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Mechanism Design of Unknown Bidding Preference and Discrete Cost Structure in Multi-Attribute Reverse Auctions

XIAOHU QIAN[1], MIN HUANG[2], LOO HAY LEE[3], (Senior Member, IEEE), XINGWEI WANG[4], AND SHANSHAN TANG[2]

[1]College of Management, Research Institute of Business Analytics and Supply Chain Management, Shenzhen University, Shenzhen 518060, China
[2]State Key Laboratory of Synthetical Automation for Process Industries, College of Information Science and Engineering, Northeastern University, Shenyang 110819, China
[3]Department of Industrial and Systems Engineering, National University of Singapore, Singapore 119260
[4]School of Computer Science and Engineering, Northeastern University, Shenyang 110819, China

Corresponding author: Min Huang (mhuang@mail.neu.edu.cn)

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ABSTRACT This paper studies a multi-attribute reverse auction in which one manufacturer/buyer purchases multi-unit identical components/goods from a group of capacity-constrained suppliers considering the procurement cost and delivery time. The unknown bidding preference and the discrete cost structure are particularly investigated. Constructing a bi-level distributed decision-making model, a novel iterative multi-attribute reverse auction mechanism embedding negotiation is proposed to improve the procurement efficiency under the decision-making framework. Specifically, in the upper level, the buyer determines the optimal allocation by solving the winner determination problem. To induce suppliers to adjust their delivery times, three guiding strategies are proposed, i.e., the guiding strategy based on the deviation of delivery time (GDD), the guiding strategy based on the deviation of objective function value (GDF), and the guiding strategy randomly based on the deviation of objective function value (GRDF). In the lower level, suppliers adopt the concession strategies for determining the bid price and delivery time in response to the buyer's feedback. The numerical experiments illustrate the effectiveness and applicability of the proposed mechanism by comparing it with the centralized model. When the buyer places higher importance on the procurement cost than on the delivery time, the GRDF achieves the best negotiation outcome; otherwise, the GDF is the buyer's best option. Also, the proposed mechanism is robust to the variance of suppliers' decision parameters and could be a useful procurement tool for the buyer.

INDEX TERMS Bidding preference, bi-level distributed decision making, discrete cost structure, negotiation, multi-attribute reverse auction.

I. INTRODUCTION

With the development of the cyber-economy and information technology, e-commerce has increasingly played a key role in the national economy and people's daily life. As an important application area of e-commerce, electronic reverse auctions (ERAs) have been widely adopted by large enterprises and government departments for centralized procurement [5], [43], [57]. In contrast to traditional auctions, ERAs are in a reverse format that the buyer is the auctioneer and suppliers are the bidders [16], [52]. Due to the opportunity of obtaining new businesses for suppliers [5] and the advantage of reducing procurement or transaction costs for buyers [18], [52], ERA becomes a useful tool for practical procurement activities. Yet price-oriented ERAs that simply consider the price attribute and neglect other key factors affecting the procurement outcome can result in serious consequences for buyers. For example, contracting with

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unqualified pet food suppliers reduced the market capitalization of Menu Foods Company by half in 2007 [54].

To release the full potential of ERAs, multi-attribute reverse auctions (MARAs) are introduced for procurement of goods and services in recent years [6], [33], [39]. In general, MARAs extend traditional ERAs by allowing the buyer and potential suppliers to negotiate over price and non-price attributes such as quality, lead time and service level [21], [47], [56]. Adopting MARAs to purchase goods and services becomes a new trend. For example, Chinese buying organizations could source goods and services using MARAs through the government procurement platform (see http://www.ccgp.gov.cn/). Yet, introducing non-price attributes into the traditional price-oriented ERAs makes suppliers involve multi-dimensional private information that can be observed by each supplier individually [6]. A big challenge faced by the manufacturer/buyer is how to design a mechanism for purchasing components/goods from multiple suppliers under the multi-dimensional asymmetric information in MARAs. In practice, suppliers generally have discrete cost structures, since the discount policy is frequently adopted to promote sales of goods [34]. In addition, the bounded rationality induced by risk aversion [10] or decision errors [50] may cause suppliers to behave heterogeneously, and it may not be reasonable for suppliers to reveal their bidding preferences for strategic concerns. For example, some suppliers might be able to have a greater quantity and a longer delivery time due to different cost structures [16]. The discrete cost structure and unknown bidding preference of suppliers would make the complex mechanism design problem more intractable. Although reverse auction mechanisms have been extensively investigated in theory [17], [41], [59], most of the existing works assumed that the bidding preference is known and the cost function is continuous. Hence, the mechanism design problem that considers the discrete cost structure and unknown bidding preference under asymmetric information in MARAs forms the main focus of the paper.

In this paper, we model a sealed-bid iterative MARA in which one manufacturer/buyer seeks to source multi-unit identical components/goods from multiple suppliers. Following the literature [16], we assume that an individual supplier is not allowed to see the offers submitted by the associated competitors. In this case, bidders would not directly compete with their rivals and attempt to affect the buyer's decision through their offers. Generally, the iterative MARA could be consist of multiple rounds. In each round, the buyer can infer the information of suppliers' discrete cost and bidding preference based on their bids, and suppliers can revise their bid decisions in response to the feedback given by the buyer. The outcome of MARA would not be determined until the termination rule is reached. Since procurement cost and delivery time are the most important factors for firms to achieve the goal of lean manufacturing [13], [32], we assume that each supplier has a limited capacity of the goods and discrete cost values associated with the supply quantity and delivery time. Without loss of generality, the unit cost could be discounted in terms of the supply quantity and delivery time [25]. Also, we assume that the cost structure is common knowledge but the cost values can only be privately observed by each individual supplier. To select the best set of suppliers satisfying the buyer's demand, constructing a bi-level distributed decision-making model, a sealed-bid iterative MARA mechanism embedding negotiation strategies is proposed under the decision-making framework. Specifically, in the upper level model, based on goal programming, a winner determination model that minimizes the total deviation ratios of the procurement cost and delivery time is established for allocating the supply quantity. To induce suppliers to adjust their delivery times, different guiding strategies of delivery time are proposed for the buyer. In the lower level model, adopting the concession strategies, each supplier could determine the bid price and delivery time according to the cost structure and the guiding delivery time given by the buyer. After simultaneously submitting bids to the buyer, the winning suppliers could be determined according to the winner determination formula. Simulation analysis shows that the competition across potential suppliers could lead them to reduce the bid price in order to obtain more supply quantity. Numerical experiments illustrate the effectiveness of the proposed mechanism.

The main contribution of this paper is to model a sealed-bid iterative MARA in which the buyer has little knowledge of suppliers' bidding preferences and the cost values of each supplier are discrete in terms of the supply quantity and delivery time. Constructing a bi-level distributed decision-making model, this paper contributes to the reverse auction literature by investigating how the negation strategies can be integrated with MARAs to design an effective procurement mechanism for the buyer. Specifically, we propose three guiding strategies for the negation process from the buyer's point of view, namely, the guiding strategy based on the deviation of delivery time (GDD), the guiding strategy based on the deviation of objective function value (GDF) and the guiding strategy randomly based on the deviation of objective function value (GRDF). Through numerical analysis, we find that the outcome of MARAs depends on the guiding strategies of buyers and the trade-off between the procurement cost and delivery time. When the procurement cost outweighs the delivery time, GRDF achieves the best negotiation outcome; otherwise, GDF is the buyer's best option. We also find that the guiding strategies are robust to the variance of supplier's decision parameters. The iterative MARA mechanism embedding negotiation could be a useful procurement tool for the buyer.

The rest of this paper is organized as follows. Section II presents the relevant literature. Section III describes the problem and assumptions. Section IV demonstrates the auction mechanism embedding negotiation strategies under a bi-level distributed decision-making framework. The centralized decision model under full information is developed for deriving the benchmarking solutions in Section V. Conducting numerical experiments, Section VI shows the bidding process in MARA and compares the guiding strategies under different parameter settings. Conclusions and future research directions are presented in Section VII.

II. LITERATURE REVIEW

This paper studies a sealed-bid iterative MARA in which suppliers' cost values are discrete in terms of supply quantity and delivery time. The literature related to our research could be divided into two groups, i.e., MARAs and iterative auctions.

In the area of MARAs, Che's work [11] was seminal. It modeled a defense system procurement event to propose three auction schemes for the buyer considering the cost and quality attributes. It showed that the traditional revenue equivalent theorem still holds for the two dimensional analysis. Yet, the cost parameters of bidders are assumed to be independently drawn from a commonly known distribution function. Branco [8] extended Che's work to allow correlated cost functions of potential suppliers. It proposed a two-stage optimal auction mechanism, in which the buyer determined the winning supplier in the first stage and adjusted the quality level in the second stage. Noting that non-price attributes could be exogenous, Kostamis *et al.* [26] modeled the sealed-bid and open-bid reverse auctions from the buyer's point of view and showed that the sealed-bid reverse auction would be the best option when suppliers could anticipate intensified competition. Subsequently, many works focused on the development of scoring auctions [2], [3], [36], [38], [45], [46]. Most of such mechanisms developed so far assumed that once the scoring rules are given, the maximum social welfare produced by each supplier could be computed for constructing equilibrium bidding strategies. To ensure the auction outcomes, bidders shall be perfectly rational, and buyers shall commit to the pre-specified scoring rule before auction [55]. In recent years, MARAs have been applied to many areas, such as supply chain management [44], [45], [48], project management [46] and quality management [12]. Assuming that the buyer has dominating decision-making power, the above studies adopted a principal-agent framework to analyze the buyer's procurement strategy. In practical applications, the buyer and suppliers could have equal decision-making power. For example, Apple Computers would have more decision-making power for purchasing flash memory from SigmaTel, but could have equal decision-making power when facing Intel [37]. In circumstances of the equal decision-making power, adopting iterative auctions to allow multiple rounds of negotiations between the buyer and suppliers becomes imperative.

