A Dynamic Scheduling Problem in Cost Estimation Process of EPC Projects

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Abstract: The cost estimation process, carried out by the contractor before the start of a project, is a critical activity for the contractor in accepting profitable EPC projects in competitive bidding situations. Thus, the contractor should devote significant time and resources to the accurate cost estimation of project orders from clients. However, it is impossible for any contractor to devote enough time and resources to all the orders because such resources are usually limited. For this reason, the contractor must dynamically decide bid or no-bid on the orders at each order arrival, and allocate the limited resources to the chosen orders. To maximize the contractor's profits, this study devises a heuristic scheduling method for dynamically selecting orders and allocating the limited resources to them, on the basis of the resource requirement of the order, the contractor's resource utilization, and the expected profit from the order. The effectiveness of our method is demonstrated through simulation experiments using a project cost estimation process model.

1 INTRODUCTION

In EPC (Engineering, Procurement, Construction) projects (Pritchard and Scriven, 2011), the contractor delivers unique facilities, such as process plants, structures, information systems, and so on, based on the client's requirements for a limited period of time under a lump sum turnkey basis. Since any EPC project includes unique and non-repetitive activities, many uncertainties exist in the project execution process. Furthermore, since the project price is fixed before the start of the project, the contractor often faces eventual loss in EPC projects. Thus, it is necessary for any contractor to precisely estimate the project cost in order to determine the bidding price. Namely, cost estimation in an EPC project is a critical task for any contractor who seeks to increase profits and reduce the possibility of realizing a loss, i.e., deficit risk, due to cost estimation error.

Cost estimation is also crucial for ensuring the stable profits and the proper volume of accepted orders. Inaccurate cost estimation could not only lead to deficit orders but could also exhaust the contractor's resources, which are necessary to carry out long-term deficit projects, as Ishii et al. (2014) stated. Moreover, a deficit order would have severely harmful effects on the client's business. For example, it would generate an additional cost and/or delay the project delivery date. Cost estimation, however, is a complex task of predicting the costs and schedule of projects based on the analysis of the client's requirements with limited data and time.

Since the quality and quantity of the data available for cost estimation determine the accuracy of estimated cost, a lot of high-quality data is required to improve accuracy. In the process plant engineering, for example, the data and methods that are required to attain the target accuracy of project cost estimation have been studied (AACE International, 2011). In any cost estimation method, such as parametric, analogy, and engineering (Kerzner, 2013), higher accuracy needs more data and, accordingly, requires more engineering Man-Hours (hereafter referred to as MH) to acquire and analyse the data for cost estimation.

Thus, experienced and skilled human resources who can acquire data for cost estimation and create project plans, including uncertainties during the project execution, are required for accurate cost estimation. Those resources are limited for any contractor; furthermore, once the orders are successfully accepted, the corresponding project execution will also need considerable human

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resources. For these reasons, the contractor should realize appropriate allocation of MH for cost estimation to each order to maximize the total expected profit under the constraint of the total MH. The contractor should also 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 produce an eventual loss due to cost estimation error, would result in a significant reduction of contractor's profits when the number of accepted orders is small.

This paper examines the cost estimation process of EPC projects in dynamic order arrival situations based on the previous study by Ishii et al. (2015 (b)). Namely, we develop a heuristic method that dynamically selects orders and allocates MH for cost estimation to each selected order to maximize the expected profits. For this purpose, we begin by building a cost estimation process model, where the cost estimation process is divided into four phases, i.e., order selection, Class 4 estimate, Class 3 estimate, and Class 2 estimate, based on the AACE cost estimate classification system (AACE, 2011) that indicates the methods, data, and the accuracy of cost estimation in each class. We next establish the order selection rules for deciding bid or no-bid on arrived orders based on the threshold function of MH utilization with respect to the expected profit of orders. This threshold function is created through simulation experiments using our cost estimation process model. We finally analyse the effectiveness of our simulation-based heuristic method through numerical examples.

2 RELATED WORK

A variety of studies have been conducted on project cost estimation from the viewpoints of cost estimation accuracy, resource allocation, order selection, and so on.

For example, Oberlender and Trost (2001) studied determinants of cost estimation accuracy and developed a system for predicting accuracy. Bertisen and Davis (2008) analysed the costs of 63 projects and evaluated the accuracy of estimated costs statistically. Jørgensen et al. (2012) studied the relationship between project size and cost estimation accuracy. Uzzafer (2013) proposed a contingency estimation model in consideration of the distribution of estimated cost and the risk of software projects to estimate contingency resources.

