	4.13
11	1.026	3.67	6.99	1.030	3.93	5.81	1.035	4.36	4.73
12	1.035	1.78	5.44	1.040	1.67	4.32	1.042	1.74	3.63
13	1.026	4.58	6.99	1.030	4.91	5.81	1.035	5.45	4.73
14	1.035	2.22	5.44	1.040	2.09	4.32	1.042	2.18	3.63
15	1.026	5.50	6.99	1.030	5.90	5.81	1.035	6.54	4.73
16	1.035	2.66	5.44	1.040	2.51	4.32	1.042	2.62	3.63

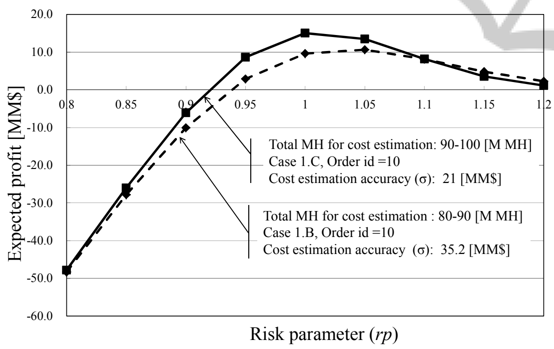

Figure 4: Relations among expected profit, total MH for cost estimation, and risk parameter. (Case 1.B, Order id =10, Total MH for cost estimation: 80-90 [M MH]; and Case 1.C, Order id =10, Total MH for cost estimation 90-100 [M MH]).

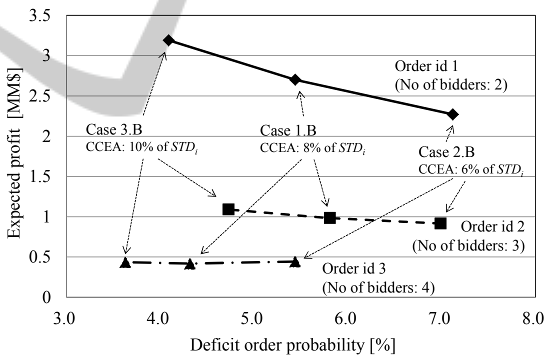

Figure 5: Relations among expected profits and deficit order probability. (Case 2B, 1B, and 3B; Order id 1, 2, and 3) (CCEA: Competitors' Cost Estimation Accuracy).

5.2.3 Effect of the Number of Bidders

Figure 5 depicts the relation of the expected profit and the deficit order probability of the order id 1, 2 and 3 in Cases 2.B, 1.B, and 3.B. Note that the number of bidders is set to two, three, and four for the order id 1, 2 and 3, respectively. Also, in Cases 2.B, 1.B, and 3.B, the competitors' cost estimation accuracy is set to 6%, 8%, and 10% of STD_i. As shown in Figure 5, the effect of the competitors' cost estimation accuracy on the expected profit and the deficit order probability becomes smaller as the number of bidders increases.

For instance, in Order id 1, i.e., when the number of bidders is two, the difference of the expected profit between Case 3.B and Case 2.B is 0.87 [MM$]. In contrast, in Order id 3, i.e., when the number of bidders is four, the difference of the expected profit between Case 3.B and Case 2.B is 0.008 [MM$]. The difference in the deficit order probability between Case 3.B and Case 2.B is also reduced from 3.03 [%] (in the case of Order id 1) to 1.81 [%] (in the case of Order id 3).

High degree of competition significantly reduces the chance of accepting orders at high prices as well as at low prices regardless of the competitors' cost estimation accuracy. Consequently, it reduces the effect of the competitors' cost estimation accuracy on the expected profit and the deficit order probability.

5.2.4 Effect of Upper Limit Constraint of the Deficit Order Probability

We examine how the upper limit constraint of the deficit order probability shown in Eq. (11) affects the expected profit. Figure 6 depicts the relation of the upper limit of the deficit order probability and the total expected profit in Case 1. As explained in Sections 2 and 3, the risk of unexpected loss from the deficit orders should be avoided especially when only a small number of orders can be accepted. As shown in Figure 6, the small upper limit of the deficit order probability decreases the total expected profit; however, it is found that the deficit order probability can be reduced from 5.0% to 1.0% at the expense of the total expected profits of 10 to 15 [MM$].

Bidding for a large-scale EPC project involves a substantial risk. Our framework developed for EPC projects will certainly be helpful for any contractor to avoid large deficit from accepted orders.

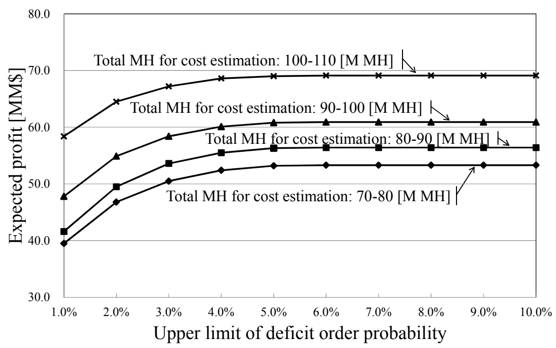

Figure 6: Relations among expected profits, total MH for cost estimation, and upper limit of deficit order probability (Case 1).

