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Nobuaki Ishii, Yuichi Takano, and Masaaki Muraki

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Tokyo Institute of Technology

2-12-1 Ookayama, Meguro-ku, Tokyo 152-8552, JAPAN
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A bidding price decision process in consideration of cost estimation accuracy and deficit order probability for Engineer-To-Order manufacturing

Nobuaki Ishii[a*], Yuichi Takano[b], and Masaaki Muraki[b]

[a] *Faculty of Information and Communication, Bunkyo University, 1100, Namegaya, Chigasaki, Kanagawa, 253-8550 Japan*
[b] *Graduate School of Decision Science and Technology, Tokyo Institute of Technology, 2-12-1, Ookayama, Meguro-ku, Tokyo, 152-8550, Japan*

E-mail addresses: ishii@shonan.bunkyo.ac.jp (N. Ishii), takano.y.ad@m.titech.ac.jp (Y. Takano),
muraki.m.aa@m.titech.ac.jp (M. Muraki)

[*] Corresponding author: Nobuaki Ishii[a]
E-mail address: ishii@shonan.bunkyo.ac.jp, Telephone number: +81-467-53-2111, Fax number: +81-467-54-3721

Abstract

In Engineer-To-Order (ETO) manufacturing or project-based manufacturing, 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, establishing an effective bidding price decision process, which maximizes the expected profits from orders in consideration of the cost estimation accuracy and the deficit order probability, is an essential profit management issue for the contractor in ETO manufacturing. In this paper, we analyse features of the bidding price decision problem in ETO manufacturing, and develop a model which represents fundamental factors and their interactive processes in the bidding price decision. Based on the model, we develop a procedure to allocate cost estimation MH (Man-Hour) for determining the cost estimation accuracy of each order and adjust the bidding price of each order to maximize the expected profit under the constraints of the total MH for cost estimation and the deficit order probability. We analyse characteristics of the bidding price decision process based on numerical examples and show that the process, which includes consideration of the cost estimation accuracy and the deficit order probability, is essential in order for the contractor to make a stable profit and to ensure sustainability in ETO manufacturing.

Key Words: Engineer-To-Order, Project-based manufacturing, Competitive bidding, Cost estimation accuracy, Profit management, Sustainable company

1. Introduction

Nowadays, the importance of Engineer-To-Order (ETO) manufacturing (Kolisch 2001) or project-based manufacturing, where contractors design and build unique products or services based on the client requirements, such as construction, civil engineering, plant engineering, industrial machinery, is widely recognized in practice.

Although several shortcomings have been pointed out, competitive bidding is widely used for selecting a contractor who carries out the order in ETO manufacturing (Elfving et al. 2005). In the competitive bidding process, the client prepares a Request For Proposal (RFP) for an order and invites several potential contractors to the 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 ETO manufacturing, accordingly, it is necessary for any contractor to determine the bidding price based on precise cost estimation. If the contractor’s bidding price, consisting of the estimated cost and the target profit, is higher than that of the competitor’s 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 possibly suffer a loss on this order.

ETO manufacturing can be regarded as a form of project-based manufacturing to create a unique product or service as a temporary endeavour. Thus, the contractor needs to manage profit on each order as he does with project management (Project Management Institute 2008).

For effective profit management on each order, it is important to determine the bidding price in consideration of several key factors such as 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 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; 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 cost estimation MH for each order to maximize the profits. 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 reduction of realized profits significantly when the number of accepted orders is limited. (In this paper, the deficit order indicates the order which suffers an eventual loss due to cost estimation error.)

In this paper, we show that establishing a bidding price decision process in consideration of cost estimation accuracy and deficit order probability is an essential profit management issue for the contractor in ETO manufacturing. Namely, we analyse features of the bidding price decision problem in ETO manufacturing and develop a bidding price decision model which represents fundamental factors and their interactive processes, showing their effects on the bid performance such as expected orders, expected profits, and deficit order probability. The model reveals the details of how MH allocation for cost estimation and bidding price adjustment by risk parameter affect the bid performance under the constraints of total HM and deficit order probability.

Based on the model, we develop a bidding price decision procedure which determines the bidding price of each order for maximizing the expected profit. The procedure is a two-step algorithm in which cost estimation MH is allocated to each order according to the ranking of orders, and then the value of risk parameter for maximizing the expected profit is realized under the deficit order probability constraint.

We analyse the characteristics of the bidding price decision process in ETO manufacturing based on numerical examples by performing our procedure, and we show that the process in consideration of the cost estimation accuracy and the deficit order probability is essential for the contractor to make a stable profit and ensure sustainability. In addition, we show that the bidding price adjustment and the allocation of the cost estimation MH for each order are key factors in the process of maximizing the expected profits.

2. Related work

Among the research that has been performed related to a competitive bidding strategy, order acceptance and project selection problems have been studied. Many researchers have studied these topics in several ways over the last decades.

Order acceptance is basically the problem of making a decision to accept each order or not in Make-To-Order (MTO) manufacturing (Kolisch 2001). MTO is a special type of ETO manufacturing, and its objective is to maximize profits with capacity limitations. As literature surveys done by Slotnick & Morton (2007), Herbots et al. (2007), and Rom & Slotnick (2009) have shown, there exists a variety of 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 Rothkopf and Harstad 1994 for detailed references). In particular, a number of papers regarding the competitive bidding strategy date back to Friedman (1956), who presents a method to determine an optimal bidding price based on the distribution of the ratio of the bidding price to cost estimate. Ioannou and Leu (1993) present a competitive bidding model for the average-bid method, which avoids bidding at unrealistically low prices, and they explore the advantages of this method. Kitchenham et al. (2003, 2005) studied a generic software bidding model for estimating the probability of a successful bid to determine whether to bid or not. The model provides profit distribution by conducting Monte Carlo simulation based on the pre-defined data, such as cost distribution, price to win, competition level, and so on. However, little attention has been paid to profit volatility risk, which cannot be ignored in ETO manufacturing. When, for instance, the number of accepted orders is limited, the realized profits might be sharply lower than expected because the profits are significantly affected by a few deficit orders. Accordingly, the deficit order probability should be considered in the decision for advancing the process of competitive bidding.