In addition, AACE International (2011), Humphreys (2004), and Towler and Sinnott (2008) demonstrated the relationship in cost estimation accuracy and the method and data used for cost estimation in the field of process plant engineering projects. Furthermore, they suggested that cost estimation accuracy is positively correlated with the volume of MH for cost estimation.

Regarding the volume of MH for cost estimation and cost estimation accuracy, Ishii et al. (2015 (a)) developed an algorithm that determines the bidding prices under the limited MH for cost estimation. Their algorithm allocates MH so as to maximize expected profits based on the cost estimation accuracy determined by allocated MH. In addition, Takano et al. (2014) developed a stochastic dynamic programming model for establishing an optimal sequential bidding strategy in a competitive bidding situation. Their model determines the optimal markup in consideration of the effect of inaccurate cost estimates. Furthermore, Takano et al. (in press) developed a multi-period resource allocation method for estimating project costs in a sequential competitive bidding situation. Their method allocates resources for cost estimation by solving a mixed integer programming problem that is formulated by making a piecewise liner approximation of the expected profit functions.

Regarding the order selection in the cost estimation process, Shafahi and Haghani (2014) propose an optimization model that combines project selection decisions and markup selection decisions in consideration of eminence and previous works as the non-monetary evaluation criterion used by owners for evaluating bids.

Based on the above literature review, we found that most of the studies have paid little attention to the project cost estimation process in practical situations. More specifically, the contractor needs to allocate MH for cost estimation dynamically to each arrived orders with different attributes in practice. To the best of our knowledge, however, none of the existing studies have investigated the project cost estimation process in dynamic order arrival situations. In light of these facts, this paper develops a heuristic scheduling method for selecting orders and determining MH allocation dynamically in consideration of the contractor's available MH and the orders' profitability.

3 A MODEL OF PROJECT COST ESTIMATION PROCESS

The project cost estimation process can be recognized as a series of activities that starts with the arrival of bid invitations and closes by the date of bidding. A variety of orders arrive, and the cost of projects is estimated through the project cost estimation process. We decide the accuracy of cost estimation by allocating MH to the cost estimation activities of newly arrived orders in consideration of the MH availability, expected profits, competitive bidding situations, and so on. When the available MH is not enough to estimate cost accurately, we must allocate less MH, thereby reducing expected profit due to inaccurate cost estimation, or no-bid on the order.

Based on the above observations, we propose a project cost estimation process model as shown in Figure 1 (Ishii et al. 2015 (b)). In the model, we assume that the cost is estimated through three classes: Class 4, Class 3, and Class 2 estimate. Each class needs MH and a period of time for cost estimation, and the accuracy of estimated cost increases through the cost estimation activities in each estimate class. The cost estimate classification matrix (AACE, 2011) can be used as the cost estimation accuracy in each class.

In the model, the order selection mechanism decides whether to bid the newly arrived order or not from the viewpoint of the volume of orders to be accepted, the expected profits, MH availability for cost estimation, and so on. The selected order is first filed in the queue for the Class 4 estimate and waits to be assigned the MH for cost estimation by the mechanism of MH allocation for cost estimation. If any MH is not assigned to the order until the bidding date, the contractor does not bid for it due to the lack of MH. If the MH is assigned to the order, its project cost is estimated with the accuracy of the Class 4 estimate. This order is then filed in the queue of the Class 3 estimate and waits for MH assignment for the Class 3 estimate. If the MH is not further assigned to the order until the bidding date, the contractor decides the bidding price based on the accuracy of the Class 4 estimate. By contrast, if the MH is assigned to the order waiting in the queue of the Class 3 estimate, its project cost is estimated with the accuracy of the Class 3 estimate, and filed in the queue of the Class 2 estimate. The same decision is made for the orders in the queue of the Class 2 estimate.

The project cost estimation problem, addressed in this paper, is a kind of dynamic scheduling problem that determines the processes dynamically for each order arriving at a system. In our problem, however, the quality of the deliverables, i.e. accuracy of cost estimation of each order, are determined dynamically under the conditions of resource availability and due date of the order so as to maximize the total profits. On the contrary, in the standard scheduling problems (Jacobs et al. 2011), the quality of the deliverables are predetermined and orders are scheduled so as to minimize the makespan. From this perspective, the project cost estimation problem in this study can be recognized as a new dynamic scheduling problem.