6 CONCLUSIONS

In this paper, we develop a two-step bidding price decision algorithm under limited MH in EPC projects. The algorithm allocates MH for cost estimation to each order under the limited volume of MH, and then determines the bidding price to maximize the expected profit under the deficit order probability constraint.

We develop a mathematical model for simulating competitive bidding. Through the numerical results obtained by using the model, we show that the bidding price decision in consideration of the cost estimation accuracy and the deficit order probability is essential for the contractor to make a stable profit in EPC projects, and that the two-step bidding price decision algorithm developed in this paper is effective for making such bidding price decisions.

There are several issues which require further research. For example, the procedure for modifying the MH allocation and adjusting the bidding price dynamically in response to each order arrival is required for practical application. In addition, our two-step algorithm does not consider the duration for estimating cost and for carrying out the project. The MH allocation procedure should consider the time cost-trade-off and its implication on the cost estimation accuracy and profit. It is also necessary to compare the performance of our procedure with other project scheduling methods dealing with the optimum allocation of resources for multiple projects.

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REFERENCES

Ballesteros-Pérez, P., González-Cruz, M[a]. C., Cañavate-Grimal, a., 2012. on Competitive Bidding: Scoring and Position Probability Graphs. *International Journal of Project Management*, in Press.

Bertisen, J., Davis, G. a., 2008. Bias and Error in Mine Project Capital Cost Estimation. *the Engineering Economist*. 53, 118-139.

Dey, P. K., 2006. Integrated Project Evaluation and Selection using Multiple-Attribute Decision-Making Technique. *International Journal of Production Economics*. 103, 90-103.

Elfving, J. a., Tommelein, I. D., Ballard, G., 2005. Consequences of Competitive Bidding in Project-based Production. *Journal of Purchasing & Supply Management*. 11, 173-181.

Friedman, L., 1956. a Competitive-Bidding Strategy. *the Journal of the Operations Research Society of America*. 4, 104-112.

Helmus, F. P., 2008. *Process Plant Design: Project Management from Inquiry to Acceptance*. Wiley-VCH, Weinheim.

Herbots, J., Herroelen, W., Leus, R., 2007. Dynamic Order Acceptance and Capacity Planning on a Single Bottleneck Resource. *Naval Research Logistics*. 54, 874-889.

Ishii, N., Muraki, M., 2011. a Strategy for Accepting Orders in ETO Manufacturing with Competitive Bidding. *Proceedings of 1st International Conference on Simulation and Modeling Methodologies, Technologies and Applications* (SIMULTECH 2011). 380-385.

Ishii, N., Takano, Y., Muraki, M., 2012. Decision on Bidding Prices under Limited Man-Hours in EPC Projects. Submitted to *Computers & Industrial Engineering*.

Jinru, Z., 2011. Study on Cost Management under EPC General Contracting Model. *Advanced Materials Research*, 181/182, 49-53.

Kerzner, H., 2009. *Project Management: a Systems Approach to Planning, Scheduling, and Controlling*. John Wiley & Sons, New Jersey.

Kolisch, R., 2001. *Make-to-Order Assembly Management*. Springer-Verlag, Berlin.

Kortanek, K. O., Soden, J. V., Sodaro, D., 1973. Profit Analyses and Sequential Bid Pricing Models. *Management Science*, 20, 396-417.

Martino, J. P., 1995. Research and Development Project Selection. John Wiley & Sons, New York.

Medaglia, a. L., Graves, S. B., Ringuest, J. L., 2007. a Multiobjective Evolutionary Approach for Linearly Constrained Project Selection under Uncertainty. *European Journal of Operational Research*. 179, 869-894.

Oberlender, G. D., 2000. *Project Management for Engineering and Construction*. Mcgraw-Hill, New York.

Oberlender, G. D., Trost, S. M., 2001. Predicting Accuracy of Early Cost Estimates based on Estimate Quality. *Journal of Construction Engineering and Management*. May/June, 173-182.

Ranjan, M., 2009. EPC: a Better Approach, *Chemical Engineering World*. 44, 7, 46-49.

Rom, W. O., Slotnick, S. a., 2009. Order Acceptance using Genetic Algorithms. *Computers & Operations Research*. 36, 1758-1767.

Rothkopf, M. H., Harstad R. M., 1994. Modeling Competitive Bidding: a Critical Essay. *Management Science*. 40, 364-384.

Slotnick, S., Morton, T. E., 2007. Order Acceptance with Weighted Tardiness. *Computers & Operations Research*. 34, 3029-3042.

Steel, G., 2004. Tender Management, in: Morris, P. W. G., Pinto, J. K., (Eds.). *the Wiley Guide to Managing Projects*. John Wiley & Sons, New Jersey.

Towler, G., Sinnott, R., 2008, *Chemical Engineering Design Principles, Practice and Economics of Plant and Process Design*. Elsevier, Burlington.

Wang, J., Xu, Y., Li, Z., 2009. Research on Project Selection System of Pre-Evaluation of Engineering Design Project Bidding. *International Journal of Project Management*. 27, 584-599.

Watt, D. J, Kayis, B., Willey, K., 2009. Identifying Key Factors in the Evaluation of Tenders for Projects and Services. *International Journal of Project Management*, 27, 250-260.