In addition to the profit volatility risk, we consider the MH allocation for cost estimation when making a decision on the bidding. Several papers have analysed the problem of allocating scarce resources in competitive bidding. Stark & Mayer (1971) and Rothkopf (1977) consider the optimal allocation of bidding prices to opened bids simultaneously. Kortanek et al. (1973) considered bidding models in a sequence of auctions in the case of when a contract is obtained which requires the use of restricted resources, such as production capacity, at the time of actual production. However, MH allocation for cost estimation in ETO manufacturing has never been studied thus far.

Regarding cost estimation accuracy, various types of research on ETO manufacturing have been performed. Oberlender & Trost (2001) studied determinants of cost estimation accuracy and developed a system for predicting the accuracy. McDonald (2005) analysed the impact of project planning team experience and revealed that less experienced teams produce lower cost estimates than more experienced teams. Bertisen & Davis (2008) analysed costs of 63 projects and evaluated the accuracy of capital cost estimation statistically. In addition, several cost estimation methods and their accuracy have been studied. For example, Page (1996), Humphreys (2004), and Towler & Sinnott (2008) studied relations among cost estimation methods, cost estimation data, and their accuracy in the field of plant engineering. More crucially, Towler & Sinnott (2008) and Gerrard (2000) suggested that the cost estimation accuracy is positively correlated with the amount of cost estimation MH.

In ETO manufacturing, the bidding price decision affects the expected profit and the deficit order probability. Accordingly, this decision is crucial for profit management. Since the bidding price is usually determined based on the estimated cost, cost estimation accuracy is clearly a major factor in ETO manufacturing. Nevertheless, few studies have never attempted to analyse the bidding price decision process in terms of cost estimation accuracy and deficit order probability.

3. Features of the bidding price decision problem in ETO manufacturing

There are several ways to select a contractor from bidders in competitive bidding (Calosso et al. 2003, Steel 2004, Elfving et al. 2005, Helmus 2008, Wang et al. 2009). In a generic competitive bidding, shown in Figure 1, the client prepares an RFP and invites several potential contractors to the bidding. The contractor first carries out the preliminary analysis followed by the bid or no-bid decision. In the preliminary analysis, 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. The preliminary cost typically has +/- 30% accuracy in a chemical plant project (Towler and Sinnott 2008). In the bid or no-bid decision, the contractor evaluates the order from the view points of profitability, technical feasibility and so on, and makes a decision whether to bid or not. If the contractor decides to place the bid, then he 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 a contractor as the successful bidder.

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. These data can be provided by several departments of the contractor or professional consultants. For example, the past project data can be provided by the project department or the engineering department. The competitive environment, such as the number of bidders, bidders' competitiveness, can be provided by the sales department or professional consultants. The target profit rate is provided by the top management based on the corporate strategy, the number of outstanding contracts, and so on.

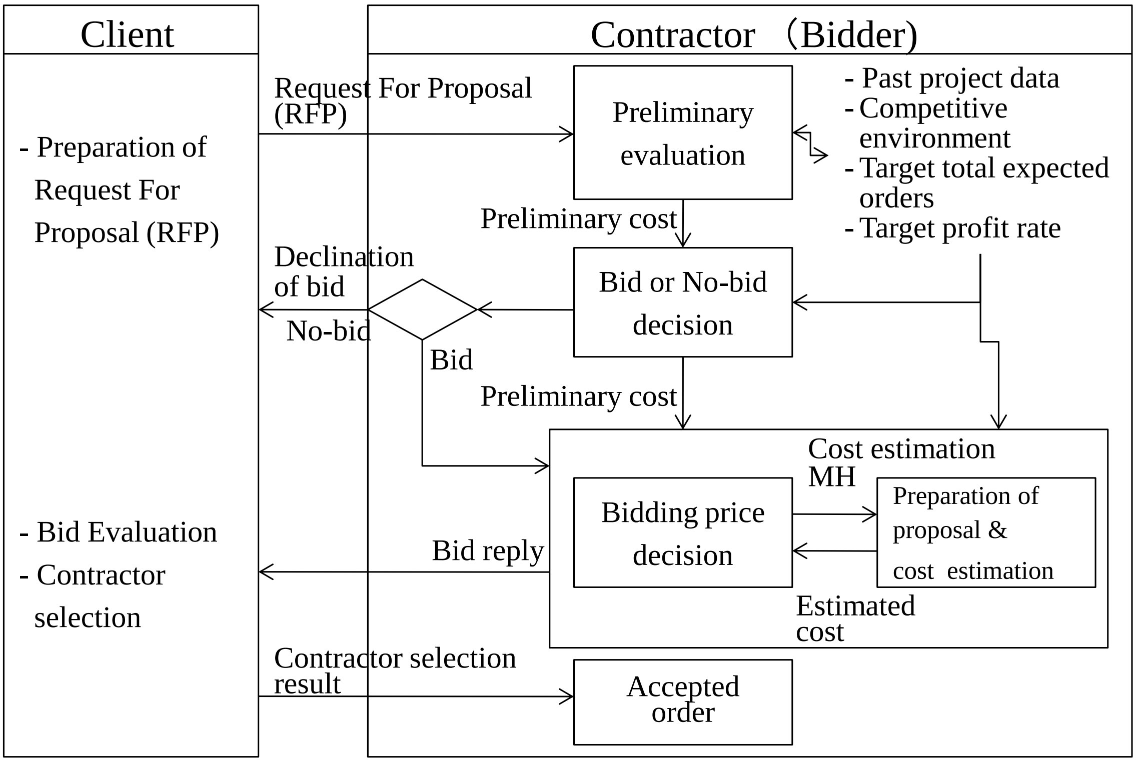

Figure 1 An overview of contractor’s activities of competitive bidding.