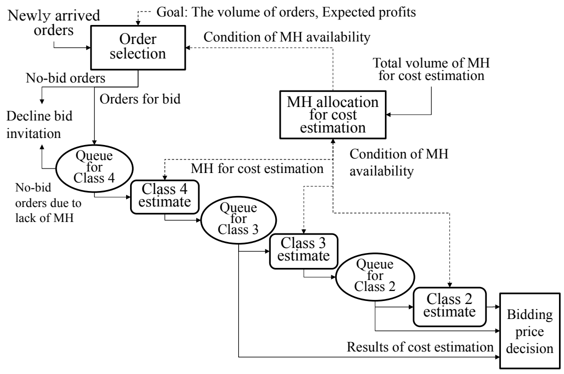

Figure 1: A project cost estimation process model.

4 HEURISTIC METHOD

This section shows a heuristic scheduling method based on the project cost estimation process shown in Figure 1. The heuristic method consists of two mechanisms, i.e. order selection, and MH allocation for cost estimation. The order selection mechanism selects orders for cost estimation based on order selection rules. The MH allocation mechanism assigns the MH for cost estimation to each selected order, so as to maximize the expected profits from orders.

Our heuristic method is developed based on the following assumptions:

Assumptions:

1) Orders for cost estimation arrive randomly;
2) Expected profit, required MH and periods for cost estimation of each estimate class are predetermined;
3) Probability of a successful bid of each order is predetermined.

Since EPC contractors can collect their own data on past projects and market situations, the assumptions 2) and 3) are appropriate.

4.1 Order Selection Mechanism

(1) Order selection method

The order selection method is based on the financial evaluation criteria and consists of the following two steps:

Step 1: Calculate the expected profit per MH for cost estimation of the new arrival order *i* as follows:

$$EPPC_i = EP_i \;/ EM_i \qquad (1)$$

where $EPPC_i$ is the expected profit per MH for cost estimation of order *i*, EP_i is the expected profit of order *i*, and EM_i is the volume of MH required to estimate the cost of order *i*. In this paper, $EPPC_i$ is calculated based on the Class 2 estimate in AACE cost estimate class (AACE, 2011).

Step 2: Make the bid/no-bid decision on the new arrival order by considering $EPPC_i$ of the order and the contractor's *MHU*, which is the volume of MH being utilized for cost estimation at the time of new order arrival. For this purpose, we use a threshold function $MHU_{up}(EPPC_i)$, which indicates the upper limit of *MHU* in selecting order *i* for cost estimation, as follows:

- The contractor selects the new arrival order *i* for cost estimation if *MHU* is lower than $MHU_{up}(EPPC_i)$;
- Otherwise, the contractor decides not to bid on the order.

The contractor can expect higher profits from the order by estimating its project cost in a higher cost estimate class. However, more MH is required for estimating cost in a higher cost estimate class. In the above steps, the new arrival orders with low expected profits are not selected for cost estimation when large volume of MH is being utilized for cost estimation. This order selection method eliminates a possible shortage of MH for cost estimation and, accordingly, allows the contractor to focus on estimating cost of profitable orders. In other words, our order selection method works to maintain the balance between order's profitability and contractor's MH utilization so that the contractor's expected profits are maximized in dynamic order arrival situations.

(2) Determination of threshold function

In our model, orders with different attributes arrive randomly in a project cost estimation process. Thus the MH utilization changes dynamically and unpredictably. Consequently, it is very difficult to find a threshold function $MHU_{up}(EPPC_i)$ for maximizing contractor's expected profits.

In view of these observations, we develop a simulation-based heuristic method by using the simulation model shown in Figure 1. This method searches three threshold points, P1(E_1, N_1), P2(E_2, N_2) and P3(E_3, N_3), sequentially by applying them in the order selection mechanism. As shown in Figure 2, the no-bid area is expressed as follows:

$$U_{k=1}^{3}\{(EPPC, MHU) \mid EPPC \le E_k, MHU \ge N_k\} \qquad (2)$$

The threshold function $MHU_{up}(EPPC_i)$ marks the boundary between the no-bid area and cost estimation area. The procedure of the simulation based method is described as follows:

Step 1: Set all the threshold points to (0, 0).

