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見積り工数制約下におけるEPCプロジェクト入札価格決定改訂アルゴリズム

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A Revised Algorithm for Competitive Bidding Price Decision under Limited Engineering Man-Hours in EPC Projects

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Abstract– To determine the bidding prices in Engineering-Procurement-Construction (EPC) projects, where contract prices are fixed, the contractor needs to consider the accuracy of estimated project cost under the limited engineering Man-Hours (MH) for cost estimation to attain maximum profit from orders. In this paper, we develop an algorithm where, in order to attain maximum profit, bidding prices are determined by allocating MH for cost estimation and adjusting bidding prices simultaneously in consideration of the competitive bidding environments, and the cost estimation accuracy under the constraint of the total MH and the deficit risk of each order. Through numerical examples delivered from the algorithm, we show that the developed algorithm is effective for bidding price decision in EPC projects.

Keywords– competitive bidding, cost estimation accuracy, deficit risk, Man-Hour allocation

1. Introduction

The importance of Engineering-Procurement-Construction (EPC) projects [1, 2] is widely recognized in practice. For example, construction, civil engineering, process plant engineering, and so on, are typical fields of EPC projects. In EPC projects, a main contractor has principal responsibility, referred to as single point responsibility, for project cost, quality, and schedule under a fixed-price, which is determined before the start of the project as a lump-sum contract [2]. Thus, a reduced project cost and shorter schedule are expected [1, 3].

In EPC projects, accordingly, it is necessary for any contractor to determine the bidding price based on a precise estimation of its project cost. Cost estimation, however, is a complex task of predicting the costs of projects to be provided in the future based on the analysis of the client's requirements. Thus, experienced and skilled human resources, represented as engineering Man-Hours (hereafter referred to as MH), are required for accurate cost estimation. Those resources are limited for any contractor; furthermore, once the orders are successfully accepted, the corresponding projects to be carried out will also need considerable human resources. For these reasons, it is important to realize appropriate allocation of MH for cost estimation to each order for maximizing the total expected profit under the constraint of the total MH. In addition, contractors should consider the possibility of realizing a loss, i.e., the deficit risk, due to cost estimation error. This is because just a few deficit orders, which suffer an eventual loss due to cost estimation error, would result in a significant reduction of realized profits when the number of accepted orders is limited, as is the case with EPC contractors.

In this paper, we develop an algorithm where bidding prices are determined, in order to attain maximum profit, by allocating MH for cost estimation and adjusting bidding prices simultaneously in consideration of the competitive bidding environments, and the cost estimation accuracy un-

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der the constraint of the total MH and the deficit risk of each order. We analyze the effectiveness of the revised algorithm on the expected profit through numerical examples.

2. Related Work

Since Friedman [4] has developed the first bidding model that decides the bidding price to maximize expected profit, a variety of studies, such as bidding theory, bidding model and auction design, have been conducted on competitive bidding (see Ballesteros-Pŕez et *al*. [5], Fuerst [6], Rothkopf and Harstad [7], for detailed references). For instance, Ioannou and Leu [8] present a competitive bidding model for the average-bid method, which avoids bidding at unrealistically low prices. Hosny and Elhakeem [9] developed a generalized approach to estimate an optimum markup under various bid evaluation options. Ishii et *al*. [10] developed an order acceptance strategy under limited MH. In addition, Takano et *al*. [11] considered sequential bidding models where the obtained contracts require the use of restricted MH. However, in these studies, the allocation of limited MH for cost estimation to each order, which affects the expected profits from orders significantly, has not been investigated.

In addition, little attention has been paid to the profit volatility risk associated with cost estimation accuracy. Since, in practice, the number of accepted orders is usually limited in EPC contractors, the realized total profit is significantly affected by a few deficit orders. Accordingly, the deficit order risk should be considered in the bidding price decision in EPC projects.

Regarding cost estimation accuracy, various types of research have been performed. Oberlender and Trost [12] studied determinants of cost estimation accuracy and developed a system for predicting the accuracy. Wright and Williams [13] studied the predictors of the completed construction cost based on various bid characteristics. Bertisen and Davis [14] analysed costs of 63 projects and evaluated the accuracy of estimated costs statistically. Jørgensen et *al*. [15] studied the relation between project size and cost estimation accuracy. Uzzafer [16] proposed a contingency estimation model considering the distribution of estimated cost and the risk of software projects to estimate contingency resources. In addition, Humphreys [17], Towler and Sinnott [1] indicated relations among cost estimation methods, cost estimation data, and their accuracy in the field of process plant engineering projects. More importantly, AACE International [18] suggested that the cost estimation accuracy is positively correlated with the volume of MH for cost estimation. However, these studies have paid little attention to the effect of the cost estimation accuracy and the relevant MH on the expected profits, and the deficit order risks in EPC projects under competitive bidding.

