

A New Dynamic Auction Mechanism in the Supply Chain: N-Bilateral Optimized Combinatorial Auction(N-BOCA)*

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In this paper, we introduce a new combinatorial auction mechanism - N-Bilateral Optimized Combinatorial Auction (N-BOCA). N-BOCA is a flexible iterative combinatorial auction model that offers optimized trading for multi-suppliers and multi-purchasers in the supply chain. We design the N-BOCA system from the perspectives of architecture, protocol, and trading strategy.

Under the given N-BOCA architecture and protocol, auctioneers and bidders have diverse decision strategies for winner determination. This needs flexible modeling environments. Hence, we propose an optimization modeling agent for bid and auctioneer selection. The agent has the capability to automatic model formulation for Integer Programming modeling. Finally, we show the viability of N-BOCA through prototype and experiments. The results say both higher allocation efficiency and effectiveness compared with 1-to-N general combinatorial auction mechanisms.

Key words : Combinatorial auction, N-Bilateral optimized combinatorial auction, Model formulation, Supply chain

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1. Introduction

In the explosive growth of business-to-business (B2B) e-commerce, the electronic auction has received a great deal of interest in recent years.

During the past few years, the popularity of auctions in B2B marketplaces has yielded diverse auction market types such as the combinatorial auction and the combinatorial exchange.

Combinatorial auctions (also called as

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multi-item auctions or bundle auctions) refer to auctions for multiple items at the same time, as opposed to single item auctions. Compared to single item auction types, they keep bidders from the risk of receiving only parts of combinations that would be valuable to the bidders. By giving more expressive power to bidders through complementary or substitute bids, the combinatorial auction has received much attention. The combinatorial auction mechanism can be classified as two types: one-sided combinatorial auction and combinatorial exchange.

Most of the combinatorial auctions proposed in the literature are the one-sided supply chain mechanisms: either multiple purchasers compete for items sold by one supplier, or, multiple suppliers compete for the right to sell to one purchaser.

The one-sided combinatorial auction mechanisms have a few limitations. First, either way in the one-sided mechanism, there is a possibility that the monopoly side has the advantage of commanding a greater portion of the market surplus. Second, the main approaches for the one-sided auction mechanism have limitations from the efficiency point of view.

When a bidder participates in independent marketplaces, there are two approaches: sequential or simultaneous auction. In the sequential auction, the bidder participates in several marketplaces sequentially to obtain all of the purchase items. In this case, the search cost is high to find out the marketplaces that are advantageous to the bidder. In a bidder's position, how to make an optimized

decision about the sequence of the contacting auctioneers is an important problem. In the simultaneous auction, on the other hand, the bidder may participate in the several independent marketplaces at the same time. Boyan et al. [18] suggested the architecture of simultaneous auctions. But in the simultaneous auctions, trading several marketplaces or auction sites at the same time and obtaining an optimized solution would be difficult. Besides, the bidder's burden is somewhat high because of the dynamic situation of the simultaneous auctions. In addition, a bid may be awarded from the several marketplaces, which may require penalty cost by the cancellation of some of the awarded bids. Furthermore, reactive allocation processes of the above two approaches can take time, which cause additional operational cost in proportional to the processing time. Third, most of the decision models for the combinatorial auction are static, which means the previous auction mechanisms don't consider the fact that each participant's trade goal and constraints are diverse, and dynamically change depending on purchase and supply situations.

Hence, a flexible modeling mechanism that reflects the diverse and dynamic trading strategies flexibly is needed to solve this problem. The first and second limitations call for the n-bilateral combinatorial auction mechanism in which multiple suppliers and purchases participate at the same time. The third limitation requires the flexible decision mechanism to meet with diverse decision strategies of the participants. These two requirements demand a new combinatorial auction

model: n-bilateral combinatorial auction with flexible modeling mechanism.

On the other hand, there are some studies on combinatorial exchange (also called as combinatorial double auction) for multi-suppliers and multi-purchasers [3, 4, 13, 14, 34]. In the combinatorial exchange, the real transaction is processed by the price based matching. The combinatorial exchange usually refers to a market for financial items such as stocks or bonds. The participants submit bids to buy or sell bundles of those items. The objective of the auction is to maximize the total trade surplus while satisfying the constraint that the number of units selected for buy bundles does not exceed the number provided by sell bundles for each component [41]. It is well known that double auctions in which both sides submit demand or supply bids are much more efficient than several one-sided auctions combined [41].

Although, the combinatorial exchanges are the auction mechanism for multiple suppliers and purchasers, it's not appropriate to tackle the problems of one-sided combinatorial auction mechanism in two points. First, trading in combinatorial exchanges overlooks the fact that each participant's trading goal and constraints may be different according to their supply or purchase strategies. Each participant, also, in a combinatorial exchange can sell or buy at the same time. Second, the combinatorial exchange mechanisms are not appropriate for general combinatorial auction trading, because the role of participants is fixed as suppliers or purchasers in general or reverse

combinatorial auction marketplaces.

Thus, we propose the iterative n-bilateral optimized combinatorial auction (N-BOCA) model using the optimization modeling method for the selection of optimal bidders and auctioneers. The advantages of iterative auctions through multi-rounds over single-round bid auctions are, first, they save bidders from specifying their bids for every possible combination in advance, second, such method can be adapted to dynamic environments where participants arrive and depart at different times, third, in settings where bidders have private information that is relevant to other bidders, such an auction (with appropriate feedback) allows for information to be revealed [12].

For the N-BOCA, we propose a web based prototype implementation to show the viability of the mechanism. In the trading strategy design phase, the decision models for the selection of optimal bids and auctioneers are identified. The models are dependent on the diverse trading strategies of market participants. Thus it needs flexible model adaptability. A model management framework is proposed for model adaptation. Then, we report on the result of the simulation test for evaluating the performance of N-BOCA.