In the area of iterative auctions, from the buyer's point of view, Beil and Wein [6] firstly modeled a procurement event in which a buyer iteratively adopted the reverse auction mechanism to solicit bids from a group of suppliers for maximizing her expected revenue by using the inverse-optimization-based method. Yet, it showed that the mechanism is too complex to be implemented. Instead, Parkes and Kalagnanam [39] proposed an efficient auction mechanism to maximize the system expected profit for procurement of configurable goods. It showed that the proposed mechanism actually generated the Vickrey-Clarke-Groves result. When the buyer provided restricted information about her utility function, Chen-Ritzo *et al.* [15] showed that the iterative reverse auction mechanism involving multiattributes could improve the buyer's utility by comparing it to the price-orientated auction. For multiobject procurement, Hohner *et al.* [20] modeled the winner determination problem under the basic framework of iterative auctions considering complex business constraints. It showed that both the buyer and suppliers could benefit from the iterative auction mechanism. Similarly, Cheng [16] modeled an iterative reverse auction under the bi-level distributed programming framework for the buyer who purchases multiple identical items from suppliers with limited capacities. From the bidder's perspective, Adomavicius and Gupta [1] introduced bid evaluation metrics to give support to bidders for determining whether they should revise the bid in a real-time iterative combinatorial auctions or not. In parallel, Kwon *et al.* [28] proposed an endogenous bidding mechanism for solving the bid determination problem by using the approximate single-item pricing. According to the existing literature, the frequently adopted methods include Lagrangian relaxation [35], heuristics [30] and linear price approximation [7]. In practice, iterative auction has been applied to many areas, such as production planning problem [19], inventory management [29], [42], scheduling [25] and capacity allocation [4], [31], [58]. However, most of these works assumed that the buyer exactly knows the bidder's bidding preferences and the cost function is continuous.

Identifying the research gap and noting that decision theory could perform better than equilibrium analysis for modeling bidding strategies in real-world auctions [49], this paper mainly focuses on a sealed-bid iterative MARA in which suppliers' bidding preferences and the discrete cost structure are particularly considered under the bi-level distributed decision-making framework. Also, since combining negotiation or bargaining strategies with auctions would generate more expected profit to the buyer [12], [14], [22], [53], we integrate the negotiation process and guiding strategies of delivery time with the bi-level distributed decision-making model to propose an effective procurement mechanism for the buyer to purchase multi-unit identical goods. Numerical experiments illustrate the effectiveness of the proposed mechanism and its robustness to the variance of suppliers' decision parameters.

III. PROBLEM DESCRIPTION

In this section, we would firstly describe the problem and assumptions. Then we will present the notations used throughout the paper.

A. PROBLEM DESCRIPTION AND ASSUMPTIONS

We study a procurement problem that consists of one manufacturer/buyer and multiple suppliers. For the sake of convenience, we use "she" and "he" to represent the "buyer" and "supplier", respectively, in the following discussion. The buyer would purchase multi-unit identical components/goods from capacity constrained suppliers using a sealed-bid iterative MARA. Because of suppliers' strategic concerns and decision behaviors, we assume that the buyer has little knowledge of suppliers' bidding preferences. Also, since suppliers have limited capacity, a set of suppliers would be selected by the buyer to fulfill the demand. Following the literature [9], we consider the scenario that the buyer would focus on two attributes, i.e., procurement cost and delivery time, since supplier's fast delivery can lower the buyer's operating costs, e.g., inventory holding and back-order penalty costs. For practical considerations, the cost structure of suppliers is assumed to be discrete in terms of supply quantity and delivery time. In specific, the unit cost of goods associated with each supplier becomes lower as the supply quantity or delivery time increases. Hence, the main challenge of the study is to face the buyer's pricing and allocation problem in the presence of unknown bidding preferences and discrete cost structures. In general, a buyer with a procurement budget will attempt to narrow down the gap between the realized procurement cost and the budget, in hopes that the realized delivery time will be very close to the target delivery time. To better make a trade-off of such two attributes, the buyer's objective is to derive a procurement strategy that could minimize the total deviation ratios of procurement cost and delivery time by comparing the realized attribute values with the corresponding target levels. To simulate the bidding preference, the objective of each supplier is assumed to sell more goods with a higher bid price at an appropriate delivery time according to the discrete cost structure and information feedback in each round of the MARA. To make the problem clear, some assumptions are given below:

(1) One buyer needs to purchase Q identical goods to satisfy her demand in a sealed-bid iterative MARA, in which an individual bidder is not allowed to see the offers submitted by his competitors [16]. In this case, bidders are assumed to indirectly compete with their competitors and attempt to affect the buyer's decision through their offers.

(2) The target procurement cost and target delivery time are assumed to be c_0 and t_0, respectively. In goal programming, given the target levels denoted by c_0 and t_0, the found solution shall simultaneously satisfy all the targets as closely as possible [24].

(3) n ($n > 2$) potential suppliers are willing to submit bids to obtain the supply quantity. Each supplier's capacity is limited and the maximum capacity of supplier i is $Q_i^{\max}$ ($Q_i^{\max} < Q$). The unit cost of goods associated with each supplier decreases as his supply quantity or delivery time increases. Noting that suppliers would involve bounded rationalities when facing uncertainty, the bidding preference of each supplier is unknown due to some decision errors [27], [51]. In the lower level model, if the supplier obtains some supply quantity, the bid price will decrease with a small probability, since it may still have competitive advantages in the next round; otherwise, the bid price will decrease with a large probability.

(4) The buyer's objective is to minimize the total deviation ratios of the realized procurement cost to the target procurement cost and the realized delivery time to the target delivery time.

(5) Each supplier's objective is to obtain some supply quantity while keep the bid price higher than his cost.

(6) The procurement quantity Q, each supplier's capacity $Q_i^{\max}$ and the set of possible delivery time D_i are assumed to be common knowledge. The cost value and the bidding preference of each supplier are assumed to be private information that can only be observed by each individual supplier.

In the iterative MARA embedding negotiation strategies, constructing a bi-level distributed decision-making model, the buyer determines the supply quantity q_i^t and the guiding delivery time $\overline{d}_i^t$ based on suppliers' bids in round t, $t = 0, 1, \ldots, T$, and supplier i determines the bid price p_i^t and delivery time $\underline{d}_i^t$ based on his own cost structure and the feedback information given by the buyer. The MARA stops if the buyer is satisfied with the auction outcome or the maximum auction round is reached. The information exchange process is illustrated in Figure 1.

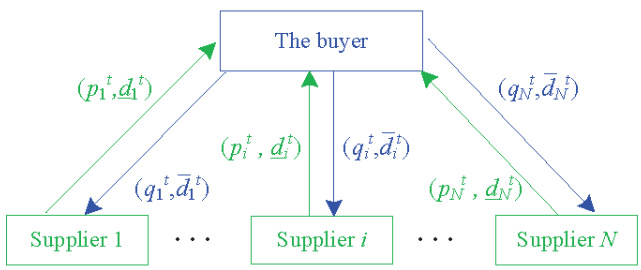

FIGURE 1. The information exchange process between the buyer and suppliers.

B. NOTATIONS

To formulate the problem, the notations used throughout the paper are introduced below.

Parameters in the Upper Level Model

T	number of auction rounds
t	index of auction round, where $t = 1, \ldots, T$
n	total number of suppliers
i	index of supplier, where $i = 1, \ldots, n$
c_0	target procurement cost
d_0	target delivery time

c_0^{t+} deviation between the realized procurement cost and the target procurement cost in round t
d_{0i}^{t+} deviation between the realized delivery time and the target delivery time of supplier i in round t
w_c weight of the deviation ratio for procurement cost, $0 < w_c < 1$
w_d weight of the deviation ratio for delivery time, $w_d = 1 - w_c$
Q total supply quantity demand of the buyer
$Q_i^{\max}$ maximum supply quantity that can be provided by supplier i
T_i transaction fee between the buyer and supplier i
p_i^{t-1} bid price of supplier i in round $t-1$
$\underline{d}_i^{t-1}$ delivery time of supplier i in round $t-1$

Decision Variables in the Upper Level Model

x_i^t binary variable, $x_i^t = 1$ if supplier i is selected in round t; otherwise, $x_i^t = 0$
q_i^t supply quantity allocated to supplier i in round t

Parameters in the Lower Level Model

$p_i^t(q_i^t, \underline{d}_i^t)$ minimum bid price of supplier i for the supply quantity q_i^t and realized delivery time $\underline{d}_i^t$; without loss of generality, the minimum bid price can be equal to the supplier's actual cost
$\overline{d}_i^t$ guiding delivery time for supplier i given by the buyer in round t
q_i^{t-1} supply quantity provided by supplier i in round $t-1$
α coefficient that suppliers' bid price may decrease
ϖ coefficient that suppliers' bid price is above his lowest bid price
δ_1 probability that the supplier's realized delivery time is equal to the buyer's guiding delivery time when the supply quantity in round t is equal to or more than that in round $t-1$
δ_2 probability that the supplier's realized delivery time is equal to the buyer's guiding delivery time when the supply quantity in round t is less than that in round $t-1$
λ_1 probability that the supplier will decrease his bid price when the supply quantity in round t is equal to or more than that in round $t-1$
λ_1 probability that the supplier will decrease his bid price when the supply quantity in round t is less than that in round $t-1$

Decision Variables in the Lower Level Model

p_i^t bid price determined by supplier i in round t
$\underline{d}_i^t$ delivery time determined by supplier i in round t

Before detailed analysis, the definitions of auction value and transaction value are introduced below.

Definition 1: Given $[x]^+ = \max\{x, 0\}$, the buyer's objective function value after the termination of the t-th round is defined as

$$G^t \triangleq w_c \frac{c_0^{t+}}{c_0} + w_d \frac{\sum_{i=1}^n x_i^t d_{0i}^{t+}}{d_0 \sum_{i=1}^n x_i^t}, \quad t = 1, 2, \ldots, T \tag{1}$$

where $c_0^{t+} = \left[\sum_{i=1}^n [q_i^t p_i^t + x_i^t T_i] - c_0\right]^+$ and $d_{0i}^{t+} = \left[x_i^t \underline{d}_i^t - d_0\right]^+$. We call G^t the auction value.

Note that supplier i would submit the bid price and delivery time as p_i^t and $\underline{d}_i^t$, respectively, in round t. In other words, supplier i is willing to have a trade with the buyer for p_i^t and $\underline{d}_i^t$. Yet in the upper level model, the buyer would allocate the supply quantity to potential suppliers based on their bids of round $t-1$. To ensure that the buyer could have a trade with the winning suppliers at the lowest bid price, we introduce the transaction value below.

Definition 2: The transaction value is defined as $G_{\min}^t \triangleq \min\{G_{\min}^{t-1}, G^t\}$, which is the minimum auction value after the termination of the t-th round.