Step 2: Search P2(E_2, N_2) that maximizes the expected profit by running a simulation under the current conditions, i.e., order arrival interval, cost estimation period and required MH in each class of cost estimate, and expected profit of each order.

Step 3: Search P1(E_1, N_1) that maximizes the expected profit by running a simulation, where P2(E_2, N_2) is fixed to the value searched in Step 2.

Step 4: Search P3(E_3, N_3) that maximizes the expected profit by running a simulation, where P1(E_1, N_1) and P2(E_2, N_2) are fixed to the values searched in Steps 2 and 3.

Step 5: Define $MHU_{up}(EPPC_i)$ as the boundary formed by P1(E_1, N_1), P2(E_2, N_2) and P3(E_3, N_3) as shown in Figure 2.

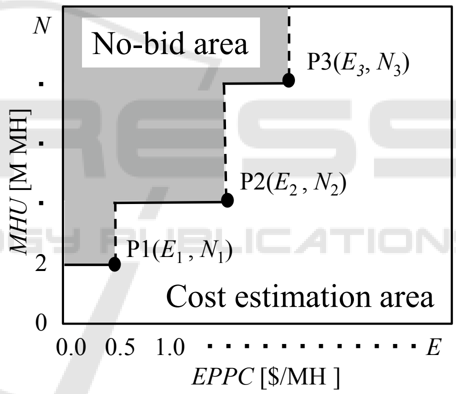

Figure 2: Area of bid/no-bid decision.

4.2 Allocation of MH for Cost Estimation

For the allocation of MH for cost estimation, we shall use a dispatching approach, as is the case with the dynamic scheduling problem in production systems (Jacobs et al. 2011).

Specifically, when MH is released from cost estimation of an order, this approach selects an order based on the dispatching rules, which prioritize orders in the queue of each estimate class. The selected order is subsequently assigned the required MH for its estimate class. If the required MH is more than the MH available, the selected order waits in the queue until the required MH is released.

One can use well-known dispatching rules for the allocation of MH, such as FIFO, SPT, and EDD (Jacobs et al. 2011). In addition, dedicated rules for a project cost estimation process can also be designed.

5 NUMERICAL EXAMPLES

This section evaluates the effectiveness of our simulation-based heuristic scheduling method. For the simulation experiments, we use a general-purpose simulation system AweSim! (Pritsker and O'Reilly, 1998).

5.1 Design of Simulation Experiments

To determine the threshold function MHU_{up} ($EPPC_i$), we use the scenario selection system developed by Nelson et al. (2001). This system statistically compares the results of simulation and chooses sequentially the best threshold points P2(E_2, N_2), P3(E_3, N_3), P1(E_1, N_1) from candidate points given by us. The volume of MH is set to 16,000 MH per period, i.e., 16 [M MH], and the simulation period is set to 1200.

It is supposed that there are orders of the three sizes, i.e., Small, Medium, Large, in our simulation experiments. For these orders, we consider three cases—Case 1, Case 2, and Case 3—that have different expected profit of the Class 3 estimate, as shown in Table 1. In addition, we consider three sub-cases—Case A, Case B, and Case C—based on the order arrival intervals defined by the triangular distribution, as shown in Table 2. In what follows, Case 1.A means that Case 1 and Case A are considered. Table 3 shows parameters of triangular distribution that represents the probability of order acceptance in each order size. It follows that by bidding for an order, the expected profit shown in Table 1 is gained with the associated probability of order acceptance. Table 4 shows cost estimation conditions of each cost estimate class, i.e., total periods available for cost estimation (due date for bidding), required periods for cost estimation, and required MH for cost estimation.

Our simulation experiments evaluated each case by using the following order selection rules and dispatching rules:

1) Order selection rule

No selection: All the arrived orders are selected for cost estimation.

MHU basis: Orders are selected for cost estimation by the heuristic method described in Section 4.

2) Dispatching rule for allocating MH for cost estimation

FIFO: Orders are selected for allocating MH on a first-in first-out basis.

HEPF: Order of the largest increment of *EPPC* is selected first for allocating MH.

Table 1: Expected profit of orders (All cases) [MM$].