To fulfill the goals of this research, this paper is organized as follows. After reviewing the previous studies on combinational auctions and related areas, we propose the multi-agent based N-BOCA mechanism derived from the combinatorial auction design model. Then, we design the web based N-BOCA system. In the next

section, the process of agent based N-BOCA is described by illustration. In particular, we evaluate the performance of the N-BOCA model from the allocation efficiency and effectiveness perspectives. Then, we conclude this research with its contributions and the further research issues.

2. RELATED WORKS

2.1 Combinatorial Auction

The combinatorial auction is used to describe any auction mechanism that simultaneously sells multiple items, and allows all-or-nothing bids on combinations of these items [31]. Generally, it is necessary to solve combinatorial optimization problems such as set packing and partitioning problems [19]. There are several applications on combinatorial auctions. Examples in real-world situations are the FCC (Federal Communications Commission) spectrum auction [28], auctions for airport landing slots [33], railroad segments [9] and, shipping [17] and scheduling [39]. In a survey by de Vries and Vohra [12], diverse combinatorial auction applications including the logistics service and the e-Procurement were investigated. Combinatorial auction models are becoming popular among the next generation of B2B marketplaces by combinatorial auction specialists such as Net Exchange (www.nex.com), CombineNet (www.combine.net) and Trade Extensions (www.tradeextensions.com). Na et al. [29] describe

the use of combinatorial auctions by Home Depot, Sears Logistics Services (SLS) for procuring logistics services. As combinatorial auction mechanisms have diversified, several studies have covered combinatorial auction design issues.

2.2 Combinatorial Auction Design

The design of new market mechanisms is a new and emerging field [7]. The market type design creates a meeting place for purchasers and suppliers and a format for transactions [6]. The electronic market design is a challenging task and involves interdisciplinary characteristics.

Bichler et al. [7] suggested several design factors for resource allocation problems on the combinatorial auction market. In the research, the primary criteria for characterizing the allocation problems are the number of participants, and the types of traded goods. Abrache et al. [2] discussed several design issues that are encountered in the design of combinatorial auctions. In particular, they presented the taxonomy of auctions composed of several factors including items, roles of the participants, and the objective of the auctions. Other research on the combinatorial auction type or mechanism design has been proposed [31, 32, 36].

On the other hand, the studies on optimized allocation reflecting the participants' supply and purchase strategies have been proposed. The optimal allocation problem in combinatorial auctions is commonly formalized as an integer programming problem [41]. Given a set of bids on subsets of the assets in a combinatorial auction, the

goal of the auctioneer is to assign subsets to the bidders such that the total revenue of the chosen bids is maximized. In case of optimization problems underlying the combinatorial auction, several studies present the constraint factors that impact the optimization model formulation. Bichler et al. [5] proposed the allocation constraints such as the supply capacity, the maximum/minimum number of winning suppliers, and the maximum/minimum amount procured from each supplier. Also, Giovannucci et al. [16] suggested the constraint factors such as maximum/minimum number of winning suppliers, supply capacity, maximum/minimum supply volume, maximum/minimum demand volume, and reserve price. Other research on the combinatorial auction presented the bidding operator constraints [1, 30, 37].

Although, several studies have emphasized the design problem of the combinatorial auction market and covered a few design factors or partial dimensions of combinatorial auction design, these only analyzed parts of the characteristics that compose combinatorial auction markets.

2.3 Agent Based Combinatorial Auction

Much research has been conducted in the field of agent based auctions or combinatorial auctions [42]. The AuctionBot [40] is an experimental internet auction server developed in the University of Michigan. AuctionBot provides a list of predefined auction types for suppliers to choose from. In the research of Sandhorn [35], he

suggested the eMediator composed of three components including eAuctionHouse, eCommitter, and eExchangeHouses. The eAuctionHouse, the configurable auction server, includes a variety of generalized combinatorial auctions exchanges, pricing schemes, bidding languages, mobile agents, and user support for choosing a wide variety of auction types. The eCommitter is a leveled commitment contract optimizer, and the eExchangeHouses is a safe exchange planner. Shin [38] propose an automated reverse auction model between one purchaser and multi suppliers for m-commerce, using collaborative mobile agents called mobile reverse auction agent system (MoRAAS).

2.4 Automatic Model Formulation

Generally, supply and purchase strategies vary depending on the situation of each organization in the supply chain. In order to support the strategies, diverse models are necessary.

Purchase and supply strategies depend on the situation of an organization. In order to support the strategies, diverse models are necessary. In combinatorial auction modeling, we have to consider diverse supply and purchase requirements. Recently, the model warehouse [8] is one of the methods to solve these issues. However, it's not easy for a model manager to reflect the dynamic strategies in that all model components such as objective functions and constraints are made in advance. So the model management mechanism for

the optimized combinatorial auction is needed. There have been studies on automating modeling processes to modify the existing models. They are structured modeling [15], rule-based formulation [11, 25], frame [24], analogical reasoning [26], and the case-based reasoning approach [10]. In this study, we use the rule-based modeling approach for the bid and auctioneer selection model.

3. N-BOCA DESIGN MODEL

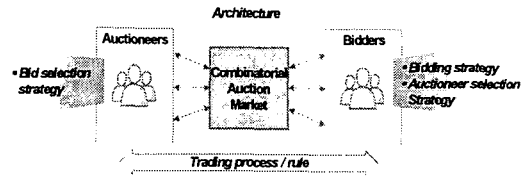
3.1 Combinatorial Auction Design Model

In combinatorial auction markets, suppliers and purchasers meet as auctioneers or bidders in the markets. They announce call-for-bids (CFB), submit combinatorial bids, select partners by their trading strategies while observing the auction rules. In general, the market should be designed with the following features when we review the market design-related literature [6, 7, 22].

1. Who meets, where do they meet, and what is their relationship with each other?
2. Which processes and rules do they trade with?
3. What are their trading strategies in the process?

The first feature addresses the architecture for the marketplace, the second addresses trading protocol for trading processes and rules, and the third addresses the trading strategy of each participant in the market. [Fig. 1] depicts this situation.