Based on the above observations, Ishii et *al*. [19] developed a heuristic bidding price decision algorithm (hereafter referred to as the HBPD algorithm) in consideration of the cost estimation accuracy in EPC projects under the limited MH. At the first step, the algorithm allocates MH for cost estimation to each order according to the ranking of orders, determined by a heuristic method in advance, under the constraints on the total MH for cost estimation. At the second step, it adjusts the bidding prices, based on the cost estimation accuracy determined by the allocated MH at the first step, to improve the expected profit under the constraint of deficit order probability. The allocation of MH for cost estimation affects the cost estimation accuracy of each order and thus the expected profits from orders. Therefore the HBPD algorithm, which specifies the ranking of orders in advance to allocate MH for cost estimation to each order without considering the effect on the expected profit adequately, cannot determine bidding prices to attain the maximum profit from orders.

In this paper, we propose a revised algorithm that determines bidding prices without using the predetermined ranking of orders that is used in the HBPD algorithm. Namely, the algorithm allocates MH for cost estimation to each order and adjusts bidding prices simultaneously, under the constraint of the total MH for cost estimation and the deficit risk of each order, to attain the maximum profit from orders.

3. Mathematical Models for Bidding Price Decision

3.1 Evaluation of Cost Estimation Accuracy

In cost engineering, cost estimation accuracy is usually defined as the percentage of deviation from the actual cost (Humphreys [17], Kerzner [20]). In this paper, we define cost estimation accuracy as the percentage representation of the coefficient of variation, such as 5% of the actual cost. It is obtained by dividing the standard deviation of the estimated cost by the actual cost. Namely, a lower deviation (σ) means higher estimation accuracy.

Since cost estimation requires a detailed analysis and design made by experienced engineers in EPC projects, it can be seen that the volume of MH for cost estimation significantly affects the cost estimation accuracy. In fact, Kerzner [20] shows the relations between project data and cost estimation accuracy in the process plant project. For instance, six kinds of data, such as process description, process flow diagram, and so on, are required for +/-35% estimation accuracy. Additionally, 34 kinds of data, such as mechanical P&Is, equipment list, and so on, are required to attain +/-5% estimation accuracy. Since any contractor can estimate the volume of MH required for creating such data, it is possible to evaluate relations between the volume of MH and the cost estimation accuracy. It is also clear that the increasing rate of cost estimation accuracy decreases gradually according to the increase of the volume of MH. Thus, in this paper, as in Ishii and Muraki [21], we define the standard deviation σ of the bidding price, which is affected by cost estimation accuracy, as the function of the MH for cost estimation per order PMH by applying the logistic curve 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 $\sigma_{\min}$ and $\sigma_{\max}$ are the minimum and the maximum value of the standard deviation, and C is a parameter of the logistic curve, which defines the sensitivity of cost estimation accuracy to the volume of MH. Namely, the larger C requires the greater volume of MH to attain the target cost estimation accuracy. In practice, the contractor could determine these parameters from past project records.

3.2 Evaluation of Bidding Price

We use the following mathematical models for evaluating the bidding price based on the HBPD algorithm. Note that a list of notations used in mathematical models is shown in Appendix.

We consider K contractors ($k = 1, 2, \cdots, K$) and the bidding for I orders ($i = 1, 2, \cdots, I$). Particularly, $k = 1$ represents one's own company, and $k \geq 2$ are those of its competitors. In addition, we suppose that there are G levels of cost estimation accuracy ($g = 1, 2, \cdots, G$) for allocating the MH for cost estimation to each order. Namely, when the order is set to a higher accuracy level, a larger volume of MH is assigned to its cost estimation.