		Order size		
		Small	Medium	Large
Case 1	Class 4	0.5	1	1.5
	Class 3	5	10	15
	Class 2	20	40	60
Case 2	Class 4	0.5	1	1.5
	Class 3	10	20	30
	Class 2	20	40	60
Case 3	Class 4	0.5	1	1.5
	Class 3	15	30	45
	Class 2	20	40	60

Table 2: Order arrival interval [Orders/Period].

	Parameters of triangular distribution	Order size		
		Small	Medium	Large
Case A	Min.	1.05	2.70	3.15
	Mode	1.50	3.00	4.50
	Max.	1.95	3.90	5.85
Case B	Min.	0.84	1.68	2.52
	Mode	1.20	2.40	3.60
	Max	1.56	3.12	4.68
Case C	Min.	0.70	1.40	2.10
	Mode	1.00	2.00	3.00
	Max	1.30	2.60	3.90

Table 3: Probability of order acceptance (All cases).

		Order size		
		Small	Medium	Large
Parameters of triangular distribution	Min.	0.05	0.05	0.05
	Mode	0.20	0.30	0.40
	Max.	0.90	0.90	0.90

Table 4: Cost estimation conditions (All cases).

		Order size		
		Small	Medium	Large
Total periods available for cost estimation		8	8	8
Periods for cost estimation	Class 4	1	1	1
	Class 3	2	2	2
	Class 2	3	3	3
MH for cost estimation [M MH]	Class 4	1	2	3
	Class 3	2	3	4
	Class 2	3	4	6

5.2 Results of Simulation Experiments

Figures 3, 4, and 5 depict the threshold function

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$MHU_{up}(EPPC_i)$ together with the threshold points P1(E_1, N_1), P2(E_2, N_2) and P3(E_3, N_3) determined by our simulation-based heuristic method for Cases 1.A, 1.B, and 1.C, respectively. For example, the arrived order with 0.8 *EPPC* and 10 *MHU* is the one for the cost estimation in Case 1.A, however, not the one for the cost estimation in Cases 1.B and 1.C.

We can see in the figures that the no-bid area becomes wider according to the increase of the number of arrived orders in the cost estimation process. Indeed, Case 1.C, where orders arrive most frequently among all cases, has the widest no-bid area.

It is also found from the figures that in making bid/no-bid decisions, Case 1.C puts a high priority on the order's expected profit, whereas Case 1.A takes into account both the order's expected profit and the contractor's MH utilization. This implies that contractors should pay attention to its MH utilization for cost estimation especially when the number of arrival orders is limited.

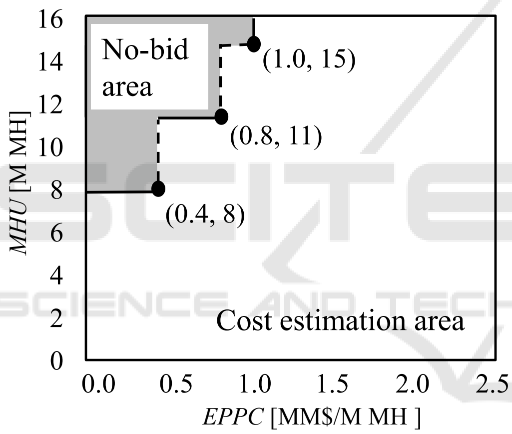

Figure 3: Area of bid/no-bid decision in Case 1.A.

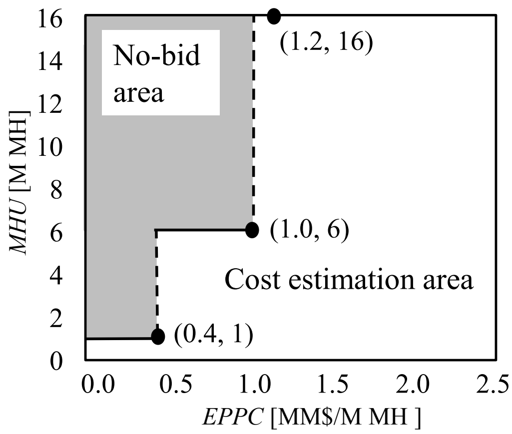

Figure 4: Area of bid/no-bid decision in Case 1.B.