In the auction process, the buyer keeps the lowest auction value as the transaction value of round t and chooses the corresponding supply quantity and delivery time as the final value to trade with the winning suppliers. On one hand, if the buyer is unsatisfied with the outcome of round t, i.e., $G^t > G_{\min}^{t-1}$, then the buyer believes that the auction outcome of round t is invalid and would trade with the suppliers that generate $G_{\min}^{t-1}$. On the other hand, if the buyer is satisfied with the outcome of round t, i.e., $G^t \le G_{\min}^{t-1}$, then the buyer will trade with the suppliers that generate G^t.

IV. THE MECHANISM OF MARA EMBEDDING NEGOTIATION

We model a sealed-bid iterative MARA embedding negotiation as a bi-level distributed decision-making process. To be specific, the proposed mechanism includes four stages, that is the initialization, buyer's decision, suppliers' decision and termination stages. In the first stage, the buyer allocates the initial supply quantity and guiding delivery time to each supplier. Based on such information, suppliers would make their bid decisions according the lower level model. After that, the initial auction value could be calculated. In the second stage, the buyer determines the supply quantity according to goal programming (i.e., optimization process) and the guiding delivery time according to the guiding strategies (i.e., concession process) using the upper level model. In the third stage, suppliers determine the bid price and delivery time according to their cost structures and concession strategies in the lower level model. In the fourth stage, the buyer evaluates the auction outcome and records the transaction value.

The reverse auction process will not stop until the buyer is satisfied with the outcome or the maximum negation round is reached. The details of the iterative MARA process are presented as follows:

Step 1: Initialization

- Step 1.1: Start the auction and set $t = 1$;
- Step 1.2: The buyer assigns the supply quantity q_i^0 and delivery time $\overline{d}_i^0$ to each supplier. If the initial quantity is more than the maximum supply quantity, then the supplier bids based on the maximum supply quantity.
- Step 1.3: Each supplier ascertains his lowest bid price $p_i^0(q_i^0, \underline{d}_i^0)$ based on the information given by the buyer, determines the initial bid price and delivery time, and then submits the bid to the buyer.
- Step 1.4: Calculate the auction value G^0 and set the transaction value $G_{\min}^0$ being equal to the auction value.

Step 2: The buyer's decision in the upper level model

- Step 2.1: The buyer assigns the supply quantity to a set of suppliers by solving the upper level model (i.e., goal programming model) according to the bid price and delivery time submitted by each supplier in round $t-1$. ← (The optimization process)
- Step 2.2: The buyer determines the guiding delivery time according to her guiding strategies and gives the associated information of the delivery time to each supplier. ← (The concession process)

Step 3: The suppliers' decision in the lower level model

- Step 3.1: Each supplier ascertains his lowest bid price $p_i^t(q_i^t, \underline{d}_i^t)$ based on the information given by the buyer in round t and $t-1$.
- Step 3.2: Each supplier determines his bid price and delivery time according to the concession strategies in the lower level model.

Step 4: The termination rule

- Step 4.1: Calculate the auction value G^t after the bidding prosess in round t.
- Step 4.2: Compare the auction value in round t with the transaction value in round $t-1$. If the buyer is satisfied with the current auction outcome, then set $G_{\min}^t = G^t$; otherwise, set $G_{\min}^t = G_{\min}^{t-1}$.
- Step 4.3: Check whether the termination rule is statisfied. If it fails, then set $t = t+1$ and go to Step 2; otherwise, stop the auction and make the deal.

A. INITIALIZATION

The buyer starts the iterative MARA by setting the supply quantity q_i^0 and the delivery time $\overline{d}_i^0$. For fairness consideration, the buyer assigns the same initial supply quantity and delivery time to all suppliers, i.e., $q_1^0 = q_2^0 = \cdots = q_n^0 = q$ and $\overline{d}_1^0 = \overline{d}_2^0 = \cdots = \overline{d}_n^0 = d$. Then each supplier sets the delivery time as $\underline{d}_i^0 = \overline{d}_i^0$ and determines the lowest possible bid price $p_i^t(q_i^0, \underline{d}_i^0)$. Then the bid price denoted by $p_i^0 = \varpi p_i^t(q_i^0, \underline{d}_i^0)$ would be submitted to the buyer by supplier i through MARA, where $\varpi > 1, i = 1, 2, \ldots, n$.

B. THE UPPER LEVEL MODEL (BUYER'S DECISION MODEL)

Based on the assumptions and the notations in Section III, we construct the upper level model that consists of two processes, that is the optimization process and the concession process for determining the supply quantity and guiding delivery time, respectively. In specific, the allocation of supply quantity is characterized by a goal programming model in the optimization process, and three guiding strategies are proposed in the concession process, namely, the guiding strategy based on the deviation of delivery time (GDD), the guiding strategy based on the deviation of objective function value (GDF) and the guiding strategy randomly based on the deviation of objective function value (GRDF). Next we will present the supply quantity decision model and characterize the guiding strategies from the buyer's point of view.

Based on the bids submitted by potential suppliers, the formulation of the supply quantity decision is described below:

$$\min \; w_c \frac{c_0^{t+}}{c_0} + w_d \frac{\sum_{i=1}^n x_i^t d_{0i}^{t+}}{d_0 \sum_{i=1}^n x_i^t} \tag{2}$$

$$\text{subject to: } \sum_{i=1}^n q_i^t = Q, \quad i = 1, 2, \ldots, n \tag{3}$$

$$q_i^t \le x_i^t Q_i^{\max}, \quad i = 1, 2, \ldots, n; \quad t = 1, 2, \ldots, T \tag{4}$$

$$\sum_{i=1}^n \left[q_i^t p_i^{t-1} + x_i^t T_i \right] - c_0^{t+} \le c_0, \quad t = 1, 2, \ldots, T \tag{5}$$

$$\underline{d}_i^{t-1} - d_{0i}^{t+} \le d_0, \quad i = 1, 2, \ldots, n; \quad t = 1, 2, \ldots, T \tag{6}$$

$$x_i^t \in \{0, 1\}, \quad i = 1, 2, \ldots, n; \quad t = 1, 2, \ldots, T \tag{7}$$

$$q_i^t, d_{0i}^{t+} \in \mathbb{Z}_+, \quad i = 1, 2, \ldots, n; \quad t = 1, 2, \ldots, T \tag{8}$$

$$c_0^{t+} \ge 0, \quad i = 1, 2, \ldots, n; \quad t = 1, 2, \ldots, T \tag{9}$$

Eq. (2) is the objective function that minimizes the total deviation ratios of the realized procurement cost to the target procurement cost and the realized delivery time to the target delivery time. Eq. (3) is the constraint that satisfies the buyer's demand. Eq. (4) constrains the supply quantity capacity of each supplier. Eq. (5) constrains the deviation between the realized procurement cost and the target procurement cost.

Eq. (6) constrains the deviation between the realized delivery time and the target delivery time. Eq. (7) represents that x_i is a 0-1 decision variable. Eq. (8) means that q_i^t and d_{0i}^{t+} are non-negative integers. Eq. (9) ensures that c_0^{t+} is a non-negative real number.

Since the sealed-bid iterative MARA involves multiple rounds, the buyer's supply quantity allocation in the current round will affect the supplier's bid decision in the next round, and will in turn be affected by the supplier's bid. In this case, suppliers who want to obtain more supply quantity will decrease their bid prices. Yet the supply quantity decision model is NP-hard [24], we propose that the small-scale problem can be solved by an enumeration algorithm and the large-scale problem can be solved by the heuristic algorithm such as Genetic Algorithm (GA) [23]. In parallel the buyer also needs to determine the guiding delivery time. From the buyer's point of view, if the realized delivery time submitted by the supplier in the current round is higher than the buyer's target delivery time in the previous round, then the buyer will suggest the supplier to reduce the realized delivery time; otherwise, the buyer will suggest the supplier to increase the realized delivery time. The details of the guiding strategies are illustrated below.

1) THE GUIDING STRATEGY BASED ON THE DEVIATION OF DELIVERY TIME

To reduce the deviation between the target delivery time and the realized delivery time, the guiding strategy based on the deviation of delivery time (GDD) is proposed. The main idea of GDD is that on one hand, if the realized delivery time is larger than the target delivery time, then the deviation ratio of delivery time can be reduced by decreasing the realized delivery time; on the other hand, if the realized delivery time is smaller than the target delivery time, then the deviation ratio of procurement cost can be reduced by increasing the realized delivery time. Let D_i denote the set of supplier i's possible delivery time, then define the direction or length that supplier i's delivery time may change in round t as

$$S_i^t = \begin{cases} -1, & \text{if } \underline{d}_i^{t-1} - d_0 > 0 \\ 1, & \text{if } \underline{d}_i^{t-1} - d_0 \le 0, \end{cases} \quad i = 1, 2, \ldots, n;\ t = 1, 2, \ldots, T, \tag{10}$$

then GDD can be defined as

$$\overline{d}_i^t = \begin{cases} \underline{d}_i^{t-1} + S_i^t, & \text{if } \underline{d}_i^{t-1} + S_i^t \in D_i \text{ and } \underline{d}_i^{t-1} + S_i^t \ge d_0 \\ \underline{d}_i^{t-1}, & \text{if } \underline{d}_i^{t-1} + S_i^t \notin D_i \text{ or } \underline{d}_i^{t-1} + S_i^t < d_0, \end{cases} \quad i = 1, 2, \ldots, n, \quad t = 1, 2, \ldots, T, \tag{11}$$

Eq. (10) represents that if the realized delivery time is larger than the target delivery time in round $t-1$, then the buyer can reduce the deviation ratio of delivery time by guiding supplier i to decrease the realized delivery time, thus $S_i^t = -1$; otherwise, the buyer can reduce the deviation ratio of procurement cost by guiding supplier i to increase the realized delivery time, thus $S_i^t = 1$. Eq. (11) represents that if the delivery time calculated in round t belongs to D_i and is larger than the target delivery time, then the guiding delivery time is equal to the delivery time calculated in round t; otherwise, the guiding delivery time is equal to the realized delivery time in round $t-1$.