Each contractor k sets a tentative bidding price of order i based on standard project cost STC_i, relative cost difference RC^i_k from STC_i, and target profit rate tpr^i_k. Each contractor's tentative bidding price TBP^i_k for order i is determined as follows:

$$TBP^i_1 = STCR^i_1 \cdot (1 + tpr^i_1) \cdot rp^i \quad (i = 1, 2, \cdots, I) , \qquad (2)$$

$$TBP^i_k = STCR^i_k \cdot (1 + tpr^i_k) \quad (i = 1, 2, \cdots, I;\ k = 2, 3, \cdots, K) , \qquad (3)$$

$$STCR^i_k = STC_i \cdot (1 + RC^i_k) \quad (i = 1, 2, \cdots, I; k = 1, 2, \cdots, K) , \qquad (4)$$

where rp^i is a risk parameter, and $STCR^i_k$ is the standard project cost with the relative cost difference. Note that tentative bidding price of one's own company TBP^i_1 can be adjusted by changing the value of risk parameter rp^i. If there is no difference in cost-competitiveness among contractors, RC^i_k is set to 0. STC_i can be specified in reference to the preliminary cost, which is calculated before deciding whether to bid or not as shown in a competitive bidding process by Ishii et *al.* [19].

Let $p^i_k(x^i_k, \bar{\mu}, \bar{\sigma})$ be the probability density function of the bidding price x^i_k of the contractor k for order i, and its average value and standard deviation are $\bar{\mu}$ and $\bar{\sigma}$, respectively. Then the expected profit in one's own company ($k = 1$) is represented as the average excess of the bidding price x^i_1 over $STCR^i_1$. However, note that only when the bidding price of one's own company x^i_1 is the lowest among those of other contractors x^i_k, ($k = 2, \cdots, K$), he can receive the order i. When order i is set to the accuracy level g, the expected profit ep^i_g in one's own company ($k = 1$) is expressed by

$$ep^i_g = \int_0^{\infty} (x^i_1 - STCR^i_1) \cdot p^i_1(x^i_1, TBP^i_1, \sigma^i_{g,1}) \cdot \prod_{k=2}^{K} \int_{x^i_1}^{\infty} p^i_k(x^i_k, TBP^i_k, \sigma^i_k)\, dx^i_k\, dx^i_1 \quad (i = 1, 2, \cdots, I; g = 1, 2, \cdots, G) , \qquad (5)$$

where $\sigma^i_{g,1}$ is the standard deviation of one's own company's bidding price and σ^i_k is that of the competitor. The value of $\sigma^i_{g,1}$ decreases with a higher accuracy level g. Additionally the expected order in one's own company ($k = 1$) is the average revenue represented as follows:

$$\int_0^{\infty} x^i_1 \cdot p^i_1(x^i_1, TBP^i_1, \sigma^i_{g,1}) \cdot \prod_{k=2}^{K} \int_{x^i_1}^{\infty} p^i_k(x^i_k, TBP^i_k, \sigma^i_k) dx^i_k\, dx^i_1 \quad (i = 1, 2, \cdots, I; g = 1, 2, \cdots, G) . \qquad (6)$$

Moreover, we employ the expected shortfall relative to $STCR^i_1$, i.e., the expected deficit from order i, as a risk measure. This risk measure is also referred to as the lower partial moment in the context of financial decision making (see, e.g., Bawa and Lindenberg [22]). When order i is set to the accuracy level g, the expected shortfall resulting from order i is calculated as follows:

$$dr_g^i = \int_0^{STCR_1^i} (STCR_1^i - x_1^i) \cdot p_1(x_1^i, TBP_1^i, \sigma_{g,1}^i) \cdot \prod_{k=2}^{K} \int_{x_1^i}^{\infty} p_k(x_k^i, TBP_k^i, \sigma_k^i) dx_k^i \, dx_1^i \quad (i = 1,2,\cdots,I; g = 1,2,\cdots,G) . \tag{7}$$

We refer to dr_g^i as the deficit risk in this paper.

4. A Revised Algorithm for Determining Bidding Prices

By using the above mathematical models, we propose a revised algorithm for determining bidding prices to attain maximum profit as follows. This algorithm allocates MH for cost estimation to each order and adjusts the bidding prices by risk parameters simultaneously under the limited MH and deficit risk constraint of each order.