As shown in Figure 1, the bidding price decision, for which this paper develops a model in Section 4, is made based on order information, such as preliminary cost, estimated cost, and competitive environment, so that the contractor can accept profit-making orders successfully. 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, can be represented as a probability density function. For example, Figure 2 shows two kinds of probability density functions corresponding to bidding prices with different cost estimation accuracies, where we assume that the bidding prices are normally distributed. We define the cost estimation accuracy as the standard deviation of the estimated cost or the bidding price depending on the probability density function required. A lower deviation indicates a higher accuracy.

As shown in Figure 2, the bidding price with the lower cost estimation accuracy (standard deviation (σ): 8 [MM$]) is more likely to be accepted as the deficit order, from which the contractor accepts the order at a rate less than the actual cost, in comparison to the bidding price with the higher accuracy (standard deviation (σ): 5 [MM$]). The bidding price with the lower 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 effective profit management in ETO manufacturing, and the bidding price decision process model 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, the contractor has more than one order at the same time, and 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 bid performance.

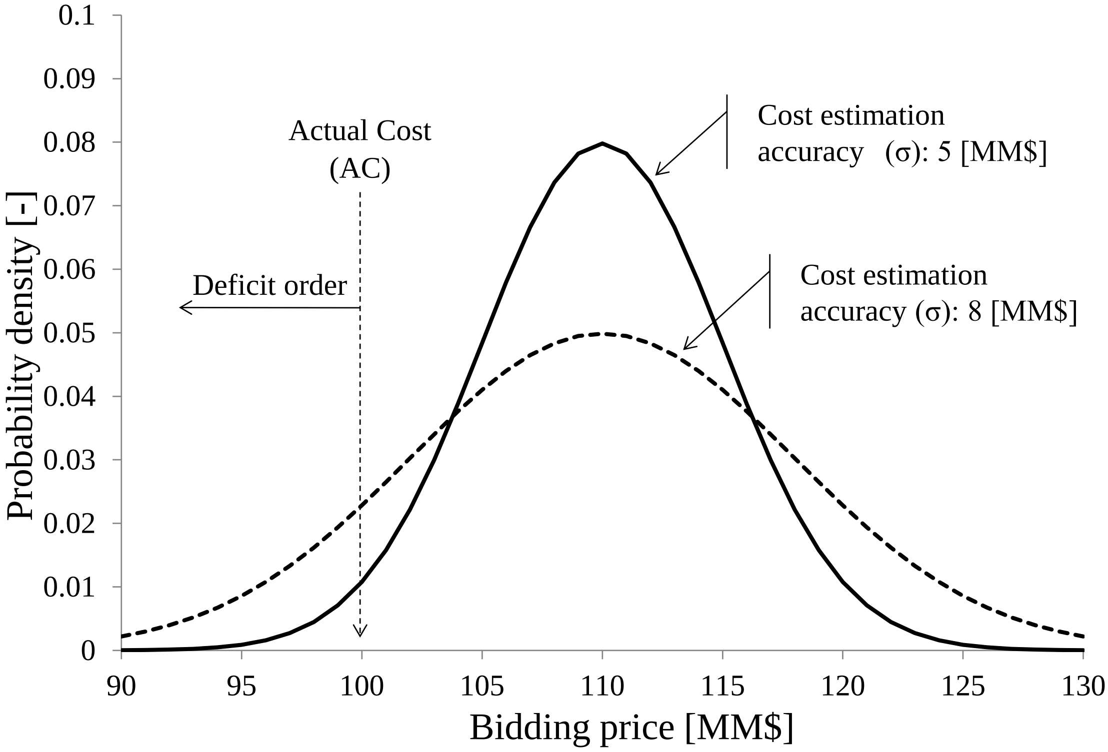

Figure 2 Bidding price distributions with different cost estimation accuracies. (Average bidding price (AC+Profit (10% of AC)): 110 [MM$], Cost estimation accuracy (σ): 5 [MM$] or 8 [MM$])

The third feature is the effectiveness of adjusting the bidding price. Figure 3, for instance, shows bidding price distributions of a contractor (his own company) and that of a competitor. We can also assume that this competitor's distribution is the synthesized one from two or more competitors' distributions. As shown in Figure 3, the contractor's profit (=BP-AC) increases as the bidding price rises. On the other hand, the probability of accepting the order, shown as dashed lines, increases as the bidding price goes down. This is because the contractor can basically accept the order when the contractor's bidding price (BP) is lower than that of the competitor's. 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 which maximizes the contractor's expected profit under a competitive environment.