2) THE GUIDING STRATEGY BASED ON THE DEVIATION OF OBJECTIVE FUNCTION VALUE

GDD only considers part of the objective function, i.e., the deviation of delivery time. However, reducing the deviation ratio of delivery time may increase the deviation ratio of procurement cost, and the objective function value may increase. Thus we proposed an improved strategy, i.e., the guiding strategy based on the deviation of objective function value (GDF). The main idea of GDF is that if the objective function value decreases, then the changing direction of supplier i's delivery time in round t is the same as that in round $t-1$; otherwise, the changing direction of supplier i's delivery time in round t is the negative direction of that in round $t-1$. The details of GDF are described below.

For the first round ($t = 1$), the guiding delivery time is determined by Eqs. (10)-(11). After that, i.e., $t \ge 2$, based on the auction value, we defined a new direction that supplier i's delivery time may change in round t as

$$S_i^t = \begin{cases} -S_i^{t-1}, & \text{if } G^{t-1} \ge G^{t-2} \\ S_i^{t-1}, & \text{if } G^{t-1} < G^{t-2}, \end{cases} \quad i = 1, 2, \ldots, n, ; \quad t = 2, 3, \ldots, T, \tag{12}$$

where G^{t-1} is the auction value in round $t-1$. Also the guiding delivery time can be calculated by Eq. (11).

Eq. (12) represents that if the objective function value in round $t-1$ is less than that in round $t-2$, the changing direction of supplier i's delivery time in round $t-1$ is a good direction, thus the guiding delivery time keeps moving as the good direction; otherwise, the changing direction in round $t-1$ is a bad one, and the guiding delivery time moves as the negative direction in round $t-1$.

3) THE GUIDING STRATEGY RANDOMLY BASED ON THE DEVIATION OF OBJECTIVE FUNCTION VALUE

GDF is based on the buyer's objective function value, it can help suppliers make a trade-off between the delivery time and the procurement cost. However, the changing direction of the total deviation ratio of the delivery time and procurement cost may be inconsistent with that of each supplier's deviation ratio. Thus, the guiding strategy randomly based on the deviation of objective function value (GRDF) is proposed. The main idea of GRDF is that if the supply quantity in the current round is higher than that in the previous round or equal to the maximum supply quantity, then the guiding delivery time keeps the same as that in the previous round with a higher probability and changes with a lower probability; otherwise, the guiding delivery time keeps the same as that in the previous round with a lower probability and changes with a higher probability. The details of GRDF are described below.

For the first round ($t = 1$), the guiding delivery time is determined by Eqs. (10)-(11). After that, i.e., $t \ge 2$,

$$\overline{d}_i^t = \begin{cases} \left.\begin{array}{lll} \underline{d}_i^{t-1}, & \text{with probability } \gamma_1 & \\ \left.\begin{array}{lll} \underline{d}_i^{t-1} + S_i^t, & \text{with probability } \upsilon_1, & \text{if } \underline{d}_i^{t-1} + S_i^t \in D_i \\ \underline{d}_i^{t-1} - S_i^t, & \text{with probability } 1-\upsilon_1, & \text{if } \underline{d}_i^{t-1} - S_i^t \geq d_0 \\ \underline{d}_i^{t-1}, & & \text{otherwise} \end{array}\right\} & \text{with probability } 1-\gamma_1 \end{array}\right\}, & q_i^t > q_i^{t-1} \text{ or } q_i^t = Q_i^{\max} \\ \left.\begin{array}{lll} \underline{d}_i^{t-1}, & \text{with probability } \gamma_2 & \\ \left.\begin{array}{lll} \underline{d}_i^{t-1} + S_i^t, & \text{with probability } \upsilon_2, & \text{if } \underline{d}_i^{t-1} + S_i^t \in D_i \\ \underline{d}_i^{t-1} - S_i^t, & \text{with probability } 1-\upsilon_2, & \text{if } \underline{d}_i^{t-1} - S_i^t \geq d_0 \\ \underline{d}_i^{t-1}, & & \text{otherwise} \end{array}\right\} & \text{with probability } 1-\gamma_2 \end{array}\right\}, & q_i^t \leq q_i^{t-1} \text{ and } q_i^t \neq Q_i^{\max}, \end{cases}$$

$$i = 1, 2, \ldots n;\ t = 2, 3, \ldots, T, \tag{13}$$

the direction that supplier i's delivery time may change is calculated by Eq. (12) and the guiding delivery time is determined by Eq. (13), as shown at the top of this page, as follows. where γ_1, γ_2, υ_1 and υ_2 are parameters. Eq. (13) represents that if the supply quantity in round t is higher than that in round $t-1$ or equal to the maximum supply quantity (indicating that the delivery time in round $t-1$ is good), then the guiding delivery time is equal to the realized delivery time in round $t-1$ with a higher probability γ_1 or will be changed with a lower probability $1-\gamma_1$. To be specific, the guiding delivery time is determined by the changing direction that the objective function value decreases with a higher probability υ_1 or by the changing direction that the objective function value increases with a lower probability $1-\upsilon_1$. If the supply quantity in round t is lower than that in round $t-1$, the guiding delivery time is equal to the realized delivery time in round $t-1$ with a lower probability γ_2 or will be changed with a higher probability $1-\gamma_2$. In specific, the guiding delivery time is determined by the changing direction that the objective function value decreases with a higher probability υ_2 or by the changing direction that the objective function value increases with a lower probability $1-\upsilon_2$. If $\overline{d}_i^t \notin D_i$ or $\overline{d}_i^t < d_0$, then the guiding delivery time is set to be equal to the realized delivery time in round $t-1$.

C. THE LOWER LEVEL MODEL (SUPPLIERS' DECISION MODEL)

After deriving the supply quantity and the guiding delivery time, each supplier will determine the delivery time and bid price according to the lower level model. Actually, the lower level model is characterized as a concession strategy model. The formula of the lower level model is constructed as follows:

Eq. (14), as shown at the bottom of the next page, is the concession strategy of the supplier's delivery time. If the supply quantity in round t is more than that in round $t-1$ or equal to the maximum supply quantity, then suppliers make the delivery time be equal to the guiding delivery time suggested by the buyer with a lower probability δ_1 and keep the delivery time unchanged with a higher probability $1-\delta_1$. If the supply quantity in round t is less than that in round $t-1$, then suppliers make the delivery time be equal to the guiding delivery time suggested by the buyer with a higher probability δ_2 and keep the delivery time unchanged with a lower probability $1-\delta_2$. Eq. (15), as shown at the bottom of the next page, is the concession strategy of bid price. If the bid price in round t is higher than that in round $t-1$, then the bid price is set as p_i^t. If the bid price in round t is lower than that in round $t-1$ and the supply quantity in round t is more than that in round $t-1$ or equal to the maximum supply quantity, then the bid price is set as p_i^t (i.e., cutting the bid price) with a lower probability λ_1 or set as p_i^{t-1} (i.e., adopting the bid price in round $t-1$) with a higher probability $1-\lambda_1$. If the bid price in round t is lower than that in round $t-1$ and the supply quantity in round t is less than that in round $t-1$ and unequal to the maximum supply quantity, then the bid price is set as p_i^t (i.e., cutting the bid price) with a higher probability λ_2 or set as p_i^{t-1} (i.e., adopting the bid price in round $t-1$) with a lower probability $1-\lambda_2$. Eq. (16), as shown at the bottom of the next page, represents the strategy of cutting the bid price, where suppliers will set the bid price as p_i^{t-1} multiplied by a coefficient α if αp_i^{t-1} is higher than the true cost (i.e., the lowest bid price $p_i^t(q_i^t, \underline{d}_i^t)$); otherwise, set the bid price being equal to the true cost.

As the lower level model describes the suppliers' concession strategies, it can be solved directly. Specifically, each supplier firstly determines his delivery time by Eq. (14) and then ascertains his lowest bid price based on his own cost structure. Finally, the bid price can be determined by Eqs. (15)-(16).

D. THE TERMINATION RULE

The auction terminates if the auction value keeps the same for 5 successive rounds or the maximum auction round is reached, i.e., $T = 50$. Check whether the termination condition is satisfied. If it fails, then the auction process will be continued; otherwise, the auction stops and the buyer's demand could be satisfied by selecting the winning suppliers.

In summary, the sealed-bid iterative MARA mechanism embedding negotiation strategies can be described by the flowchart as shown in Figure 2.

V. THE CENTRALIZED DECISION MODEL

To illustrate the effectiveness of the proposed mechanism, we construct a centralized decision model where

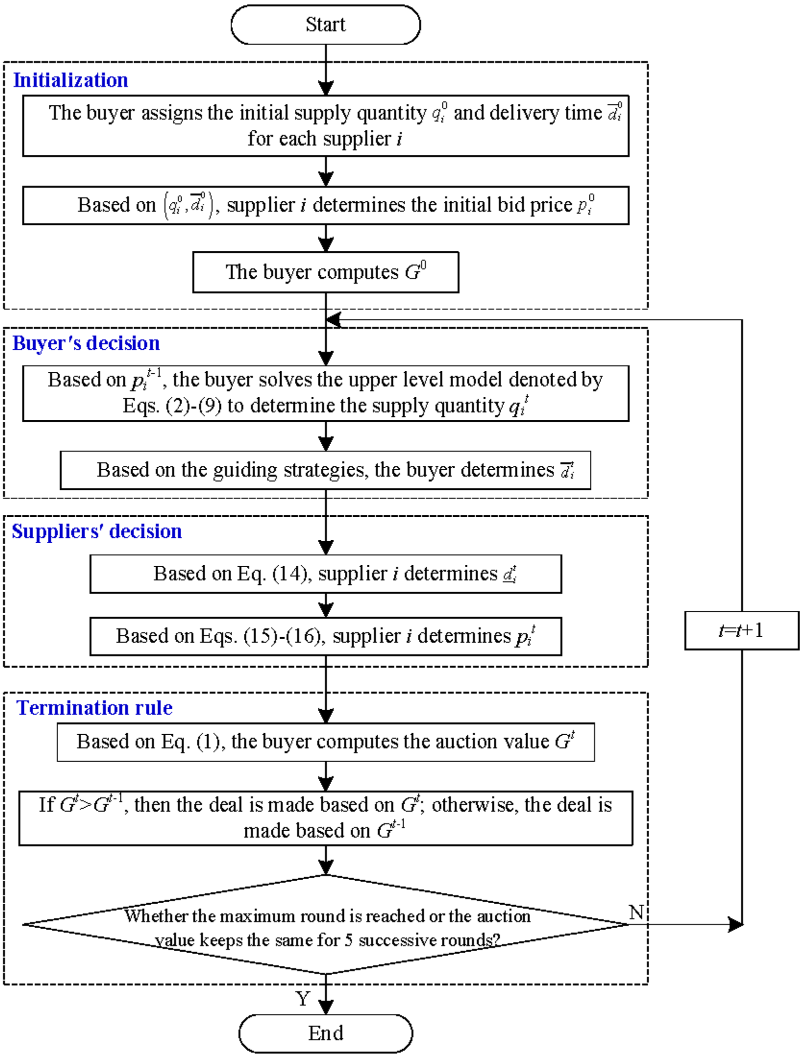

FIGURE 2. **Flowchart of the sealed-bid iterative MARA mechanism embedding negotiation strategies.**