Let a_g^i be a 0-1 integer decision variable for setting each order to a level of estimation accuracy ($g = 1,2,\cdots,G$). If $a_g^i = 1$, then order i is set to the accuracy level g. We determine the optimal value of the risk parameter and MH allocation for cost estimation by solving the following optimization problem with decision variables rp^i and a_g^i:

$$\textbf{Maximize} \quad \sum_{i=1}^{I} \sum_{g=1}^{G} a_g^i \cdot ep_g^i \tag{8}$$

subject to

$$\sum_{g=1}^{G} a_g^i \cdot dr_g^i \le rpf_i \quad (i = 1,2,\cdots,I) , \tag{9}$$

$$\sum_{i=1}^{I} \sum_{g=1}^{G} a_g^i \cdot PMH_g^i \le TMH , \tag{10}$$

$$\sum_{g=1}^{G} a_g^i = 1 \quad (i = 1,2,\cdots,I) , \tag{11}$$

$$a_g^i \in \{0.1\} \quad (i = 1,2,\cdots,I; g = 1,2,\cdots,G) , \tag{12}$$

where PMH_g^i is the volume of MH required for estimating the cost of order i with accuracy level g, TMH is the total MH for cost estimation, and rpf_i is the upper limit of the expected deficit from order i. It should be noted that the relation $\sigma_{g,1}^i = \sigma(PMH_g^i)$ holds (see also Eq. (1)).

In the above optimization problem, the objective is to maximize the total expected profit. Eq. (9) is the deficit risk constraint on each order. Eq. (10) is the upper limit constraint on the available MH for cost estimation. Eq. (11) and (12) force each order to be set to one accuracy level.

The optimization problem (8)-(12) is a mixed integer nonlinear program that is difficult to solve directly. Thus, we take a simple decomposition approach to solve it. Specifically, we first calculate the expected profits by optimizing the risk parameter of each order ($i = 1,2,\cdots,I$) for each accuracy level ($g = 1,2,\cdots,G$). Next we assign the MH for cost estimation to each order based on the expected profits. The solution procedure is described as follows:

Solution Procedure for the Optimization Problem (8)-(12)

Step1: Solve the following optimization problems:

$$oep_g^i = \max\{ep_g^i \mid dr_g^i \le rpf_i\} \quad (i = 1,2,\cdots,I;\ g = 1,2,\cdots,G) \tag{13}$$

with a decision variable rp^i.

Step2: Solve the following optimization problems:

$$\max \left\{ \sum_{i=1}^{I} \sum_{g=1}^{G} a_g^i \cdot oep_g^i \;\middle|\; (10), (11), (12) \right\} \tag{14}$$

with decision variables a_g^i

$$(i = 1,2,\cdots,I; g = 1,2,\cdots,G) .$$

It is clear that if we obtain optimal solutions to the optimization problems (13) and (14), the above solution procedure provides an optimal solution to the optimization problem (8)-(12). We use a simple iterative algorithm to search for a solution of rp^i by gradually eliminating search space at Step 1, and we use the basic solver included with Excel 2010 to solve optimization problem (14).

Let orp^i and oa_g^i be the optimal value of risk parameter rp^i and the optimal assignment of the accuracy level a_g^i, respectively. Then the optimal volume of MH, $PMH_{g(i)}^i$, is allocated to the order i to estimate its cost, where $g(i) \in \{g \mid oa_g^i = 1\}$ is an optimal accuracy level for order i. After completing the cost estimation, the estimated cost EST^i is obtained. Finally, the bidding price to attain the maximum profit for order i is determined based on the estimated cost as follows (see also Eq. (2)):

$$EST^i \cdot (1 + tpr_1^i) \cdot orp^i . \tag{15}$$

5. Numerical Examples

In this section, we show the following through the numerical examples by using the revised algorithm explained in the previous section: (1) effects of the cost estimation accuracy and the available MH on the expected profit; (2) significance of the MH allocation method for the cost estimation; (3) effectiveness of bidding price adjustment by risk parameter; (4) effect of the deficit risk constraint on the expected profit; and (5) performance of the revised algorithm compared to that of the HBPD algorithm.

5.1 Problem setting

5.1.1 Setting of cases

We use the cases shown in **Table 1** for numerical examples. Risk parameter rp^i is set to 1.0 for all orders in Cases 0, 1, and 2; and it is optimally determined by solving the optimization problems (13) in Cases 3 and 4. It is assumed in Case 0 that one's own company can estimate the costs of all orders without estimation error, i.e., $\sigma^i_{g,1} = 0$ $(i = 1,2,\cdots,I;\ g = 1,2,\cdots,G)$. Accordingly in Case 0, the MH allocation, which affects the cost estimation accuracy, does not make any difference. By contrast in Cases 1 to 4, the cost estimation accuracy of one's own company $\sigma^i_{g,1}$ is a function of the volume of MH, PMH^i_g, that is, $\sigma^i_{g,1} = \sigma(PMH^i_g)$ (see also Eq. (1)). We consider four conditions of the total MH available for cost estimation TMH, i.e., (A) 80, (B) 90, (C) 100, and (D) 110 thousand man-hours ([M MH]). TMH is set so that the average MH for cost estimation is approximately 1.5% to 2.0% of STC_i. In Cases 1 and 3, according to the total MH for cost estimation TMH, the MH for cost estimation is allocated to each order so that the cost estimation accuracy of every order calculated based on Eq. (1) will be the same. **Table 2** shows the cost estimation accuracy of all orders, which is defined as a percentage of the standard project cost STC_i, of one's own company in Cases 1 and 3. For instance in Cases 1 and 3, the cost estimation accuracy for all orders $(i = 1,2,\cdots,I)$ is equal to 8.45% of STC_i when the total MH for cost estimation TMH is 80 [M MH]. Meanwhile in Cases 2 and 4, the MH for cost estimation is optimally allocated to each order by solving the optimization problem (14).