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

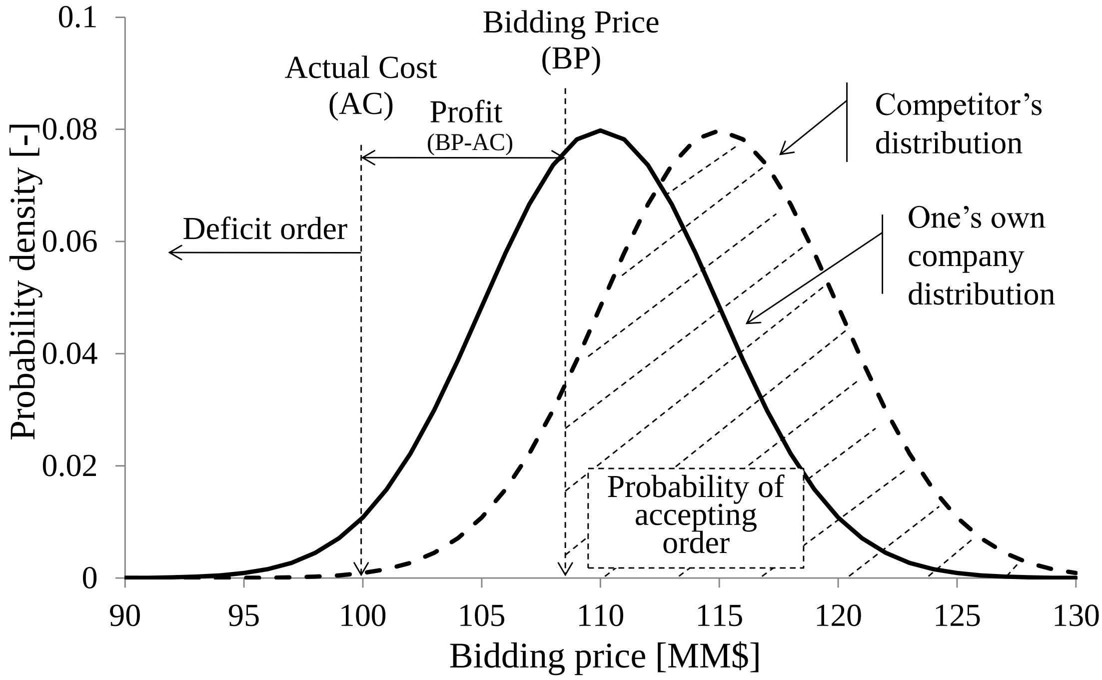

Figure 3 An example of bidding price distributions at competitive bidding. (One's own company: Average bidding price (AC+Profit (10% of AC)): 110 [MM$], Cost estimation accuracy: (σ): 5 [MM$]; Competitor's: Average bidding price: 115 [MM$], Cost estimation accuracy (σ): 5 [MM$])

4. A bidding price decision process model

We have developed a bidding price decision process model, which represents fundamental factors and their interactive processes, to determine the bidding price in ETO manufacturing as shown in Figure 4 based on the observations in the previous section. The model consists of three kinds of factors, i.e., decision processes, constraints, and given conditions. There are seven decision processes, which are depicted as a circular shape, two constraints and four given conditions, which are depicted as a square shape. In addition, the information which flows among those factors indicates interactive processes.

The model enables us to evaluate the bid performance, i.e., 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.

Most of the literature has discussed neither the effects of the cost estimation accuracy associated with cost estimation MH nor the deficit order probability on the expected profits in competitive bidding. Since these factors affect the expected profits as analysed in the previous section, the bidding price decision process model shown in this paper can contribute to the improvement of the contractor’s profit management capability and sustainability in ETO manufacturing.

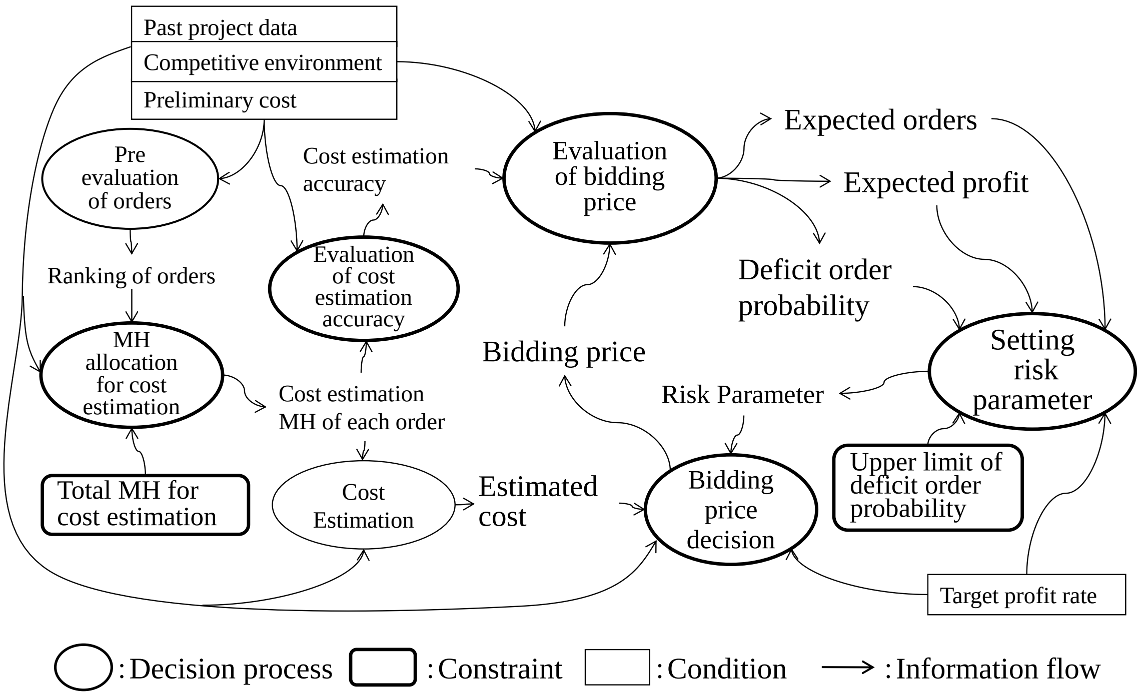

Figure 4 A bidding price decision process model in ETO manufacturing.