the buyer has full information about the cost value in terms of the delivery time and supply quantity of each supplier. In this case, the buyer only needs to solve the centralized decision model for selecting the winning suppliers and set the supply quantity and delivery time accordingly. The centralized decision model is described as

$$\underline{d}_i^t = \begin{cases} \left.\begin{array}{ll} \overline{d}_i^t, & \text{with probability } \delta_1 \\ \underline{d}_i^{t-1}, & \text{with probability } 1-\delta_1 \end{array}\right\} q_i^t > q_i^{t-1} \text{ or } q_i^t = Q_i^{\max} \\ \left.\begin{array}{ll} \overline{d}_i^t, & \text{with probability } \delta_2 \\ \underline{d}_i^{t-1}, & \text{with probability } 1-\delta_2 \end{array}\right\} q_i^t \le q_i^{t-1} \text{ and } q_i^t \ne Q_i^{\max} \end{cases}, \quad i = 1, 2, \ldots, n;\ t = 1, 2, \ldots, T \tag{14}$$

$$p_i^t = \begin{cases} \left.\begin{array}{ll} p_i^t, & \text{with probability } \lambda_1 \\ p_i^{t-1}, & \text{with probability } 1-\lambda_1 \end{array}\right\} p_i^t < p_i^{t-1}, q_i^t > q_i^{t-1} \text{ or } q_i^t = Q_i^{\max} \\ p_i^t, \qquad\qquad\qquad\qquad p_i^t \ge p_i^{t-1} \\ \left.\begin{array}{ll} p_i^t, & \text{with probability } \lambda_2 \\ p_i^{t-1}, & \text{with probability } 1-\lambda_2 \end{array}\right\} p_i^t < p_i^{t-1}, q_i^t \le q_i^{t-1} \text{ and } q_i^t \ne Q_i^{\max} \end{cases}, \quad i = 1, 2, \ldots, n;\ t = 1, 2, \ldots, T \tag{15}$$

$$\text{subject to: } p_i^t = \max\left\{\alpha p_i^{t-1},\ p_i^t(q_i^t, \underline{d}_i^t)\right\}, \quad i = 1, 2, \ldots, n;\ t = 1, 2, \ldots, T \tag{16}$$

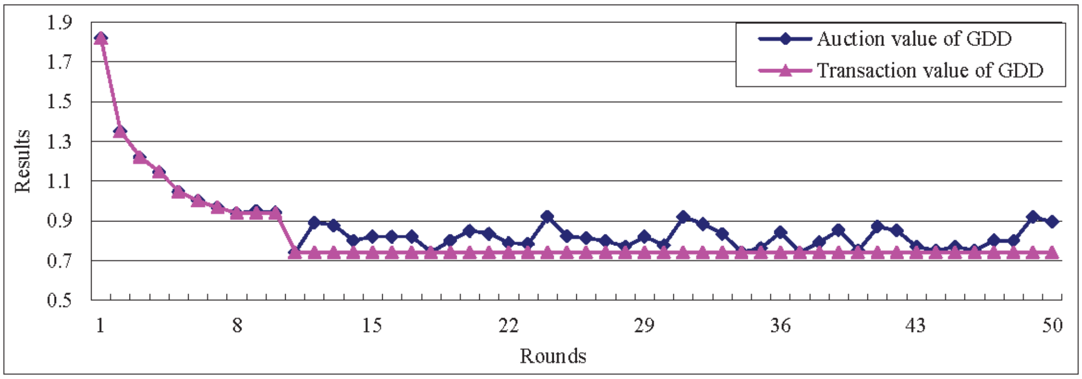

FIGURE 3. The comparison of auction value and transaction value based on GDD.

follows.

$$\min\ w_c \frac{c_0^+}{c_0} + w_d \frac{\sum_{i=1}^n x_i d_{0i}^+}{d_0 \sum_{i=1}^n x_i} \tag{17}$$

$$\text{subject to: } \sum_{i=1}^n q_i = Q \tag{18}$$

$$q_i \le x_i Q_i^{\max}, \quad i = 1, 2, \ldots, n \tag{19}$$

$$\sum_{i=1}^n [q_i p_i(q_i, d_i) + x_i T_i] - c_0^+ \le c_0 \tag{20}$$

$$d_i - d_{0i}^+ \le d_0, \quad i = 1, 2, \ldots, n \tag{21}$$

$$x_i \in \{0, 1\}, \quad i = 1, 2, \ldots, n \tag{22}$$

$$d_i \in D_i, \quad i = 1, 2, \ldots, n \tag{23}$$

$$q_i, d_{0i}^+ \in \mathbb{Z}_+, \quad i = 1, 2, \ldots, n \tag{24}$$

$$c_0^+ \ge 0, \quad i = 1, 2, \ldots, n \tag{25}$$

where x_i is a binary decision variable that $x_i = 1$ if supplier i is selected, otherwise $x_i = 0$. q_i is the integer decision variable that denotes the supply quantity assigned to supplier i. d_i is the integer decision variable that represents the delivery time of supplier i. c_0^+ represents the deviation between the realized procurement cost and the target procurement cost, $c_0^+ \ge 0$. d_{0i}^+ denotes the deviation between the realized delivery time and the target delivery time, $d_{0i}^+ \ge 0$. $p_i(q_i, d_i)$ is the lowest bid price of supplier i and can be assumed to be supplier i's true cost.

Eq. (17) is the buyer's objective function that minimizes the total deviation ratios of the procurement cost and the delivery time. Eq. (18) ensures that the buyer's demand is satisfied. Eq. (19) represents that each supplier is limited by his maximum capacity. Eqs. (20) and (21) are the constraints of the deviation of the procurement cost and delivery time, respectively. Eqs. (22) and (23) are the constraints of the binary variable and the delivery time. Eq. (24) ensures that the supply quantity and the deviation of delivery time are positive integers. Eq. (25) ensures that the deviation of procurement cost is positive.

VI. NUMERICAL EXPERIMENTS

In this section, numerical experiments are conducted to investigate the performance of the proposed iterative MARA mechanism embedding negotiation under the bi-level distributed decision-making framework. Firstly, a given example is used to illustrate the convergence process and the effectiveness of the proposed mechanism by comparing the auction value and the transaction value under the different guiding strategies (i.e., GDD, GDF, GRDF). Then, we randomly generate 50 groups of numerical examples. The best guiding strategy is examined by comparing the transaction values found by the decentralized model using three guiding strategies with that under the centralized model. Finally, the impact of the buyer's decision weights and suppliers' decision parameters on the proposed mechanism under different guiding strategies is discussed.

A. EFFECTIVENESS ANALYSIS OF THE PROPOSED MECHANISM

In this subsection, to illustrate the feasibility and effectiveness of the proposed mechanism, a given example is presented to show the auction process under different guiding strategies in a MARA.

Example 1: One buyer wants to purchase Q identical goods in a MARA, where $Q = 1500$. The auction format is an iterative low price sealed bid auction. The target procurement cost and target delivery time are assumed to be $c_0 = 7500$ and $d_0 = 2$, respectively. The weights of procurement cost and delivery time are assumed to be $w_c = 0.7$ and $w_d = 0.3$, respectively. The initial supply quantity and delivery time assigned to each supplier are assumed to be $q = 200$ and $d = 2$. The number of potential suppliers is assumed to be $n = 10$. Since the cost or the lowest bid price is each supplier's private information, to obtain more profit, suppliers will not submit their lowest bid price in the first round. When the supplier wants to obtain more supply quantity, he would decrease his bid price with some probability. The parameters of suppliers' concession strategy associated with delivery time are assumed to be $\delta_1 = 0.3$ and $\delta_2 = 0.7$, respectively. The parameters of suppliers' concession strategy associated with bid price are assumed to be $\lambda_1 = 0.3$ and $\lambda_2 = 0.7$, respectively. The cost information of each supplier is presented in Appendix A.

The simulation result of Example 1 based on GDD is shown in Figure 3. We see that the auction value decreases

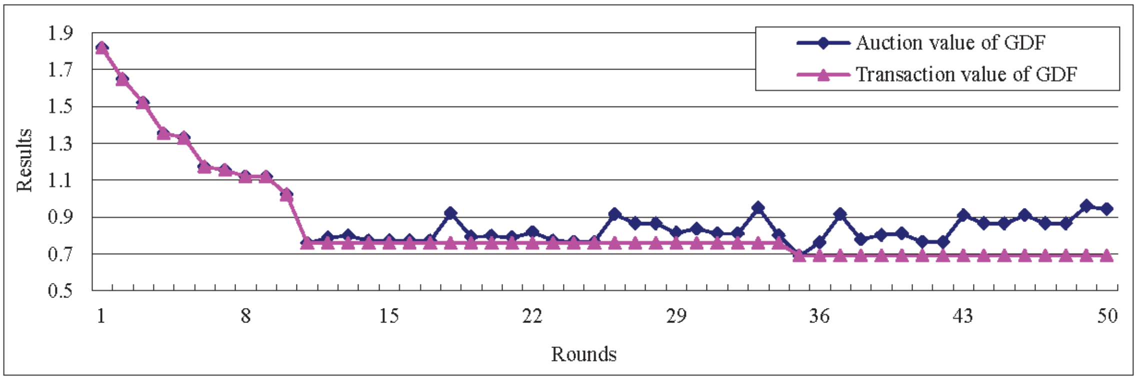

FIGURE 4. The comparison of auction value and transaction value based on GDF.