Table 1: Cases for numerical examples

(Equally allocated: MH is allocated to equalize the cost estimation accuracy of all orders)

Case	Risk parameter rp^i	MH allocation
Case 0	1.0	(No cost estimation error)
Case 1	1.0	Equally allocated
Case 2	1.0	Optimally allocated by Eq. (14)
Case 3	Optimally determined by Eq. (13)	Equally allocated
Case 4	Optimally determined by Eq. (13)	Optimally allocated by Eq. (14)

Table 2: Cost estimation accuracy of all orders in Cases 1 and 3

Total MH for cost estimation TMH [M MH]	80	90	100	110
Cost estimation accuracy [%]	8.45	7.80	7.23	6.75

5.1.2 Setting of parameters

In this paper, we assume a mid-size EPC contractor in the chemical plant engineering business whose annual sales are approximately one billion US dollars (1000 [MM$]), and we consider 16 orders in a term in each case as shown in **Table 3**. Namely, we suppose that one's own company has the capability to accept 20% of the orders.

We set the following parameters in all the cases: Relative cost difference $RC^i_k = 0.0$ $(i = 1,2,\cdots,I; k = 1,2,\cdots,K)$; target profit rate $tpr^i_k = 0.1$ $(i = 1,2,\cdots,I; k = 1,2,\cdots,K)$; and standard deviation of the bidding price σ^i_k is set to 8% of STC_i for all competitors $(i = 1,2,\cdots,I; k = 2,3,\cdots,K)$. We evaluate the result of the bidding on the basis of the total expected profit in Section 5.2.1, 5.2.2, 5.2.3, and 5.2.5. Accordingly, the upper limit of the expected deficit rpf_i is set to infinity in Section 5.2.1, 5.2.2, 5.2.3, and 5.2.5. The effect of the deficit risk constraint is assessed in Section 5.2.4.

We suppose in Eqs. (5), (6), and (7) that the bidding price x^i_k follows lognormal distribution as in Bertisen and Davis [14]. We set C to $0.25 \cdot 100/STC_i$, and σ_{min} and σ_{max} to 0.5% and 30% of STC_i, respectively, in Eq. (1). These parameters are determined so that the average of cost estimation accuracy in Cases 1 and 3 are between 5% to 10%. In addition, we set 11 levels of the cost estimation accuracy $\sigma^i_{g,1}$ $(g = 1,2,\cdots,11)$ to 5%, 6%, $\cdots$, 15% of STC_i $(i = 1,2,\cdots,I)$. Each order i is set to one accuracy level g, where the volume of MH PMH^i_g to be allocated to the order i is determined based on Eq. (1) and $\sigma^i_{g,1}$.

Table 3: Conditions of orders

Order id (i)	1	2	3	4	5	6	7	8	9
STC_i [MM$]	100.0			200.0			300.0		
# Bidders (K)	2	3	4	2	3	4	2	3	4

Order id (i)	10	11	12	13	14	15	16
STC_i [MM$]	400.0			500.0		600.0	
# Bidders (K)	2	3	4	3	4	3	4

5.2 Results of numerical calculation

5.2.1 Effects of the cost estimation accuracy and the available MH on the expected profit

Since the total MH for cost estimation is limited in practice, project costs are subject to unavoidable estimation error. Nevertheless, it is assumed in Case 0 that there is no cost estimation error. As shown in **Table 4**, the total expected profit in Case 0 is significantly higher than those in Cases 1 to 4. From this, we can say that if the contractor does not take the cost estimation accuracy into consideration, he will overestimate the profit from orders, and moreover he might fail to make a correct decision.