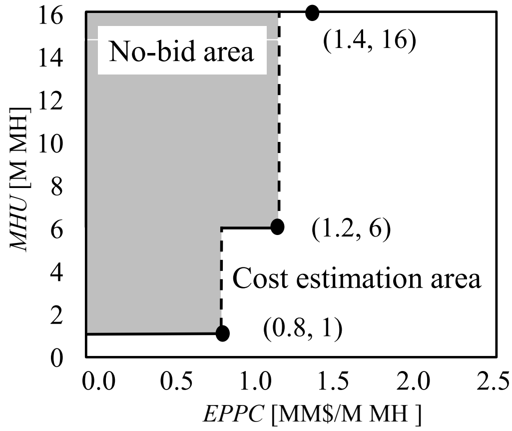

Figure 5: Area of bid/no-bid decision in Case 1.C.

Figures 6, 7, and 8 show the expected profits of each combination of order selectin rules and MH allocation rules. Regarding the order selection rule, the MHU basis rule gains larger expected profits than the no selection rule does. For example, in Case 1.C, the expected profit by MHU basis HEPF is 167 [MM$], and that by no selectin HEPF is 111 [MM$]. In addition, the improvement in the expected profits by the MHU basis rule increases according to the increase of the number of arrived orders in the project cost estimation process. In fact, the ratio of improvement in the expected profits by MHU basis HEPF is about 22%, 34%, and 50% against the no section rule, in Cases 1.A, 1.B and 1.C, respectively.

On the other hand, as shown in Figure 8, the effects of the MHU basis rule on the expected profits are very small in Case 3. The main reason is that in Case 3, the expected profits of the Class 3 estimate are close to those of the Class 2 estimate as shown in Table 1. No selection rules allocate MH for cost estimation evenly to all the orders and, accordingly, increase the number of Class 3 estimates. As a result, this rule works well only in Case 3. By contrast, the MHU basis rules make bid/no-bid decisions based on the threshold functions as shown in Figures 3-5, and thus, they work effectively in all the cases.

Regarding the dispatching rules for allocating MH, HEPF rules perform slightly better than FIFO rules. However, they make no significant difference in the expected profits, especially when the MHU basis rule is used for order selection.

Tables 5, 6, and 7 show the ratio of cost estimate class determined by the HEPF rule. The MHU basis rule makes many Class 2 estimates compared with the no selection rule in Cases 1 and 2. Additionally, we observe that the number of no-bid orders is also large in the MHU basis rule. For example, the MHU basis rule makes no-bid decisions on 38.7% of arrived orders in Case 1.A as shown in Table 5. In the case of the MHU basis rule, the ratio of no-bid orders increases according to the increase of number of arrived orders in the project cost estimation process. Namely, the ratio of no-bid orders increases as 38.7%, 50.4%, and 62.0% according to the increase of the number of arrived orders in Case 1.A, Case 1.B, and Case 1.C. This maintain the number of the Class 2 and Class 3 estimates, which bring more expected profits than the Class 4 estimate.

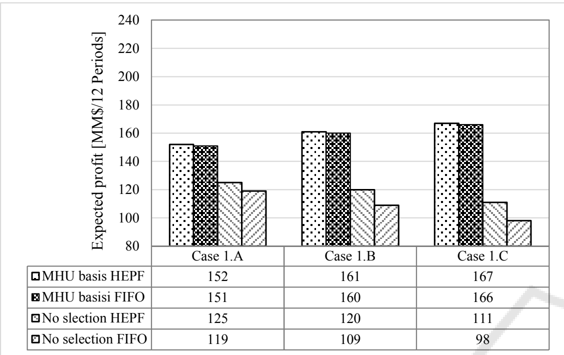

Figure 6: Expected profits in Case 1.

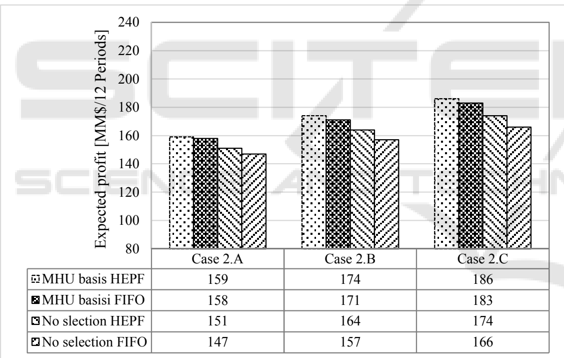

Figure 7: Expected profits in Case 2.