This leads to a combinatorial auction market design with a three-phased approach: architecture



[Fig. 1] Framework of the Combinatorial Auction Market

design, trading protocol design, and trading strategy design. Combinatorial auction market requirements are actualized as a specific combinatorial auction market through architecture design, protocol design, and trading strategy design successively. The architecture design produces architecture types. The trading protocol design produces process types. While trading between bidders and auctioneers, they select trading partners, which needs bid selection or auctioneer selection models reflecting trading strategies. These are designed in the phase of trading strategy design.

3.2 Architecture Design for N-BCA

The factors that determine the market structure are the market place, the cardinality of participants, and the relationship between participants. The market place defines an e-marketplace where the real transaction among participants is formed. In a general N-BCA Model, auctioneers and bidders meet at the intermediary market. The cardinality of participants means the numeric relationship between suppliers and purchasers. A general N-BCA model has the cardinality of m suppliers - n purchasers. The

relationship between participants is determined by the role of each market participant. In a general N-BCA Model, suppliers and purchasers meet as auctioneers and bidders in intermediary's e-Marketplaces. <Table 1> shows the architecture factors and their values for N-BCA.

<Table 1> Architecture for General N-BCA

Factor	Value
Marketplace	Intermediary's e-Marketplace
Cardinality	m suppliers - n purchasers
Relationship	Auctioneer - Intermediary - bidder

3.3 Protocol Design for N-BCA

In the protocol design phase, the rules for bidding, bid selection, and stopping are defined as presented in <Table 2>. The intermediary, which is auction agency, specifies the auction rules for N-BCA.

The bidding rule refers to the rule that bidders follow in the auction process. They include the bidding type, maximum number of bidding rounds, upper limit of bidding rounds per bidder, upper limit of total bids per bidder, and upper limit of bids in each round per bidder. The alternatives for bidding type are the simultaneous or continuous bid. The simultaneous bid means simultaneous sealed bid. The continuous bid means continuous open cry or continuous sealed bid. The maximum number of bidding rounds, upper limits of bidding rounds per bidder, total bids per bidder, and bids in each round per bidder are determined according to the specified number of rounds or bids. The bid

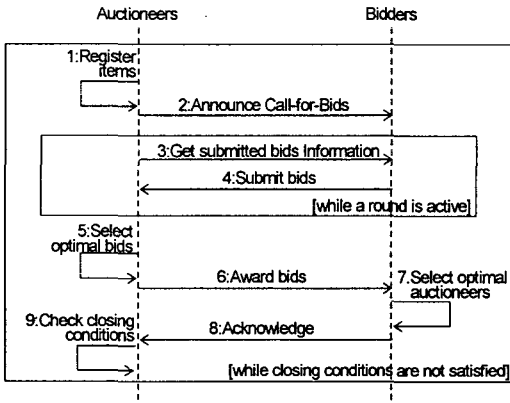
<Table 2> Protocol Designs for N-BCA

Rules	Factors	Alternatives
Bidding rule	Bidding type	Simultaneous*
		Continuous open cry
		Continuous sealed bid
	Max No of bidding rounds	No. of rounds
	Upper limit of bidding rounds per bidder	No. of rounds
Bid selection rule	Bidder selection unit	Round*
		Bid
Stopping rule	Closing condition	When bids aren't submitted in a round
		Predetermined No of rounds*

selection rule is the policy on the selection of bidders. This includes bid selection unit and pricing scheme. The bid selection unit concerns the timing of bid selection. The alternatives of bid selection unit are round or bid. Thus, bid selection occurs at the end of each round or whenever a new bid is submitted. Finally, the stopping rule refers to the rule on the termination of the auction process. For the market closing condition factor, there are two alternatives; when bids aren't submitted in a round and the predetermined number of rounds.

Bidding type, bid selection unit, and closing condition are factors that affect the auction process. If an auction agency specifies the values of the

factors with the * mark in <Table 2>, the auction processes for N-BCA are as in [Fig. 2].



[Fig. 2] An Illustration of the Process of General N-BCA

3.4 Trading Strategy Design for N-BOCA

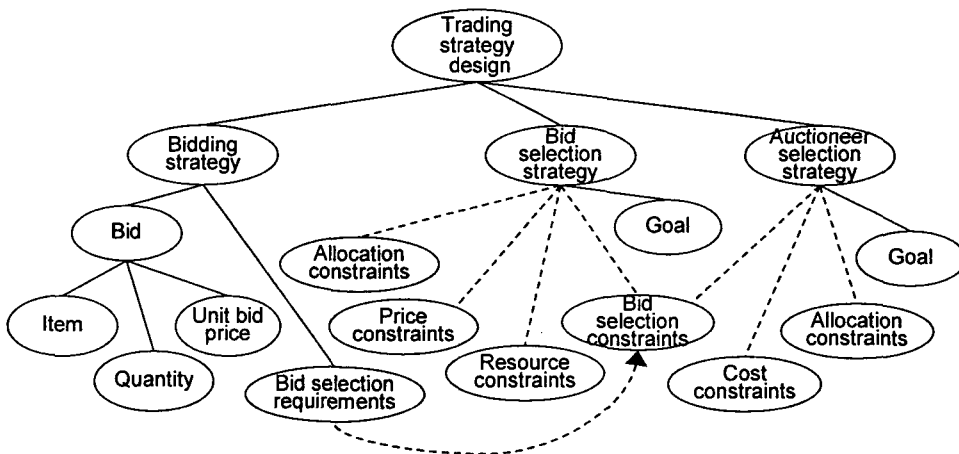
After protocol design, by the intermediary, the design information is delivered to the suppliers and purchasers. Then they decide their trading strategies. In the trading strategy design phase, the bidding, bid selection, and auctioneer selection

strategies are defined as shown in [Fig. 3]. Bid and auctioneer selection need optimization models with bid selection constraints reflecting bid selection requirements. The N-BOCA mechanism is the N-BCA model equipped with the optimization model. Our study introduces a method for selecting optimal bids or auctioneers using Integer Programming (IP).