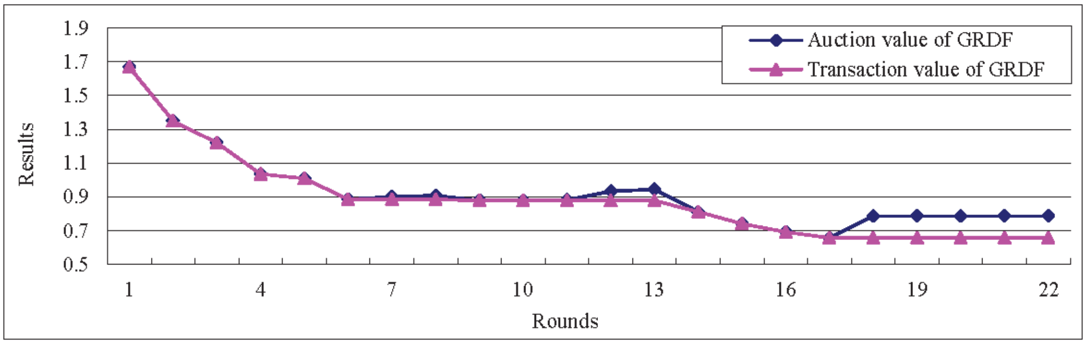

FIGURE 5. The comparison of auction value and transaction value based on GRDF.

in the first 8 rounds, and could be minimized in the 11th round. Indeed, the buyer has to make a trade-off between the procurement cost and the delivery time. In the first 8 rounds, since the bid price keeps decreasing with some probability, the impact of the procurement cost on the auction value is higher than that of the delivery time. However, when the bid price is close to the actual cost, the impact of the delivery time on the auction value is higher than the procurement cost, and the auction value fluctuates after the 8th round. Noting that the buyer would choose the lowest auction value to make a deal with these suppliers, the final transaction value based on GDD is 0.741253. This example illustrates the feasibility and effectiveness of the proposed mechanism integrating GDD. Yet, the final transaction value based on GDD under the decentralized model is higher than the optimal value under the centralized model by 40.3%.

The simulation result of Example 1 based on GDF is shown in Figure 4. We can see that the auction value decreases in the first 11 rounds since the impact of the procurement cost on the auction value is higher than that of the delivery time, and could be minimized in the 35th round. The final transaction value based on GDF is 0.690792, which is lower than that of GDD, since the auction mechanism based on GDF may have a larger searching space of the delivery time and a better direction to decrease the objective function value compared with GDD. Hence, the auction mechanism based on GDF is effective. Yet, the final transaction value based on GDF under the decentralized model is higher than the optimal value under the centralized model by 30.8%.

The simulation result of Example 1 based on GRDF is shown in Figure 5. We find that the auction value decreases in the first 6 rounds, and could be minimized in the 17th round. In addition, the termination rule is satisfied in the 22nd round such that the reverse auction stops. The final transaction value based on GRDF is 0.65733, which is lower than GDD and GDF, since GRDF may have a larger searching space of the delivery time than GDF. Hence we see that the proposed mechanism integrating GRDF is effective. However, the final transaction value based on GRDF under the decentralized model is still higher than the optimal value under the centralized model. This is mainly because of the asymmetric information between the buyer and potential suppliers.

From the above analysis, we find that the proposed iterative MARA mechanism embedding negotiation is feasible and effective. In next subsection, we will do some comparison analysis between these guiding strategies using randomly generated examples to further show the performance of the proposed mechanism.

B. COMPARISON ANALYSIS OF THE PROPOSED MECHANISM

In this subsection, 50 groups of numerical examples are randomly generated to find the best guiding strategies for the buyer in the iterative MARA. One buyer wants to purchase 1500 identical goods and 10 potential suppliers are willing to provide the goods by competitive bidding. The parameters are assumed to be $c_0 = 7500$, $d_0 = 2$, $w_c = 0.7$, $w_d = 0.3$, $\delta_1 = 0.3$, $\delta_2 = 0.7$, $\lambda_1 = 0.3$, $\lambda_2 = 0.7$.

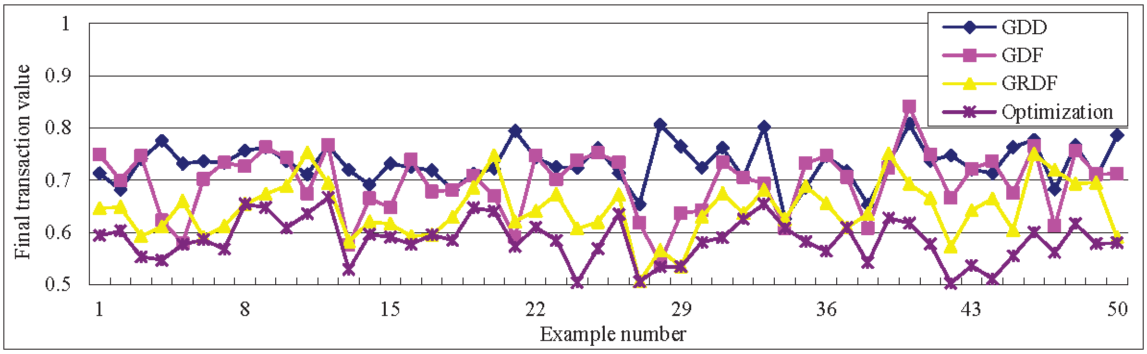

FIGURE 6. The comparison of final transaction value and the optimal value.

The cost information of each supplier is randomly generated. In specific, each supplier's cost information can be described by a matrix, where the rows represent the supply quantity, and the columns indicate the delivery time. The element of the matrix represents the cost value or the lowest bid price of each supplier in terms of the supply quantity and delivery time. The cost structure is similar to Example 1. Let $c_i^{\max}$, $Q_i^{\max}$ and $d_i^{\max}$ be the maximum cost, supply quantity and delivery time of supplier i, respectively. Let ϵ and ξ denote the discount factors of the supply quantity and delivery time, respectively. Firstly, given the first element of the matrix $c_i^{\max}$, the rest elements of the first row are randomly generated by a uniform distribution on the support $[\epsilon c_i^{\max}, c_i^{\max})$ and would be placed in a descending order in that row. Then the elements in the first column are generated. Specifically, the second element equals to $c_i^{\max}$ multiplied by a randomly generated number following a uniform distribution on the support $[\xi^{\frac{1}{d_i^{\max}-1}}, 1)$; the third element equals to $c_i^{\max}$ multiplied by a randomly generated number following a uniform distribution on the support $[\xi^{\frac{1}{d_i^{\max}-2}}, \xi^{\frac{1}{d_i^{\max}-1}})$; and the rest elements in the other columns can be generated in a similar way. Finally, the rest elements in the matrix are generated by rows. Specifically, the rest elements in each row are equal to the first element in that row multiplied by randomly generated numbers following a uniform distribution on the support $[\epsilon, 1]$ and then wound be placed in a descending order in that row. The parameters used to generate the suppliers' costs are presented in Appendix B.

Definition 3: Let π_{jk} denote the final transaction value of the j-th guiding strategy for example k, and π_k denote the optimal value of the centralized decision model for the k-th example, where $j = 1, 2, 3$ corresponds to the strategy of GDD, GDF and GRDF, respectively, and $k = 1, 2, \ldots, 50$ denotes the serial number of an example. Then the evaluation criterion of each guiding strategy is defined as the average deviation ratio, that is,

$$\overline{G}_j = \frac{1}{50}\sum_{k=1}^{50}\frac{\pi_{jk}-\pi_k}{\pi_k}, \quad j = 1, 2, 3. \tag{26}$$

Definition 3 is used to compare the guiding strategy of GDD, GDF and GRDF. Eq. (26) measures the average deviation difference between the final transaction value obtained by each guiding strategy and the optimal value under the centralized model for 50 randomly generated examples. A lower $\overline{G}_j$ means that the j-th guiding strategy performs better, since the final transaction value under the decentralized model is closer to the optimal value under the centralized model.

To obtain the best parameter combination of each guiding strategy, some tests are required. The major steps of parameter tests can be summarized below. Firstly, the initial delivery time is fixed and the initial supply quantity varies. Then, the initial supply quantity is fixed and the initial delivery time changes. Finally, both the initial delivery time and supply quantity are fixed, and other parameters are tested for the strategy of GRDF. The best parameter combination of each guiding strategy could be derived, that is, $q = 200$, $d = 5$ for GDD, $q = 400$, $d = 5$ for GDF, and $q = 300$, $d = 4$, $\gamma_1 = 0.6$, $\gamma_2 = 0.2$, $\upsilon_1 = 0.6$, $\upsilon_2 = 0.6$ for GRDF.

Based on the above parameter combinations, the final transaction values under different guiding strategies based on 50 randomly generated examples can be calculated as shown in Figure 6. We see that GRDF is the best option for the buyer, and GDF performs better than GDD, which means that to enlarge the searching space of delivery time under the decentralized model could result in a better auction outcome. In addition, the average deviation ratios of GDD, GDF and GRDF are 0.255875, 0.191141 and 0.102091, respectively. Moreover, given 50 randomly generated examples, GRDF performs better than GDD for 45 times and than GDF for 40 times. Also, GDF performs better than GDD for 35 times. Hence, GRDF performs best compared to the other two guiding strategies.

C. ROBUSTNESS ANALYSIS OF SUPPLIERS' DECISION PARAMETERS FOR THE PROPOSED MECHANISM

To illustrate the robustness of suppliers' decision parameters $\alpha, \lambda_1, \lambda_2, \delta_1$ and δ_2 for the proposed mechanism, 50 randomly generated examples are used to conduct the simulation analysis. Given $w_c = 0.7$, $w_d = 0.3$, $\alpha \in \{0.9, 0.8, 0.7\}$, $\lambda_1 \in \{0.5, 0.3, 0.7\}$, $\lambda_2 \in \{0.5, 0.7, 0.3\}$, $\delta_1 \in \{0.5, 0.3, 0.7\}$ and $\delta_2 \in \{0.5, 0.7, 0.3\}$, we would compute the average deviation ratio for each guiding strategy. In this case,

$\lambda_1 = \lambda_2 = 0.5$ means that suppliers determine the bid price randomly; $\lambda_1 = 0.7,\ \lambda_2 = 0.3$ means that suppliers determine the bid price abnormally; $\delta_1 = \delta_2 = 0.5$ means that suppliers determine the delivery time randomly; $\delta_1 = 0.7,\ \delta_2 = 0.3$ means that suppliers determine the delivery time abnormally. The average deviation ratio between the final transaction value of the each strategy and the optimal value of the centralized model is shown in Table 1.