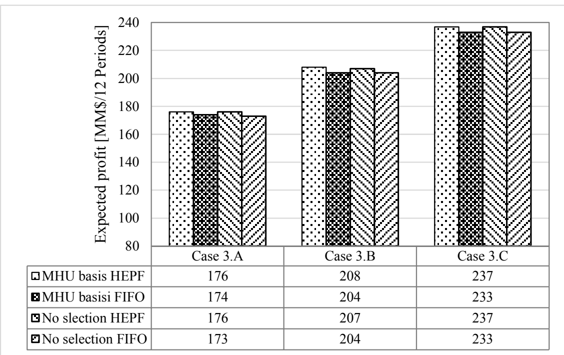

Figure 8: Expected profits in Case 3.

In our simulation, the average number of arrived orders is 1465, 1827, and 2195 in Cases A, B, and C, respectively. In Case 3, however, the ratio of cost estimate class provided by the MHU basis rules is very similar to that provided by no selection rules as shown in Table 7. Since the expected profits per MH of the Class 3 estimate is higher than that of the Class 2 estimate in Case 3, the MHU basis rule focuses MH for cost estimation on the Class 3 estimates.

These observations confirm that our heuristic method for the order selection works well to allocate MH for cost estimation appropriately so that the expected profits from orders are maximized in the dynamic order arrival situations.

Table 5: Ratio of cost estimate class in Case 1 HEPF rule (MHU: MHU basis, No: No selection) [%].

	Case 1.A		Case 1.B		Case 1.C	
	MHU	No	MHU	No	MHU	No
No-bid	38.7	0.0	50.4	0.0	62.0	0.0
Class 4	0.0	0.0	0.0	0.1	0.0	0.6
Class 3	7.6	50.1	8.5	71.9	6.2	87.0
Class 2	53.7	49.9	41.2	28.1	31.8	12.3

Table 6: Ratio of cost estimate class in Case 2 HEPF rule (MHU: MHU basis, No: No selection) [%].

	Case 1.A		Case 1.B		Case 1.C	
	MHU	No	MHU	No	MHU	No
No-bid	31.8	0.0	32.7	0.0	47.4	0.0
Class 4	0.0	0.0	0.0	0.1	0.0	0.6
Class 3	13.3	50.1	28.4	71.9	21.5	87.0
Class 2	54.9	49.9	38.9	28.1	31.1	12.3

Table 7: Ratio of cost estimate class in Case 3 HEPF rule (MHU: MHU basis, No: No selection) [%].

	Case 1.A		Case 1.B		Case 1.C	
	MHU	No	MHU	No	MHU	No
No-bid	0.6	0.0	0.7	0.0	0.9	0.0
Class 4	0.0	0.0	0.1	0.1	0.6	0.6
Class 3	49.4	50.1	71.3	71.9	85.5	87.0
Class 2	50.0	49.9	28.0	28.1	13.0	12.3

6 CONCLUSIONS

This paper explores the project cost estimation process of EPC projects in the dynamic order arrival situations. Specifically, we develop a heuristic method that selects orders for cost estimation based on order selection rules and allocates MH for cost estimation to each selected order to maximize the expected profits from orders. The order selection rules decide bid or no-bid on arrived orders by using the threshold function MHU_{up} ($EPPC_i$). This function is defined through simulation experiments using a project cost estimation process model proposed based

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on the AACE cost estimate classification system (AACE, 2011). We analyse the effectiveness of our heuristic method in terms of the expected profit through numerical examples.

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

- Our heuristic method developed for the order selection works well to allocate MH for cost estimation appropriately so that the expected profits from orders are maximized in the dynamic order arrival situations.
- HEPF and FIFO rules, which are used to dispatch orders waiting for cost estimation, make no significant difference in the expected profits, especially when the MHU basis rule is used for order selection.

There are several issues that require further research. For example, dispatching rules that significantly improve the expected profit should be developed. An advanced procedure to effectively determine the threshold function $MHU_{up}(EPPC_i)$ should be devised. In addition, a mechanism that changes rules of the order selection and MH allocation dynamically according to the change of cost estimation conditions, such as order arrival intervals, order sizes, and so on, should be developed.

In practice, there are dynamic scheduling problems similar to the project cost estimation problem, where profitable orders are selected and the cost estimate class is determined under the conditions of resource availability. Such examples are sales activities, facility maintenance activities, and so on. In these examples, the scope of work and the quality level of deliverables can be determined dynamically with limited resources. Research on the project cost estimation problem can contribute to the development of management technologies for such problems.

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