3.4.1 Bidding Strategy

As the first process for trading between bidders and auctioneers, when the CFB is announced in the bidding stage, the bidders specify the bidding strategy. The bidding strategy is to define the bid requirements on bid items. The bid requirements, based on endogenous bidding strategy, are composed of bids on items, quantity, and unit bid price, and bid selection requirements as shown in [Fig. 3].

Bid selection requirements can be expressed using bid selection operators: AND, OR, XOR,



[Fig. 3] Trading Strategy Factors for General N-BCA

PRIORITY, and **IF-THEN**. <Table 3> shows the Bid Selection Requirements. β , β_1 , and β_2 mean subsets of bids. Eq. (1) ~ (4) depicts bid requirements from a bidder.

<Table 3> Factors for Bidding Strategy

Factors	Alternatives	
Bid selection requirements	AND (β)	d_1
	OR (β)	d_2
	XOR (β)	d_3
	PRIORITY (β)	d_4
	IF-THEN (β_1, β_2)	d_5

Bid Requirements =

$$\{\text{Bid}\}, \{\text{Bid Selection Requirements}\}, \quad (1)$$

where Bid = (item, quantity, unit bid price) and (2)

Bid Selection Requirements =

$$\text{Bid Selection Operator } (\beta) \text{ or} \quad (3)$$

$$\text{Bid Selection Operator } (\beta_1, \beta_2). \quad (4)$$

All bids without bid selection requirements are basically interpreted as the **OR** condition and bidders can add bid selection requirements such as Eq. (3) or Eq. (4) according to their strategies. **AND**, **XOR**, and **PRIORITY** operators obey Eq. (3) and **IF-THEN** obeys Eq. (4). **AND** means all bids in a bid set should be executed. **OR** means at least one bid in a bid set should be executed. **XOR** means just one bid in a bid set should be executed. **PRIORITY** means the ordering of the executed bids, namely, the first proposed bid should be accepted before the next proposed bids are accepted. **IF-THEN** means one subset of a bid set should be executed when the other subset of a bid

set is executed.

3.4.2 Bid Selection Strategy

Each auctioneer sets up the bid selection strategy and obtains the optimal bids after receiving bids from the bidders. The bid selection strategy is composed of endogenous and exogenous strategies as presented in <Table 4>. The endogenous strategy is composed of a goal and constraints sets.

The goal is dependent on the auctioneer's objective. Therefore we call it the endogenous goal. The possible goals of the auctioneers may be the maximization of sales or profit.

The constraints are classified into two categories. One is exogenous constraints by the auctioneer's trading strategies and the other is exogenous constraints by the bid selection requirements from the bidders. The former is the endogenous strategies and the latter exogenous strategies. The allocation, price, and resource constraints are endogenous constraints derived from endogenous strategies. The maximum or minimum number of winning purchasers, the maximum or minimum number of accepted bids, and the maximum or minimum allocation volume per purchaser comprise the allocation constraints. Especially, the maximum or minimum number of winning purchasers means that the suppliers want to restrict the number of purchasers for each item, either for security or strategic reasons. The constraints of the maximum or minimum number of accepted bids and the maximum or minimum

allocation volume per purchaser mean that the number of accepted bids or allocation volume that single purchasers may gain per item is restricted. The price-related constraint - reserve price - means the purchasers' bids for a specific item should be submitted above the minimum unit price. In many situations, suppliers reserve the right not to sell the item if the price determined in the auction is lower than some threshold amount. Such a price is called the reserve price [20, 34]. The supply capacity constraint is one of the resource-related constraints.

<Table 4> Factors for Bids Selection

Factors		Alternatives	
Endogenous strategy	Goal	Max total sales	G_1
		Max total profit	G_2
	Allocation constraints	Max No of winning purchasers	C_1
		Min No of winning purchasers	C_2
		Max No of accepted bids	C_3
		Min No of accepted bids	C_4
		Max allocation volume per purchaser	C_5
		Min allocation volume per purchaser	C_6
	Price constraints	Reserve price	C_7
Resource constraints	Supply capacity	C_8	
Exogenous strategy	Bid selection constraints	AND (β)	D_1
		OR (β)	D_2
		XOR(β)	D_3
		PRIORITY (β)	D_4
		IF-THEN (β_1, β_2)	D_5

Finally, the bid selection constraints, derived from the bid selection requirements by each bidder, affect the bid selection model as an exogenous strategy. Each bidder selection model has a goal and may have one or more constraints as shown in <Table 4>, and there exist no conflicts among the constraints.

The bidder selection model has a goal and one or more constraints as depicted in the semantic representation in Eq. (5).

Bid Selection Model =

$$(\text{Model_Goal}(G_i); \text{Model_Constraints}\{C_j, D_k\}). \quad (5)$$

Here, the model components are identified by model identification rules (6), (7), and (8).

$$\begin{aligned} & \text{IF Endogenous_Strategy } (G_i) \\ & \quad \text{THEN Model_Goal } (G_i). \end{aligned} \quad (6)$$

$$\begin{aligned} & \text{IF Endogenous_Strategy } (C_j) \\ & \quad \text{THEN Model_Constraint } (C_j). \end{aligned} \quad (7)$$

$$\begin{aligned} & \text{IF Exogenous_Strategy}(\text{Bid_Selection_Requirements } (d_k)) \\ & \quad \text{THEN Model_Constraint } (D_k). \end{aligned} \quad (8)$$

The optimization model can be used to solve the semantic bid selection model. The following mathematical expressions mean the IP model for the identified bid selection model Eq. (9). The notations are as follows: i is the index of purchasers, $\{1, 2, \dots, l\}$; j is the index of bids, $\{1, 2, m[i]\}$; k is the index of items, $\{1, 2, \dots, n\}$; O_{ink} means the unit bid price for item k in bid j of purchaser i ; R_k means the reserve price for item k of the supplier; Q_{ijk} means the bid item quantity of

purchaser i for item k in bid j ; $N_{max,k}$ means the maximum number of selected purchasers for item k ; $D_{min,k}$ means the minimum allocation volume per purchaser for item k ; C_k means the supply capacity of supplier for item k ; X_{ij} is 1 if bid j is allocated to purchaser i , and 0 otherwise; Y_{ik} is 1 if item k is sold to purchaser i , 0 otherwise.