4.1 A mathematical model of bidding price decision and evaluation

This section presents mathematical models of the decision processes, i.e., evaluation of cost estimation accuracy and determination of bidding price, in which the risk parameter and the cost estimation MH of each order are decision variables. Other parts of the model are explained along with the bidding price decision procedure discussed in Section 4.2.

(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, Gerrard (2000), Towler & Sinnott (2008) suggest that the cost estimation accuracy is positively correlated with the volume of cost estimation MH. 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 cost estimation MH per order (*PMH*) based on the logistic curve as follows:

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

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.

(2) Evaluation of bidding price

In the sequel, we consider *n* contractors (*k=1,2,…,n*) and the bidding for *L* orders (*i=1,2,…,L*). Particularly, *k=1* represents one's own company, and *k>=2* are those of 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 order 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 lower than *STDR* is set.

$$\int_{0}^{STDR_1^i} p_1(x_1^i, TBP_1^i, \sigma_1^i) \cdot \prod_{k=2}^{n} \int_{x_1^i}^{+\infty} p_k(x_k^i, TBP_k^i, \sigma_k^i) dx_k^i \cdot dx_1^i \qquad (6)$$

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, sales staff, and professional consultants. For example, *STD* can be specified in reference to the preliminary cost, which is calculated before deciding whether to bid or not as shown in Figure 1.

4.2 A bidding price decision procedure

In this section, we develop a bidding price decision procedure, which determines the allocation of cost estimation MH and searches the value of *rp*, for maximizing the expected profit of each order under the deficit order probability constraint.

4.2.1 An overview of the procedure

The procedure is a two-step algorithm as shown in Figure 5; the first step is allocating the MH for cost estimation according to the ranking of orders, and the second step is searching the value of *rp* for profit maximization. The first step is related to the decision processes of the pre evaluation of orders and the MH allocation for cost estimation, and the second step is related to the decision processes of the setting risk parameter and the bidding price decision shown in Figure 4.

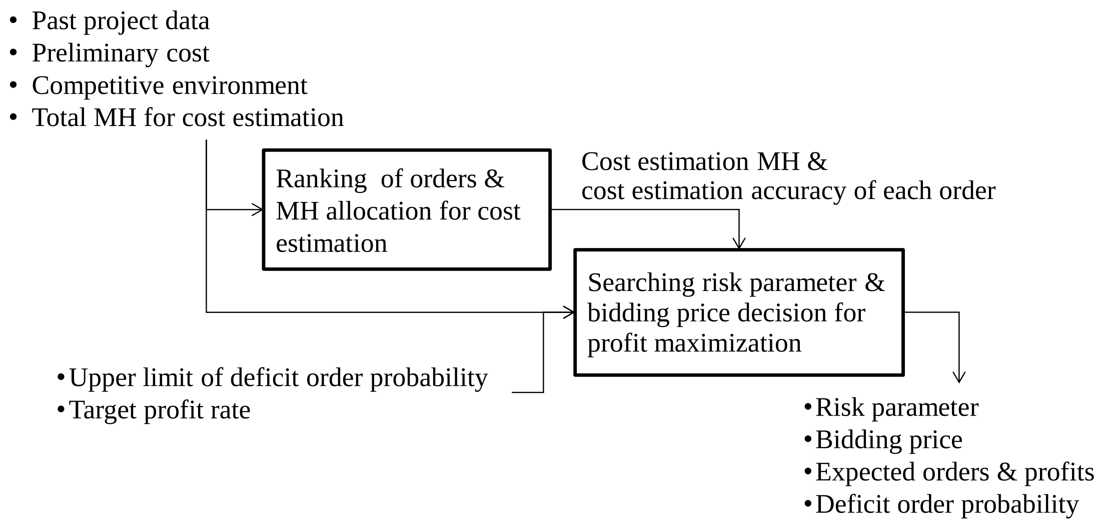

Figure 5 An overview of the procedure.

4.2.2 A procedure for ranking of orders and MH allocation for cost estimation

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 define the ranking score (*Score*) of the order (*i*) as the expected profit based on the tentative bidding price at *rp* =1 (*TBPF*) as follows:

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

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

In the following MH allocation procedure, the order with the high *Score* is ranked high because it is expected that such an order generates 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: Set the range of allowable total MH for cost estimation, and set the accuracy level from (σ_{min}, σ_{max}) to each grade; A (high accuracy), B (average), and C (low accuracy).

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

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

4.2.3 A procedure for searching a risk parameter 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 $$\sum_{i=1}^{L}\int_0^{+\infty}(x_1^i - STDR_1^i)\cdot p_1(x_1^i, TBP_1^i, \sigma_1^i)\cdot\prod_{k=2}^{n}\int_{x_1^i}^{+\infty} p_k(x_k^i, TBP_k^i, \sigma_k^i)dx_k^i \cdot dx_1^i \quad (9)$$

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

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

$$(i=1,2,\ldots.L) \quad (11)$$

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) shows 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,…,L*). As a result, *rp* of one's own company (*k=1*) is the single decision variable of each problem. Since the purpose of this paper is to analyse the characteristics of ETO manufacturing, 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 1, is the estimated cost that is calculated by the allocated MH after the bid or no-bid decision.

5. Numerical examples

In this chapter, we analyse and discuss the characteristics of the bidding price decision process in ETO manufacturing based on the numerical examples from the following perspectives; relations between cost estimation accuracy and expected profit, effectiveness of bidding price adjustment, effect of the upper limit constraint of the deficit order probability, and importance of ranking of orders.

5.1 Problem setting

(1) Setting of cases

In this paper, we use the cases shown in Table 1 for numerical examples. We set other parameter values through all the cases as follows: $rp_k^i = 1.0$ ($k >= 2$), $RC_k^i = 0.0$ ($k >= 2$), $rprob_i = 1.0$, 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].