TABLE 1. The average deviation ratio as supplier's decision parameters vary.

α	λ_1	λ_2	δ_1	δ_2	GDD	GDF	GRDF
0.9	0.3	0.7	0.3	0.7	0.255875	0.191141	0.102091
			0.5	0.5	0.267643	0.231407	0.133498
			0.7	0.3	0.278418	0.249147	0.152854
	0.5	0.5	0.3	0.7	0.254959	0.188747	0.12147
			0.5	0.5	0.26171	0.222706	0.132622
			0.7	0.3	0.266641	0.239245	0.133392
	0.7	0.3	0.3	0.7	0.256507	0.190469	0.133524
			0.5	0.5	0.25978	0.221155	0.136663
			0.7	0.3	0.263304	0.228148	0.137783
0.8	0.3	0.7	0.3	0.7	0.215695	0.115278	0.085177
			0.5	0.5	0.239065	0.148173	0.073051
			0.7	0.3	0.239355	0.172662	0.103769
	0.5	0.5	0.3	0.7	0.21344	0.103871	0.086952
			0.5	0.5	0.227281	0.113943	0.065977
			0.7	0.3	0.229164	0.13676	0.091718
	0.7	0.3	0.3	0.7	0.207789	0.097832	0.082225
			0.5	0.5	0.224342	0.097134	0.083535
			0.7	0.3	0.230961	0.10866	0.101281
0.7	0.3	0.7	0.3	0.7	0.199862	0.068902	0.06351
			0.5	0.5	0.211831	0.118809	0.073154
			0.7	0.3	0.226174	0.148762	0.099004
	0.5	0.5	0.3	0.7	0.191613	0.072381	0.059022
			0.5	0.5	0.201556	0.077256	0.059361
			0.7	0.3	0.218485	0.093506	0.079662
	0.7	0.3	0.3	0.7	0.182176	0.068378	0.067779
			0.5	0.5	0.202312	0.07479	0.065859
			0.7	0.3	0.212361	0.093083	0.091877

From Table 1, we see that the coefficient that describes the decreasing intensity of suppliers' bid prices, i.e., α, has a significant impact on the guiding strategies. Given other parameters being equal, the average deviation ratio between the final transaction value of each strategy and the optimal value of the centralized model decreases as α decreases. The decrease of α indicates the intensified competition across suppliers, which could benefit the buyer. In contrast, the probabilities that suppliers' bid price decreases, i.e., $\lambda_1,\ \lambda_2$, have no significant impact on the guiding strategies. Yet, given other things being equal, if suppliers determine the delivery time abnormally or randomly, the buyer will get a worse outcome compared to the case that suppliers determine the delivery time normally. More importantly, we find that GRDF performs the best compared to the other two and GDF is better than GDD under different combinations of parameter values. This analysis implies that the guiding strategies are robust to suppliers' decision parameters. Hence, the iterative MARA mechanism embedding negotiation could be a useful procurement tool for the buyer.

D. THE IMPACT OF THE BUYER'S WEIGHT PARAMETERS

To illustrate the impact of the buyer's weight parameters w_c and w_d, the comparison between the final transaction value based on each guiding strategy and the optimal value of the centralized decision model, the comparison of the average deviation ratio and the statistical analysis are discussed below. We set $\alpha = 0.9$, $\lambda_1 = 0.3$, $\lambda_2 = 0.7$, $\delta_1 = 0.3$, $\delta_2 = 0.7$ for further analysis.

TABLE 2. The average deviation ratio as the weight parameters vary.

w_c	w_d	GDD	GDF	GRDF
0.7	0.3	0.255875	0.191141	0.102091
0.5	0.5	0.049885	0.029082	0.077034
0.3	0.7	0.039135	0.025585	0.097733

1) COMPARISON OF THE FINAL TRANSACTION VALUE OF DIFFERENT STRATEGIES

For 50 randomly generated examples, the final transaction values based on each guiding strategy are calculated under different weight parameters. Given $w_c = 0.7$ and $w_d = 0.3$, the procurement cost outweighs the delivery time for the buyer. For $w_c = 0.5$ and $w_d = 0.5$, the procurement cost and the delivery time are equally important for the buyer. When $w_c = 0.3$ and $w_d = 0.7$, the procurement cost is less important than the delivery time for the buyer. Given such parameter values, the results are illustrated in Figure 7.

From Figure 7, we see that GRDF performs the best if the weight of procurement cost is higher than the weight of delivery time ($w_c = 0.7$ and $w_d = 0.3$). In contrast, GDF is the best option if the weight of procurement cost is lower than or equal to the weight of delivery time ($w_c = 0.3$ and $w_d = 0.7$, or $w_c = 0.5$ and $w_d = 0.5$). This is because on one hand, GRDF has a larger searching space for the delivery time than GDF, and the suppliers with a higher delivery time and lower procurement cost are more likely to be selected. Thus, if the weight of procurement cost is higher than the weight of delivery time, GRDF would be better than GDF. However, if the weight of procurement cost is lower than or equal to the weight of delivery time, the impact of the deviation of delivery time becomes more important than that of procurement cost, thus suppliers with a lower delivery time and higher procurement cost are more likely to be selected. In this case, GDF could be better than GRDF. In addition, from Section VI-A we see that the MARA process stops faster under GRDF compared to GDF and GDD, which means that the convergence rate of GRDF is faster than the other two. Since GRDF has a larger searching space such that the MARA would stop with fewer negotiation rounds, it is possible that the deep search of GRDF is not enough such that only local minimum could be found when the weight of procurement cost is lower than or equal to the weight of delivery time. In this case, GDF could be better.

2) COMPARISON ANALYSIS OF THE AVERAGE DEVIATION RATIO FOR DIFFERENT STRATEGIES

For 50 randomly generated examples, the average deviation ratio between the final transaction value based on each guiding strategy and the optimal value of the centralized decision model is calculated under different weight parameters. The results are presented in Table 2.

From Table 2, we find that GRDF is better than the other two guiding strategies if the weight of procurement cost is higher than that of the delivery time, and GDF is better than

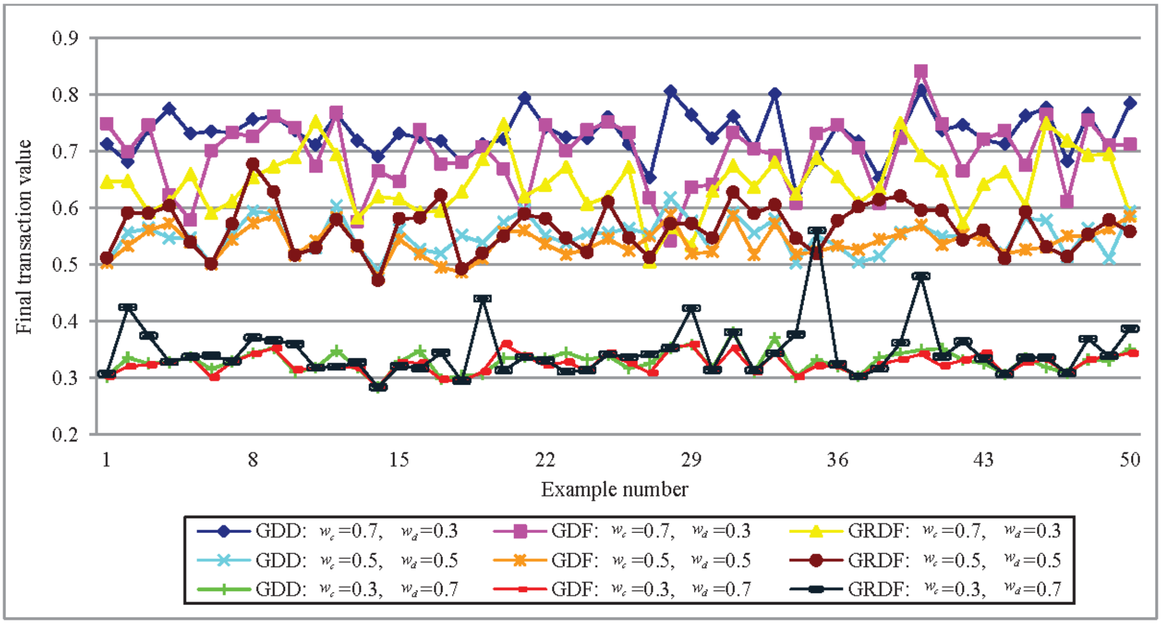

FIGURE 7. The comparison of the final transaction value under different weights.

TABLE 3. The test results for different strategies with Statcrunch.

w_c	w_d	H_0	H_A	Difference	Sample Diff.	Std. Err.	DF	T-Stat	P-value	Results
0.7	0.3	$\mu_1 - \mu_2 = 0$	$\mu_1 - \mu_2 > 0$	$\mu_1 - \mu_2$	0.03639716	0.010229074	98	3.5582068	0.0003	Reject H_0
		$\mu_1 - \mu_3 = 0$	$\mu_1 - \mu_3 > 0$	$\mu_1 - \mu_3$	0.08750294	0.0093978585	98	9.3109446	<0.0001	Reject H_0
		$\mu_2 - \mu_3 = 0$	$\mu_2 - \mu_3 > 0$	$\mu_2 - \mu_3$	0.05110578	0.011490241	98	4.4477552	<0.0001	Reject H_0
0.5	0.5	$\mu_1 - \mu_2 = 0$	$\mu_1 - \mu_2 > 0$	$\mu_1 - \mu_2$	0.01076006	0.0056906766	98	1.8908226	0.0308	Reject H_0
		$\mu_1 - \mu_3 = 0$	$\mu_1 - \mu_3 < 0$	$\mu_1 - \mu_3$	−0.01497668	0.0073203859	98	−2.0458867	0.0217	Reject H_0
		$\mu_2 - \mu_3 = 0$	$\mu_2 - \mu_3 < 0$	$\mu_2 - \mu_3$	−0.02573674	0.0070367864	98	−3.6574565	0.0002	Reject H_0
0.3	0.7	$\mu_1 - \mu_2 = 0$	$\mu_1 - \mu_2 \neq 0$	$\mu_1 - \mu_2$	0.0043201	0.0036929507	98	1.1698233	0.2449	Accept H_0
		$\mu_1 - \mu_3 = 0$	$\mu_1 - \mu_3 < 0$	$\mu_1 - \mu_3$	−0.0185023	0.0074206573	98	−2.4933506	0.0072	Reject H_0
		$\mu_2 - \mu_3 = 0$	$\mu_2 - \mu_3 < 0$	$\mu_2 - \mu_3$	−0.0228224	0.0073143656	98	−3.1202159	0.0012	Reject H_0

the other two guiding strategies if the weight of procurement cost is lower than or equal to the weight of delivery time.