<Table 5> Model Components in Mathematical Representation

Alternatives		Mathematical representations for IP model
Max total sales	G_1	$\max \sum_{i=1}^I \sum_{j=1}^{m_{ij}} \sum_{k=1}^n Q_{ijk} U_{ijk} X_{ij}$. (9)
		$X_{ij} \in \{0,1\}$ for all i, j (10)
Max No of winning purchasers	C_1	if $\sum_{j=1}^{m_{ij}} Q_{ijk} X_{ij} \geq 0$, then $Y_{ik} = 1$, (11)
		else $Y_{ik} = 0$ for all i, k
		$\sum_{i=1}^I Y_{ik} \leq N_{max,k}$ for all k (12)
		$Y_{ij} \in \{0,1\}$ for all i, j . (13)
Min allocation volume per purchaser	C_6	$\sum_{j=1}^{m_{ij}} Q_{ijk} X_{ij} \geq D_{min,k}$ for all i, k (14)
Reserve price	C_7	if $Q_{ijk} X_{ij} > 0$ then $U_{ijk} X_{ij} > R_k$ for all i, j, k (15)
Supply capacity	C_8	$\sum_{i=1}^I \sum_{j=1}^v Q_{ijk} X_{ij} \leq C_k$ for all k (16)
XOR(β)	D_3	$\sum_{j=1}^{m_{ij}} X_{ij} \leq 1$ for all i (17)

Here, the objective function (9) corresponds to the goal of maximizing total sales. Constraint (10) is a binary condition for the decision variables, which is a mandatory constraint for the bidder selection model. Constraints (11) and (12) correspond to the constraint maximum number of

winning purchasers. Constraint (13) is a binary condition. Constraint (14) corresponds to the constraint minimum allocation volume per purchaser. Constraint (15) corresponds to the reserve unit price. Constraint (16) corresponds to the constraint supply capacity. Constraint (17) corresponds to the constraint XOR.

To solve a valid optimization model, data for indices and coefficients is needed. Eq. (18) depicts data for the bid selection model in semantic representation.

Bid Selection Model Data =

(Indices{ i, j, k };
Coefficients{ $Q_{ijk}, U_{ijk}, N_{max,k}, D_{min,k}, R_k, C_k$ }). (18)

Here, the indices are mandatory and the coefficients are dependent on the model components. The coefficients are identified by data identification rules (19) ~ (24).

IF Model_Goal (G_1) OR

Model_Constraint (C_1 OR C_6 OR C_7 OR C_8)
THEN Model_Data (Q_{ijk}). (19)

IF Model_Goal (G_1) OR Model_Constraint (C_8)
THEN Model_Data (U_{ijk}). (20)

IF Model_Constraint (C_1)
THEN Model_Data ($N_{max,k}$). (21)

IF Model_Constraint (C_6)
THEN Model_Data ($D_{min,k}$). (22)

IF Model_Constraint (C_7)
THEN Model_Data (R_k). (23)

IF Model_Constraint (C_8)
THEN Model_Data (C_k). (24)

3.4.3 Auctioneer Selection Strategy

After bidders receive bids awarded by auctioneers, they set up an auctioneer selection strategy and select optimal auctioneers. The auctioneer selection strategy is composed of endogenous strategy as presented in Table 6. The auctioneer selection model is composed of a goal and constraint sets. The goal and constraints are all endogenous for bidders.

The bidder's goal is to select the optimal bids among bids awarded by auctioneers. The possible goal for purchasers is minimization of

total purchase price or maximization of total purchase utility. There are several constraints related to allocation, cost, and bid selection as shown in <Table 6>. There is the maximum or minimum number of winning suppliers for the allocation constraints. This means that the purchasers want to restrict the number of suppliers to whom each item is awarded. Other allocation constraints are the maximum or minimum number of accepted bids, and the maximum or minimum allocation volume per supplier. Finally, the alternatives of cost constraints are maximum unit item price or budget limit. The auctioneer selection model has basically the same form as the bid selection model. Finally, auctioneer selection constraints, derived from bid selection requirements by each bidder, affect the auctioneer selection model as an endogenous strategy.

The auctioneer selection model has a goal and one or more constraints as depicted in semantic representation in Eq. (25).

<Table 6> Factors for Auctioneer Selection

Factors		Alternatives	
Endogenous strategy	Goal	Min total purchase price	H_1
		Max total purchase utility	H_2
	Allocation constraints	Max No of winning suppliers	F_1
		Min No of winning suppliers	F_2
		Max No of accepted bids	F_3
		Min No of accepted bids	F_4
		Max allocation volume per supplier	F_5
		Min allocation volume per supplier	F_6
	Cost constraints	Max unit item price	F_7
		Budget limit	F_8
	Bid selection constraints	AND (β)	D_1
		OR (β)	D_2
		XOR(β)	D_3
		PRIORITY (β)	D_4
		IF-THEN (β_1, β_2)	D_5

Auctioneer Selection Model =
 (Model_Goal(H_i); Model_Constraints{ F_j, D_k }). (25)

Here, the model components are identified by model identification rules (26), (27), and (28).

IF Endogenous_Strategy (H_i)
 THEN Model_Goal (H_i). (26)

IF Endogenous_Strategy (F_j)
 THEN Model_Constraint (F_j). (27)

IF Endogenous_Strategy(Bid_Selection_Requirements(D_k))
 THEN Model_Constraint (D_k). (28)

4. N-BOCA SYSTEM

4.1 The Desired Features of N-BOCA

For effective implementation of N-BOCA where multi-suppliers and multi-purchasers having their own trading strategies participate for optimized trading through multiple rounds, the following desired features should be included.