The significant difference in the total expected profit is caused by the total MH for cost estimation except in Case 0 as shown in Table 4. For instance, the expected profits in Case 1.A (80 [M MH]), Case 1.B (90 [M MH]), Case 1.C (100 [M MH]), and Case 1.D (110 [M MH]) are 51.5, 61.3, 69.5, and 76.3 [MM$], respectively. As shown in Table 1, Cases 1 to 4 differ in the method for setting a risk parameter and for allocating the MH for cost estimation to each order. Based on the above observations, we can say that the increase of the volume of total MH for cost estimation contributes to the increasing total expected profit regardless of the value of risk parameter and the method of MH allocation to each order for cost estimation.

Table 4: Total expected profit of each case [MM$]

	Total MH for cost estimation (*TMH*) [M MH]			
	80	90	100	110
Case 0	128.5			
Case 1	Case 1.A	Case 1.B	Case 1.C	Case 1.D
	51.5	61.3	69.5	76.3
Case 2	Case 2.A	Case 2.B	Case 2.C	Case 2.D
	52.2	62.2	70.5	77.2
Case 3	Case 3.A	Case 3.B	Case 3.C	Case 3.D
	60.7	66.9	72.8	78.2
Case 4	Case 4.A	Case 4.B	Case 4.C	Case 4.D
	67.3	72.3	77.1	81.3

5.2.2 Significance of MH allocation method for cost estimation

It is found from Table 4 that the total expected profits in Case 2 are larger than those in Case 1. Similarly, the total expected profits in Case 4 are larger than those in Case 3. These results show that the optimal allocation of the MH for cost estimation improves the total expected profit. In addition, the point to observe is that the difference in the total expected profit between Case 3 and Case 4 is larger than that between Case 1 and Case 2. This demonstrates that the MH allocation to each order for cost estimation has a synergistic effect on the adjustment of the bidding price. Moreover it should be noticed that the difference in the total expected profit between Case 3.A and Case 4.A is 6.6 [MM$] whereas it is 3.1 [MM$] between Case 3.D and Case 4.D. That is, the synergistic effect is large when the MH for cost estimation is limited.

Table 5 shows the MH allocated to each order, the expected profit, and the deficit risk in Cases 3.A and 4.A. For instance, more MH is allocated to the orders 1, 2, 4, 5, 7, 8, 10, 11, 13, and 15 in Case 4.A than in Case 3.A. As shown in Table 5, the orders, where more MH is allocated in Case 4.A by the revised algorithm than in Case 3.A, increase the expected profit and decrease the deficit risk compared to those in Case 3.A. In addition, the orders, where less MH is allocated in Case 4.A, decrease the deficit risk, although the expected profit is decreased. As the result, the total expected profit is higher in Case 4.A (67.3 MM$) than in Case 3.A (60.7 MM$), and the deficit risk is lower in Case 4.A (5.52 MM$) than in Case 3.A (8.63 MM$).

Since the cost estimation accuracy depends on the MH allocated to the order for cost estimation, the contractor can expect a higher profit as well as lower deficit risk by assigning a larger volume of MH. However, there is usually a limit to the available MH for cost estimation. Thus, it can be concluded that a method of MH allocation to each order for cost estimation is critical for the contractor in maximizing the total expected profit under the constraint of the total MH for cost estimation and the deficit risk in EPC projects.

5.2.3 Effectiveness of bidding price adjustment by risk parameter

As shown in Table 4, there is a significant difference in the total expected profits between Case 1 and Case 3, and similarly between Case 2 and Case 4. For example, the total expected profit in Case 2.A and in Case 4.A are 52.2 and 67.3 [MM$], respectively. These results show that the bidding price adjustment by risk parameter is effective in improving the total expected profit from orders regardless of the method of MH allocation for cost estimation.

It can be seen in **Table 6** that the optimal value of risk parameter decreases according to the increase of the total MH for cost estimation in Case 3. A larger volume of the total MH for cost estimation increases the cost estimation

Table 5: MH allocation and expected profit of each order

(*OI* : Order id, *EP* : Expected profit, *DR* : Deficit risk, Total MH for cost estimation *TMH*: 80 [M MH])