Table 1 Cases for numerical examples.

Case	rp_1^i	σ_k^i (k>=2)	RC_1^i
Base Case 0	1.0	8% of STD_i	0.0
Base Case 1	To be searched	8% of STD_i	0.0
Case 2	To be searched	6% of STD_i	0.0
Case 3	To be searched	10% of STD_i	0.0
Case 4	To be searched	8% of STD_i	-0.05
Case 5	To be searched	8% of STD_i	+0.05

(2) Setting of orders

In this paper, 16 orders are considered 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.

Table 2 Conditions of orders.

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

5.2 Results of numerical calculations

(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 ETO manufacturing. However, there is usually a limit to the available MH for cost estimation. Thus we can conclude that an effective mechanism to allocate the cost estimation MH for each order is necessary in the bidding price decision process.

(2) Cost competitiveness and expected profit

As shown in Table 3, cost competiveness against competitors has a large effect on the expected profits. The expected profits in Base Case 1 are more than three times larger than those in Case 5 ($RC_1^i = +0.05$), and less than half of those in Case 4 ($RC_1^i = -0.05$). That is, a twofold profit can be gained by improving cost competitiveness by 5%, and by decreasing cost competitiveness by 5%, the profit is less than a third. Namely, we can say that the cost competitiveness against competitors is critical in ETO manufacturing in order to increase expected profits.

Table 3 Total expected orders (Eq. (3)) and total expected profits (Eq. (4)).

	The Range of Allowable Total MH for Cost Estimation [M MH]			
	70-80	80-90	90-100	100-110
Base Case 0	Case 0.A	Case 0.B	Case 0.C	Case 0.D
Total Expected Orders [MM$]	1858.2	1817.9	1823.3	1809.0
Total Expected Profits [MM$]	28.6	46.3	51.7	61.5
Base Case 1	Case 1.A	Case 1.B	Case 1.C	Case 1.D
Total Expected Orders [MM$]	1141.6	1238.1	1269.5	1357.2
Total Expected Profits [MM$]	53.3	56.4	60.9	69.1
Case 2	Case 2.A	Case 2.B	Case 2.C	Case 2.D
Total Expected Orders [MM$]	1275.2	1395.2	1437.6	1547.3
Total Expected Profits [MM$]	48.0	51.3	56.3	65.5
Case 3	Case 3.A	Case 3.B	Case 3.C	Case 3.D
Total Expected Orders [MM$]	1061.6	1143.7	1168.1	1236.6
Total Expected Profits [MM$]	60.2	63.5	67.5	74.8
Case 4	Case 4.A	Case 4.B	Case 4.C	Case 4.D
Total Expected Orders [MM$]	2078.3	2100.1	2190.9	2239.0
Total Expected Profits [MM$]	136.5	137.8	151.2	157.6
Case 5	Case 5.A	Case 5.B	Case 5.C	Case 5.D
Total Expected Orders [MM$]	452.4	487.0	493.6	553.8
Total Expected Profits [MM$]	16.3	17.0	17.2	22.4

(3) Effectiveness of bidding price adjustment by risk parameter

Based on the results of Base Case 0 and Base 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 Base Case 1, and the value of *rp* is fixed in Base Case 0.

As shown in Table 3, there is a significant difference in the expected profits between Base Case 0 and Base 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 Base 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.

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 Cases 0.A, and between 0.777% and 5.81% in Base Case 1.A. In Case 0.A, the 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. However, in Case 1.A, the bidding price adjustment decreases the deficit order probabilities of these orders and improves the expected profits as shown in Table 5.

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 the table, as the competitors' cost estimation accuracy increases, the value of *rp* searched for by the procedure decreases and the deficit order probability of each order increases. We suppose that 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 6 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 7 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 6 shows that the expected order decreases as the value of *rp* increases. However, from Figures 6 and 7 we see the value of *rp* which maximizes the expected profit. Furthermore, Figure 7 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
Base Case 0	Case 0.A 11.0-25.8	Case 0.B 11.0-12.1	Case 0.C 3.20-12.1	Case 0.D 2.98-12.1
Base Case 1	Case 1.A 0.777-5.81	Case 1.B 4.33-5.81	Case 1.C 1.77-5.81	Case 1.D 1.77-5.81
Case 2	Case 2.A 0.847-7.1	Case 2.B 5.44-7.12	Case 2.C 3.02-7.12	Case 2.D 3.02-7.12
Case 3	Case 3.A 0.808-4.73	Case 3.B 3.63-4.73	Case 3.C 0.947-4.73	Case 3.D 0.947-4.73
Case 4	Case 4.A 4.04-7.20	Case 4.B 4.40-7.20	Case 4.C 0.719-7.20	Case 4.D 0.719-7.20
Case 5	Case 5.A 0.216-4.84	Case 5.B 0.216-4.84	Case 5.C 0.897-4.84	Case 5.D 0.897-4.84

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

Order id (i)	Case 0.A rp_1^i	Case 0.A *EP* [MM$]	Case 0.A *DOP* [%]	Case 1.A rp_1^i	Case 1.A *EP* [MM$]	Case 1.A *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

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 rp_1^i	Case 2.B *EP* [MM$]	Case 2.B *DOP* [%]	Case 1.B rp_1^i	Case 1.B *EP* [MM$]	Case 1.B *DOP* [%]	Case 3.B rp_1^i	Case 3.B *EP* [MM$]	Case 3.B *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