- Multi-suppliers and multi-purchasers auction mechanism: The framework where multi-purchasers and multi-suppliers can trade simultaneously or continuously through one combinatorial auction market.
- Flexible optimization modeling mechanism: Generally, supply and purchase strategies vary depending on the situation of each organization in the supply chain. In order to support the strategies, diverse models are necessary.
- Coordinated mechanism among participants: Tie bids occur when two or more bids from more than two bidders have equal bidding price and terms. In addition, tie occurs when two or more equal allocation results for one bidder from auctioneers exist. Tie bids or tie-breaking rules can influence the outcome of an auction. A general auction may either break ties arbitrarily or use preference information, or favor earlier bids. If multiple awards are not made, the tie bids or tie allocation modeling results must be resolved. Thus the coordination mechanism to break tie bids or conflicting modeling results should be included for the N-BOCA model.
- The iterative contracting process allowing

round-to-round update of bids: The iterative combinatorial auction mechanism, modification of bids to be winner in the next time, should be possible. Although the iterative combinatorial auctions are more complex than general auctions, the iterative mechanism allows bidders to learn about their competitors' valuations through the bidding process, which might lead them to adjust their own valuations. There are continuous auctions or multi-rounds auctions for the iterative auction mechanism. We consider, in this paper, an iterative auction mechanism that permits multi-rounds auctions.

4.2 Web-based N-BOCA System

We propose a web-based N-BOCA system, based on the desired features stated in the above section. The N-BOCA system is composed of a market manager agent, auctioneer manager agents, bidder manager agents, and optimization modeling agent. The market manager agent plays a role of building a market, opening the market, and coordinating trades between the auctioneers and bidders. The auctioneer manager agents help auctioneers register auction items and select optimal bidders while communicating with the optimization modeling agent. The bidder manager agents help bidders submit bids and select optimal auctioneers while communicating with the optimization modeling agent. The optimization modeling agent identifies optimization models reflecting modeling strategies from bidders or auctioneers, gets model components, builds the

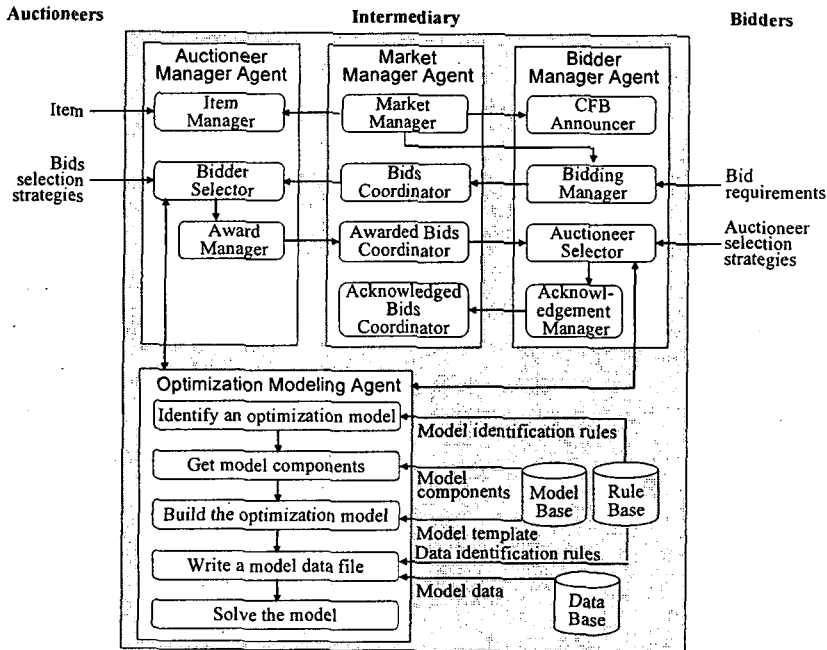
model, writes a data file for the model, and solves the model. [Fig. 4] shows the overall architecture for the web-based N-BOCA system.

The optimization modeling agent needs an IP solver, and model representation is dependent on each solver. We use LINGO version 8.0 as the IP solver. <Table 7> shows illustrative model components in the form of LINGO [27].

[Fig. 5] depicts the template of bid selection model in the form of LINGO [27]. It is composed of three part: model template, objective, and constraints. The objective and constraints in the lower part of the model template vary according to the auctioneer strategies or bid requirements from bidders.

<Table 7> Model Components in the LINGO Format

Alternatives	LINGO format
Max total sales G_1	$\max = @\text{sum}(\text{links3}(i,j,k): Q(i,j,k) * U(i,j,k) * X(i,j));$ $@\text{for}(\text{links1}(i,j): @\text{bin}(X(i,j)));$
Max No of winning purchasers C_1	$@\text{for}(\text{links2}(i,k): Y(i,k) =$ $@\text{if}(@\text{sum}(\text{bid}(j): Q(i,j,k) * X(i,j))$ $\#GT\# 0, 1, 0));$ $@\text{for}(\text{item}(k): @\text{sum}(\text{purchaser}(i):$ $Y(i,k) <= N(k));$ $@\text{for}(\text{links2}(i,k): @\text{bin}(Y(i,k)));$
Min allocation volume per purchaser C_6	$@\text{for}(\text{links2}(i,k): @\text{sum}(\text{bid}(j): Q(i,j,k)$ $* X(i,j)) >= D(k));$
Reserve price C_7	$@\text{for}(\text{links3}(i,j,k): U(i,j,k) * X(i,j) >=$ $@\text{if}(Q(i,j,k) * X(i,j) \#GT\# 0, R(k), 0));$
Supply capacity C_8	$@\text{for}(\text{item}(k): @\text{sum}(\text{links1}(i,j):$ $Q(i,j,k) * X(i,j)) <= C(k));$
XOR(β) D_3	$@\text{for}(\text{purchaser}(i): @\text{sum}(\text{bid}(j):$ $X(i,j)) <= 1);$