3) SIGNIFICANCE OF DIFFERENT STRATEGIES

To further investigate the performance of the proposed strategies (i.e., GDD, GDF and GRDF) under different weights assigned by the buyer, significance tests are conducted based on 50 randomly generated examples. Let μ_1, μ_2 and μ_3 denote the mean of the transaction value using GDD, GDF, and GRDF, respectively. Let $\mu_i - \mu_j$ denote the difference between the two means, where $i, j \in \{1, 2, 3\}$ and $i \neq j$. H_0 is the null hypothesis. i.e., there is no difference between the two strategies. H_A is the alternative hypothesis. We assume that the significance level are at least 0.05, i.e., if p-value is less than 0.05, then reject H_0; otherwise, accept H_0. Using the Statcrunch solver for statistical analysis, we could derive the results of t-test as shown in Table 3.

From Table 3, we see that when $w_c = 0.7, w_d = 0.3$, i.e., the buyer places a higher weight on the procurement cost, GDF is better than GDD, and GRDF is better than the other two. When $w_c = 0.5, w_d = 0.5$, i.e., the buyer places equal weights on the procurement cost and delivery time, GDD is better than GRDF, and GDF is better than the other two. When $w_c = 0.3, w_d = 0.7$, i.e., the buyer places a higher weight on the delivery time, both GDD and GDF perform better than GRDF, and there is no significant difference between GDD and GDF. Therefore, we conclude that GRDF performs best when the weight of procurement cost is higher; otherwise, GDF is the best option for the buyer.

VII. CONCLUSION

For practical procurement applications, the buyer views MARA as a pricing discovery tool to solicit bids from multiple suppliers and could generally adopt it to purchase different kinds of goods or services. In this paper, we consider a procurement scenario in which the manufacturer/buyer purchases multiple identical components/goods and cares about the procurement cost and delivery time. Capacity-constrained suppliers are assumed to have discrete cost structures and private bidding preferences. Based on the theory of decision making, a sealed-bid iterative MARA mechanism embedding negotiations under a bi-level distributed decision-making framework is proposed. The upper level model describes the buyer's decision of allocating the supply quantity to potential suppliers and three guiding strategies to help suppliers determine the delivery time. The lower level model describes each supplier's concession strategy to determine the bid price and delivery time. Numerical experiments illustrate

TABLE 4. Suppliers' cost information.

S	DT	Supply quantity						TF	MSQ
		(0-100]	(100-200]	(200-300]	(300-400]	(400-500]	(500-600]		
S_1	1	12	11.83	11.45	11.31	10.61	9.93	500	600
	2	11.94	11.58	11.01	9.71	9.68	9.56		
	3	9.69	8.92	8.87	8.61	7.94	7.83		
	4	9.06	8.78	7.88	7.55	7.5	7.43		
	5	6.02	5.97	5.85	5.11	4.99	4.9		
S_2	1	13	12.67	12.54	12.3	11.94	11.67	450	600
	2	10.7	10.67	10.16	9.78	9.35	9.27		
	3	10.49	10.26	9.96	9.71	9.34	9.23		
	4	9.35	8.74	8.73	8.59	8.46	8.29		
	5	6.24	6.23	6.13	5.98	5.94	5.39		
S_3	1	14	13.82	13.53	12.75	11.47	11.33	480	600
	2	10.76	10.68	9.98	9.92	9.06	8.97		
	3	10.27	10.18	8.34	8.29	8.26	8.26		
	4	7.88	7.5	7.28	6.81	6.32	6.32		
S_4	1	13	12.97	12.81	12.18	11.89	-	420	500
	2	11.75	11.2	10.81	10.45	9.86	-		
	3	10.37	9.82	8.92	8.89	8.62	-		
	4	10.01	9.65	8.86	8.73	8.47	-		
	5	8.68	8.54	8.41	8.26	7.32	-		
S_5	1	14	13.51	12.97	12.53	12.27	-	390	500
	2	13.73	13.47	12.2	12.18	12.09	-		
	3	10.9	10.55	9.7	9.5	9.3	-		
	4	9.86	9.77	8.63	8.53	8.42	-		
	5	7.24	7.02	6.81	6.76	6.62	-		
S_6	1	15	14.81	14.38	13.31	12.88	-	400	500
	2	11.57	11.22	10.56	10.1	9.71	-		
	3	10.67	10.04	9.52	8.8	8.55	-		
	4	7.07	6.76	6.62	6.14	5.69	-		
S_7	1	13	12.74	12.41	11.74	-	-	290	400
	2	12.96	11.57	11.12	11.08	-	-		
	3	10.68	10.36	9.63	9.11	-	-		
	4	9.99	9.57	8.97	8.95	-	-		
	5	8.92	8.88	8.43	8.26	-	-		
S_8	1	14	13.69	12.94	12.88	-	-	320	400
	2	12.85	11.99	11.37	10.59	-	-		
	3	10.08	9.97	9.65	9.22	-	-		
	4	7.77	6.98	6.98	6.27	-	-		
S_9	1	14	13.6	12.35	-	-	-	180	300
	2	12.78	11.21	10.95	-	-	-		
	3	11.45	10.17	10.03	-	-	-		
	4	10.09	9.35	8.97	-	-	-		
	5	7.27	7.03	6.77	-	-	-		
S_{10}	1	15	13.12	12.46	-	-	-	210	300
	2	14.12	11.54	11.41	-	-	-		
	3	10.61	9.9	9.13	-	-	-		
	4	7.23	6.93	6.65	-	-	-		

the effectiveness and applicability of the proposed mechanism by comparing it with the centralized model. In particular, if the procurement cost is more important than the delivery time for the buyer, then the guiding strategy randomly based on the deviation of objective function value performs better than the other two; otherwise, the guiding strategy based on the deviation of objective function value is the buyer's best option. We also find that the proposed mechanism is robust to the variance of suppliers' decision parameters.

It is interesting to further investigate some extensions of this study. First, the buyer may need to consider more attributes like quality, supplier reputation and warranty time in practice. In this case, our work provides a general framework for designing the more complicated MARA mechanism. Second, the behavior of the decision maker can be involved. For example, we may consider that the suppliers are risk averse or have fairness concerns. However, simulating the bid decisions of suppliers becomes more complex in the bounded rationality scenario.

APPENDIX

A. SUPPLIERS' COST INFORMATION

Let S denote suppliers, DT denote delivery time, TF denote transaction fee, MSQ denote maximum supply quantity, and S_i denote supplier i, $i = 1, \cdots, 10$, then the cost information of each supplier is presented in Table 4.

TABLE 5. Parameters used to generate random examples.

Supplier No.	$c_i^{\max}$	ϵ	ξ	$Q_i^{\max}$	$d_i^{\max}$
S_1	12	0.8	0.5	600	5
S_2	13	0.85	0.45	600	5
S_3	14	0.8	0.45	600	4
S_4	13	0.8	0.5	500	5
S_5	14	0.85	0.45	500	5
S_6	15	0.8	0.45	500	4
S_7	13	0.85	0.5	400	5
S_8	14	0.8	0.45	400	4
S_9	14	0.85	0.5	300	5
S_{10}	15	0.8	0.45	300	4

B. PARAMETERS USED TO GENERATE RANDOM EXAMPLES

The parameters adopted to generate random cost information for potential suppliers are presented in Table 5.

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XIAOHU QIAN received the Ph.D. degree in systems engineering from Northeastern University, China. He is currently an Assistant Professor with the Department of Management, Shenzhen University, China. His research interests include optimization and operations management.

MIN HUANG received the B.S. degree in automatic instrument, the M.S. degree in systems engineering, and the Ph.D. degree in control theory from Northeastern University, Shenyang, China, in 1990, 1993, and 1999, respectively. She is currently a Professor with the State Key Laboratory of Synthetical Automation for Process Industries, College of Information Science and Engineering, Northeastern University. She has authored over 100 journal articles, books, and refereed conference papers. Her research interest includes modeling and optimization for logistics and supply chain systems.

LOO HAY LEE (S'93–M'97–SM'04) received the M.S. and Ph.D. degrees from Harvard University, Cambridge, MA, USA, in 1994 and 1997, respectively.

He is currently an Associate Professor with the Department of Industrial and Systems Engineering, National University of Singapore, Singapore. He is also appointed by the Shanghai Municipal Education Commission as the Eastern Scholar Professor for Shanghai Maritime University, Shanghai, China. He has coauthored a book entitled *Stochastic Simulation Optimization-Optimal Computing Budget Allocation* (World Scientific) and co-edited a book entitled *Advances in Maritime Logistics and Supply Chain Systems*. He has co-led a team with Dr. Peng and E. P. Chew to win the grand prize for the next-generation container port challenge, in 2013 by proposing a revolutionary double-storey container terminal design, called SINGA Port.

Dr. Lee has served as an Associate Editor for the IEEE Transactions on Automatic Control, the *IIE Transactions*, the IEEE Transactions on automation science and engineering, *Flexible Services and Manufacturing Journal*, *Simulation: Transactions of the Society for Modeling and Simulation International*, the *Asia Pacific Journal of Operational Research*, and the *International Journal of Industrial Engineering: Theory, Applications and Practice*. He is currently a Co-Editor of the *Journal of Simulation* and an Advisory Board Member of *OR Spectrum*.

XINGWEI WANG received the B.S., M.S., and Ph.D. degrees in computer science from Northeastern University, Shenyang, China, in 1989, 1992, and 1998, respectively. He is currently a Professor with the College of Computer Science and Engineering, Northeastern University. He has authored over 100 journal articles, books and book chapters, and refereed conference papers. His research interests include cloud computing and the future Internet. He was a recipient of several best paper awards.

SHANSHAN TANG was born in Tangshan, China, in 1993. She received the B.S. degree from the Department of Automation, Yanshan University, Qinhuangdao, China. She is currently pursuing the Ph.D. degree with the School of Information Science and Engineering, Northeast University, Shenyang, China. Her main research interests include machine learning and data mining.