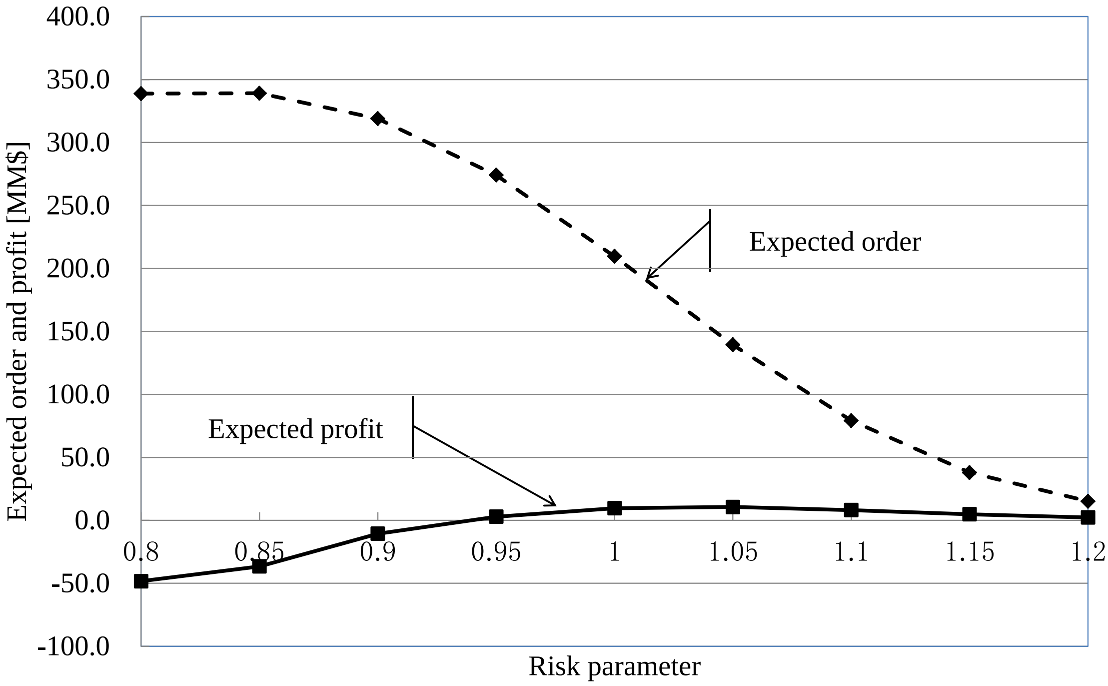

Figure 6 Relations among expected order, expected profit, and risk parameter. (Case 1.B; Order id = 10)

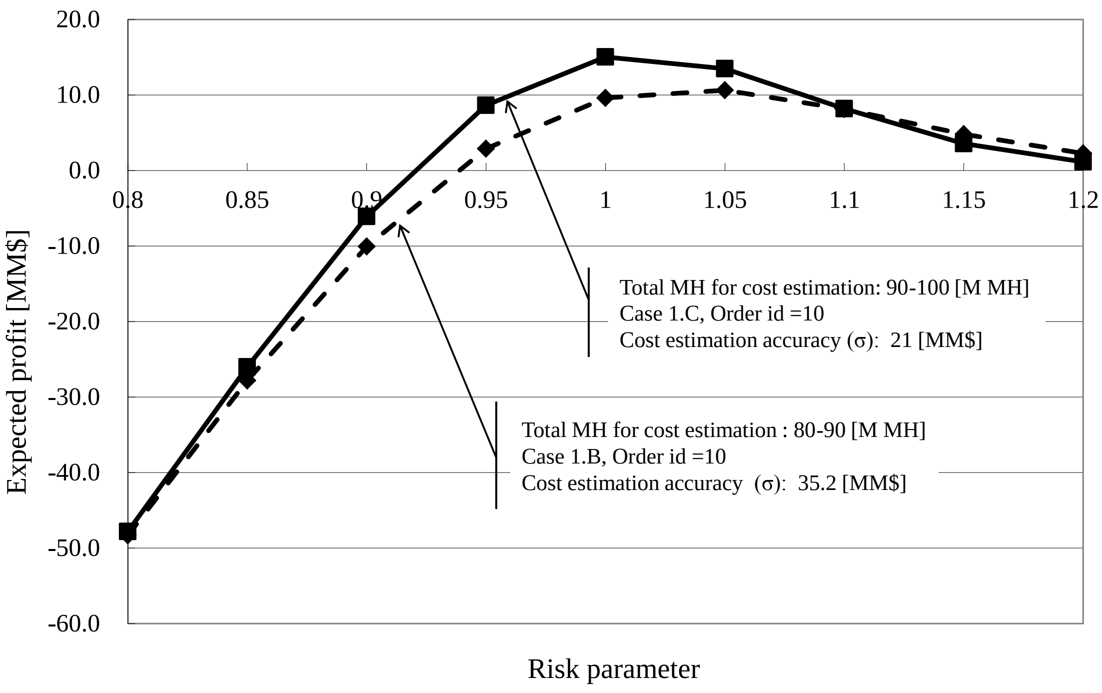

Figure 7 Relations among expected profit, total MH for cost estimation, and risk parameter. (Case 1.B, Order id =10, Total MH for cost estimation: 80-90 [M MH]; and Case 1.C, Order id =10, Total MH for cost estimation 90-100 [M MH])

(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 8 depicts the relation of the upper limit of the deficit order probability and the total expected profit in Base Case 1. 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 Figure 8, the small upper limit of the deficit order probability decreases the total expected profit, however, 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 project involves a substantial risk. Our framework developed for ETO manufacturing will certainly be helpful for any contractor.