[Fig. 4] Overall architecture for the N-BOCA system

```

model:
title Bid selection model in N-BOCA;
!!!!!!!!!! [1] Model template;
sets:
  buyer/@FILE('CA.LDT'):
  .
  bid/@FILE(' CA.LDT '):
  .
  item/@FILE(' CA.LDT '):
    N, D, R, C;
links1(buyer, bid):
  X;
links2(buyer, item):
  Y;
links3(buyer, bid, item):
  Q, U;
endsets
data:
Q = @FILE(' CA.LDT ');
U = @FILE(' CA.LDT ');
N = @FILE(' CA.LDT ');
D = @FILE(' CA.LDT ');
R = @FILE(' CA.LDT ');
C = @FILE(' CA.LDT ');
enddata
!!!!!!!!!! [2] The objective;

!!!!!!!!!! [3] The constraints;

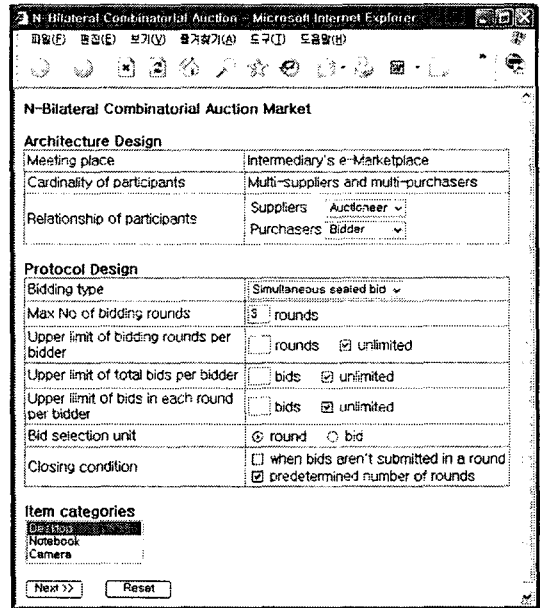
end
    
```

[Fig. 5] Model Template for Bid Selection

Data for indices and coefficients is necessary for solving a model. According to the data identification rules, a data file is presented in the form of LINGO [27].

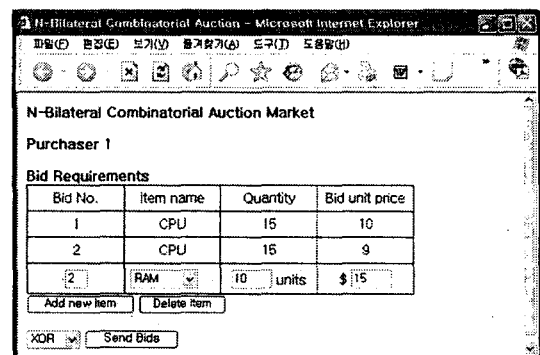
5. AN ILLUSTRATION FOR N-BOCA WITH A PROTOTYPE

In this section, we give a brief description of a prototype for the N-BOCA system. The intermediary designs the architecture and protocol. This process leads to the opening of the market. [Fig. 6] depicts it.



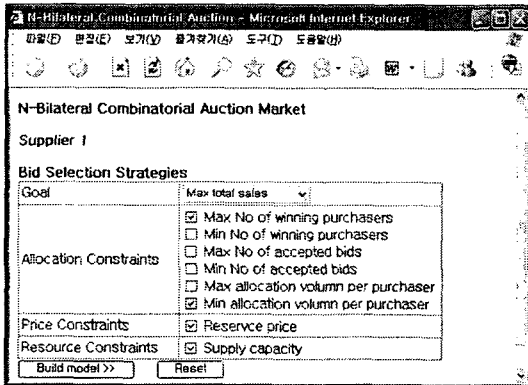
[Fig. 6] Market Opening through Architecture and Protocol Design

After auction items are registered by auctioneers and CFBs are announced to bidders, bidders submit bids on items and bid selection requirements according to their bidding strategies. [Fig. 7] shows bid requirements for XOR bid selection.



[Fig. 7] Bidding Strategies

To select optimal bids, auctioneers set up their goals and constraints. [Fig. 8] shows the strategies with G_1 , C_1 , C_6 , C_7 , C_8 .



[Fig. 8] An Illustration of Bid Selection Strategies by an Auctioneer

Optimization modeling agent identifies a Bid Selection Model as Eq. (29) using model identification rules (6), (7), and (8). D_3 is caused by bid selection requirements from bidder.

Bid Selection Model =
 (Model_Goal(G_1);
 Model_Constraints{ C_1 , C_6 , C_7 , C_8 , D_3 }). (29)

Then, the agent gets model components from model base and inserts them into the model template as shown in Figure 5. And the agent uses data identification rules (19) ~ (24), writes a data file for the model, and finds optimal bids by solving the model. The auctioneer selection case of bidders is the same with the bid selection method.

6. PERFORMANCE EVALUATION

In this section, the performance of N-BOCA is analyzed by comparing it with the general 1-to-N(one-auctioneer to multi-bidders) combinatorial auction approaches. The experiments consist of simulating of our auction mechanism under various conditions to analyze the mechanism's performance. The measures used to evaluate the combinatorial action's performance are allocation efficiency, assignment optimality, bidder profit, and the length of the auction [21, 23]. Efficiency is the most obvious choice of a performance measure [23]. Generally, efficiency is a measure of speed and cost. In this paper, we evaluate the performance of N-BOCA from the perspective of allocation efficiency by comparing it with the efficiency of 1-to-N independent combinatorial auction approaches. In any auction, each bidder has a set of valuations for target bidding items.

The allocation efficiency of the auction mechanism is:

Allocation Efficiency

$$= \sum_{j=1}^m V^j / V^* \text{ for all bid } j. \quad (30)$$

where V^j is the bidder's value on target item set, which is the amount that each bidder will pay if he/she obtains the item set and V^* is the maximum possible total valuation. In our experiments, we specify only the purchase price for the target item set. Thus we evaluate the allocation efficiency

from the perspective of the purchase price.

Specifically, there are the 10 suppliers and 10 purchasers who sell or buy two or more items among heterogeneous items labeled a, b, c, d, e as shown in <Tables 8> and <Table 9>.