	Case 3.A			Case 4.A		
OI	MH [M MH]	*EP* [MM$]	*DR* [MM$]	MH [M MH]	*EP* [MM$]	*DR* [MM$]
1	1.54	2.78	0.152	3.14	3.89	0.021
2	1.54	1.07	0.188	2.48	1.61	0.116
3	1.54	0.50	0.151	0.56	0.12	0.090
4	3.08	5.56	0.304	4.96	7.10	0.107
5	3.08	2.14	0.376	4.03	2.73	0.302
6	3.08	1.00	0.302	1.12	0.24	0.179
7	4.62	8.34	0.455	7.44	10.65	0.160
8	4.62	3.21	0.563	6.04	4.10	0.452
9	4.62	1.49	0.453	1.68	0.37	0.269
10	6.16	11.12	0.607	9.92	14.20	0.213
11	6.16	4.29	0.751	8.05	5.46	0.603
12	6.16	1.99	0.604	2.23	0.49	0.359
13	7.70	5.36	0.939	10.66	6.83	0.754
14	7.70	2.49	0.755	2.79	0.61	0.448
15	9.24	6.43	1.127	12.08	8.19	0.905
16	9.24	2.99	0.906	3.35	0.73	0.538
Total	80.0	60.7	8.63	79.9	67.3	5.52

accuracy as shown in Table 2. The higher cost estimation accuracy reduces volatility of the bidding price. Thus, when a large volume of the total MH is available, we can certainly receive an order by setting a risk parameter to relatively low value, without the risk of suffering a large loss. For instance, the cost estimation accuracy of order 1 in Case 3.A and in Case 3.D are 8.45% and 6.75% (see Table 2), and the values of the risk parameter are 1.035 and 1.021, respectively.

Based on the above observations, it can be said that the adjustment of the bidding price of each order in consideration of the cost estimation accuracy is effective in increasing the expected profit.

Table 6: Optimal value of risk parameter rp^i in Case 3 (*Order id:* 1- 3)

(The total MH for cost estimation *TMH* of each case is shown inside the parentheses. [M MH])

Order id (i)	Case 3.A (80)	Case 3.B (90)	Case 3.C (100)	Case 3.D (110)
1	1.035	1.029	1.026	1.021
2	1.028	1.020	1.013	1.007
3	1.034	1.023	1.015	1.007

5.2.4 Effect of the deficit risk constraint on the expected profit

We examine how the deficit risk constraint affects the expected profit. **Fig. 1** depicts the relation of the upper limit of the expected deficit rpf_i and the total expected profit in Cases 3.A, 3.D, 4A, and 4D. In Fig. 1, the value of rpf_i, which is defined as a percentage of the target profit $STC_i \cdot tpr^i_1$, is chosen from 0.25%, 0.5%, 0.75%, 1.0%, 1.25%, 1.5%, 1.75%, 2.0%. As explained in Section 2, 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 Fig.1, although the low upper limit of the expected deficit decreases the total expected profit, the expected deficit can be reduced. For example, the total expected deficit is reduced from 8.65 to 1.37 [MM$] by changing the upper limit of the deficit order from 2.0 to 0.25 [%] at the expense of the total expected profit of 12.5 [MM$] in Case 3.A. In addition, Fig.1 shows that the method of MH allocation for cost estimation has significant influence on the total expected profit under the constraint of the upper limit of the expected deficit. For example, the

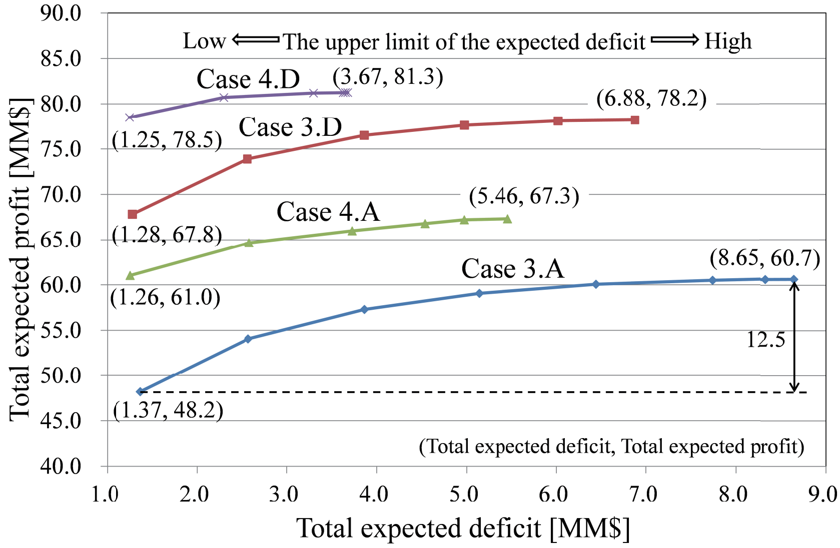

Fig. 1: Relations between the total expected deficit and the total expected profit.