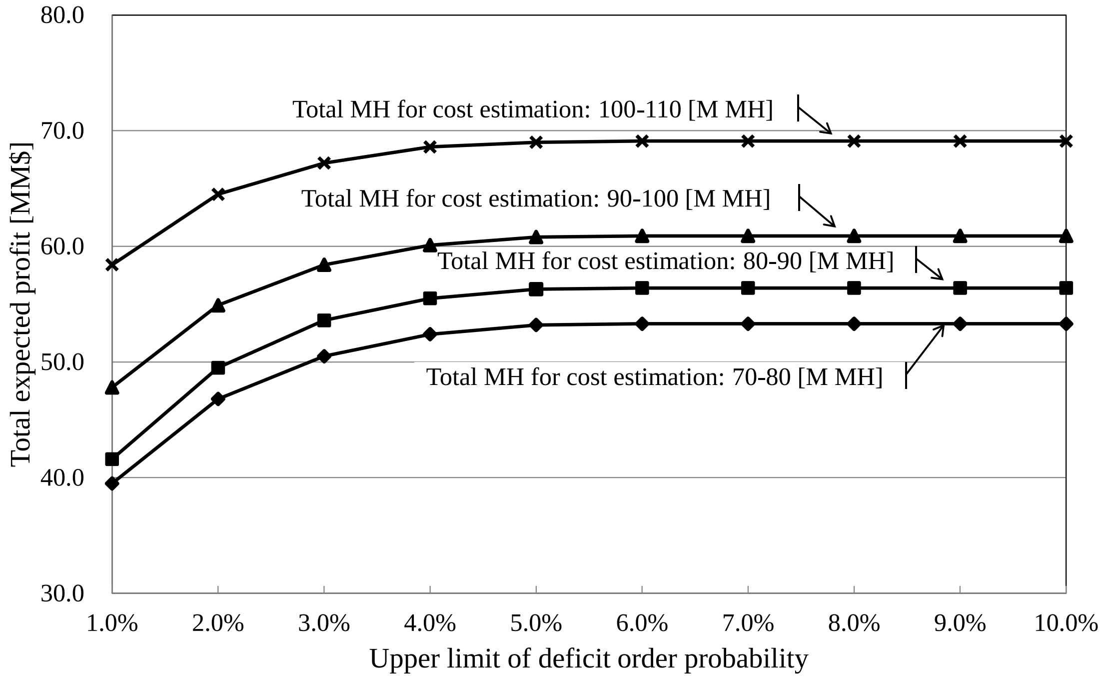

Figure 8 Relations among expected profits, total MH for cost estimation, and upper limit of deficit order probability (Base Case 1)

(5) Importance of ranking of orders and MH allocation for cost estimation

We evaluate the effect of the ranking of orders in Base Case 0 by comparing the profits obtained by the procedure shown in section 4.2.2 with those of 100 different kinds of ranking of orders randomly generated. The results of the calculations are shown in Table 7, in which we show the sum of expected profits of high-ranked orders accounting for the expected orders of 1,000 [MM$]. The contractor generally sets a limit to the expected orders when selecting profit-making orders for which he bids. Moreover, the comparison of high-ranked orders, which account for the same level of expected orders, makes clear the difference between the rankings of orders.

As shown in Table 7, the ranking of orders significantly affects the expected profits. For instance, the maximum expected profits are about twice as much as those of the minimum expected profits in all the cases. Since the MH allocation for cost estimation by the procedure depends on the ranking of orders, we can say that the ranking of orders and MH allocation for cost estimation are critical to improve the expected profits in ETO manufacturing.

In addition, the expected profits by the procedure are 4th or better among randomly generated ranking of orders as shown in Table 7. We can conclude that the procedure for the ranking of orders shown in the previous section is effective enough to analyse the bidding price decision in ETO manufacturing.

Table 7 Comparison of expected profits by ranking of orders (Base Case 0). (The sum of expected profits of high-ranked orders accounting for the expected orders of 1,000 [MM$] is shown.)

		The range of allowable total MH for cost estimation [M MH]			
		70-80	80-90	90-100	100-110
Expected profit by the procedure		36.5	36.5	39.4	51.7
Expected profit by random ranking of orders	Maximum	36.6	34.7	40.3	49.7
	Minimum	16.3	18.4	25.0	26.9
	Average	26.9	26.9	32.2	39.0
Rank of profit over 100 random ranking of orders		2nd	1st	4th	1st

6. Summary and Conclusions

In this paper, we explain the necessity of a bidding price decision process in consideration of cost estimation accuracy and deficit order probability in ETO manufacturing. We develop a bidding price decision process model which represents fundamental factors and their interactive processes to determine the bidding price. Based on the model, we develop a procedure to allocate cost estimation MH to each order, and determine the bidding price of each order by adjusting the price to maximize the expected profit under the deficit order probability constraint.

Through the analysis of the numerical examples by performing our procedure, we conclude that the bidding price decision process in consideration of cost estimation accuracy and deficit order probability is essential for the contractor to make a stable profit and ensure sustainability in ETO manufacturing.

In addition, the numerical examples show that factors and their interactive processes included in the model represent the characteristics of the competitive bidding enough to use the model for the profit management in ETO manufacturing. For example, the model can analyse how cost estimation accuracy and cost competitiveness affect the expected profit, and how risk parameter (*rp*) works to maximize the expected profit under the deficit order probability constraints. The model can also analyse the relations between the total MH for cost estimation and the expected profits. Furthermore, the model represents cross-organizational activities in ETO manufacturing. Thus the model is useful as a reference for the contractor to analyse and design his bidding price decision process from a global optimization point of view.

There are several further directions of this study. For example, it will be necessary to develop a procedure which searches the MH allocation and the *rp* values simultaneously for determining a global optimum solution. In addition, the procedure which modifies the MH allocation and searches the *rp* values dynamically in response to the arrival of new orders will be required for applying the model to generalized situations in practice.

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