Table 7: Total expected profits by the revised algorithm (Case 4) and HBPD algorithm. [MM$]

	Total MH for cost estimation (*TMH*) [M MH]			
	80	90	100	110
	Case 4.A	Case 4.B	Case 4.C	Case 4.D
Revised algorithm	67.3	72.3	77.1	81.3
HBPD algorithm	61.6	65.0	68.9	76.1

total expected profit decreased from 81.3 to 78.5 [MM$] by reducing the upper limit of the deficit order from 2.0 to 0.25 [%] in Case 4.D; however, the total expected profit decreased more sharply in Case 3.D, i.e., 78.2 to 67.8.

Bidding for a large-scale project involves a substantial risk. Our framework developed for EPC projects will certainly be helpful for any contractor in making a stable profit under the constraints of the total MH for cost estimation and the deficit risk of each order.

5.2.5 Performance of the revised algorithm

Table 7 shows the expected profits obtained by the revised algorithm (Case 4) in this paper and those by the HBPD algorithm under the same problem setting determined in Section 5.1. As stated in Section 2, the HBPD algorithm allocates MH for cost estimation to each order according to the predetermined ranking of orders, and then adjusts bidding prices. In contrast, the revised algorithm determines bidding prices by allocating MH for cost estimation and adjusting bidding prices by risk parameters simultaneously, without using the predetermined ranking of orders.

As shown in Table 7, there is a significant difference in the total expected profits between Case 4 and those obtained by the HBPD algorithm for all conditions on the total MH for cost estimation. It can be concluded that the revised algorithm can perform better than the HBPD algorithm on the total expected profit from orders.

6. Conclusions

In this paper, we develop an algorithm where bidding prices are determined so that the total expected profit from orders is maximized in consideration of the cost estimation accuracy under the constraint of the total MH for cost estimation and the deficit risk of each order. Namely, the revised algorithm determines bidding prices by allocating MH for cost estimation and adjusting bidding prices by risk parameters simultaneously, without using the predetermined ranking of orders that is used in the HBPD algorithm, so that the total expected profit from orders is maximized.

The following conclusions can be drawn from the analysis of the numerical examples:

- A method of MH allocation to each order for cost estimation is critical for the contractor in maximizing the total expected profit under the limited MH for cost estimation.
- The bidding price adjustment by risk parameter based on the cost estimation accuracy is effective in improving the total expected profit from orders.
- The MH allocation to each order for cost estimation has a synergistic effect on the bidding price adjustment.
- The revised algorithm is helpful for any contractor in making a stable profit under the constraints of the total MH for cost estimation and the deficit risk of each order.
- The revised algorithm can perform better than the HBPD algorithm on the total expected profit from orders.

There are several issues that 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.

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Appendix

The notations used in mathematical models are as follows:

σ: Standard deviation of bidding price.
PMH: MH for cost estimation per order.
C: Parameter of the sensitivity of cost estimation accuracy to the volume of MH.
TBP^i_k: Tentative bidding price of the contractor k for order i.
$STCR^i_k$: Standard project cost of order i in contractor k.
tpr^i_k: Target profit rate of the contractor k for order i.
rp^i: Risk parameter of order i.
STC_i: Standard project cost of order i.
RC^i_k: Relative cost difference from STC_i in contractor k.
$p^i_k(x^i_k, \bar{\mu}, \bar{\sigma})$: Probability density function of the bidding price x^i_k of the contractor k for order i.
$\bar{\mu}$: Average value of the bidding price.
$\bar{\sigma}$: Standard deviation of the bidding price.
ep^i_g: Expected profit in one's own company from order i at the accuracy level g.
σ^i_k: Standard deviation of the bidding price in the contractor k.
dr^i_g: Deficit risk in one's own company from order i at the accuracy level g.
a^i_g: 0-1 integer decision variable for order i at the accuracy level g.
rpf_i: Upper limit of the expected deficit from order i.
PMH^i_g: Volume of MH required for estimating the cost of order i with accuracy level g.
TMH: Total MH for cost estimation.
orp^i: Optimal value of risk parameter rp^i.
oa^i_g: Optimal assignment of the accuracy level a^i_g.
EST^i: Estimated cost of order i.
M MH: Thousand man-hours.
MM$: Million US dollars.

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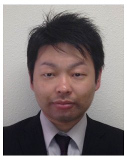

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