<Table 8> Supplier Items

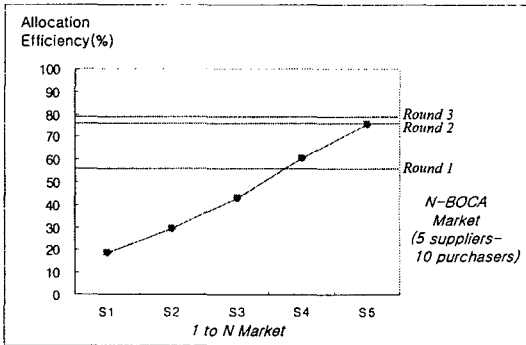
Supplier	Supply Item (item, capacity)
Supplier 1	(a, 20), (b, 20), (c, 40), (d, 20)
Supplier 2	(b, 25), (d, 20), (e, 15)
Supplier 3	(a, 15), (b, 20), (d, 30), (e, 25)
Supplier 4	(b, 10), (c, 50), (e, 20)
Supplier 5	(a, 15), (b, 20), (c, 10), (d, 30), (e, 20)
Supplier 6	(b, 10), (d, 15), (e, 50)
Supplier 7	(a, 40), (b, 15), (d, 25), (e, 15)
Supplier 8	(a, 15), (b, 25), (c, 15), (d, 20)
Supplier 9	(a, 10), (b, 15), (c, 30)
Supplier 10	(b, 25), (c, 45), (d, 20), (e, 10)

<Table 9> Purchaser Bid Requirements

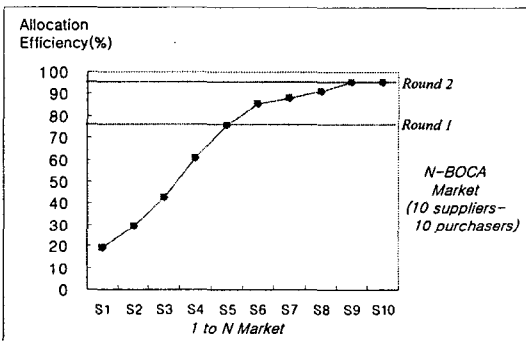
Purchaser	Bid No	Bid requirements {(bid item, quantity, unit bid price)}
Purchaser 1	Bid_1	{(a, 15, 10)}
	Bid_2	{(b, 10, 16)}
	Bid_3	{(a, 15, 9) (b, 10, 15)}
Purchaser 2	Bid_1	{(b, 20, 16)}
	Bid_2	{(c, 20, 20)}
	Bid_3	{(b, 20, 15) (c, 20, 19)}
Purchaser 3	Bid_1	{(a, 20, 12)}
	Bid_2	{(e, 30, 34)}
	Bid_3	{(a, 20, 11) (e, 30, 33)}
Purchaser 4	Bid_1	{(a, 15, 12)}
	Bid_2	{(b, 30, 16)}
	Bid_3	{(d, 30, 30)}
	Bid_4	{(a, 15, 10) (b, 30, 15) (d, 30, 29)}
Purchaser 5	Bid_1	{(c, 20, 22)}
	Bid_2	{(d, 20, 31)}
	Bid_3	{(c, 20, 20) (d, 20, 30)}

Purchaser	Bid No	Bid requirements {(bid item, quantity, unit bid price)}
Purchaser 6	Bid_1	{(a, 10, 12)}
	Bid_2	{(a, 20, 17)}
	Bid_3	{(c, 20, 21)}
	Bid_4	{(a, 10, 10) (a, 20, 15) (c, 20, 20)}
Purchaser 7	Bid_1	{(b, 25, 17)}
	Bid_2	{(c, 20, 22)}
	Bid_3	{(b, 25, 15) (c, 20, 21)}
Purchaser 8	Bid_1	{(c, 30, 21)}
	Bid_2	{(e, 20, 36)}
	Bid_3	{(c, 30, 20) (e, 20, 35)}
Purchaser 9	Bid_1	{(b, 20, 16)}
	Bid_2	{(d, 10, 30)}
	Bid_3	{(e, 20, 36)}
	Bid_4	{(b, 20, 15) (d, 10, 29) (e, 20, 35)}
Purchaser 10	Bid_1	{(a, 10, 11)}
	Bid_2	{(d, 20, 31)}
	Bid_3	{(a, 10, 10) (d, 20, 30)}

[Fig. 9] and [Fig. 10] shows the comparison results of the proposed N-BOCA and the general 1-to-N combinatorial auction from the perspective of the allocation efficiency. In conclusion, N-BOCA yields much higher allocation efficiency and contract ratio than 1-to-N general combinatorial auction approach. [Fig. 9] is the simulation result of the test market in which 5 suppliers and 10 purchasers participate. The allocation efficiency of the general market changes from 18.9% to 75.7% as the purchasers move from one market to the other market in sequence. In contrast, the allocation efficiency of the 1st round in N-BOCA is 58%, and the efficiency of the 2nd and 3rd is 75.7% and 78.9% respectively. Thus, the accumulated efficiency of three rounds in just one N-BOCA market is the same as the accumulated allocation efficiency of independent five auction markets, which is 1-to-N general combinatorial



[Fig. 9] Comparison of the Allocation Efficiency: N-BOCA vs. 1-to-N General Combinatorial Auction Market (5 supplier and 10 purchasers)

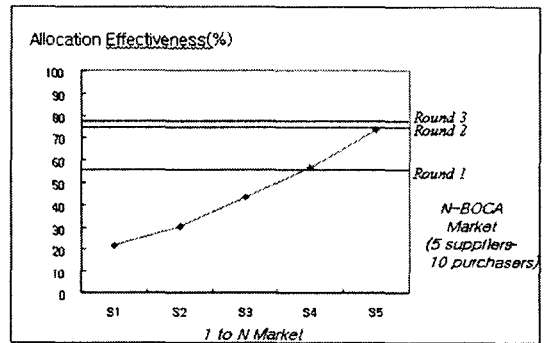


[Fig. 10] Comparison of the Allocation Efficiency: N-BOCA vs. 1-to-N General Combinatorial Auction Market (10 supplier and 10 purchasers)

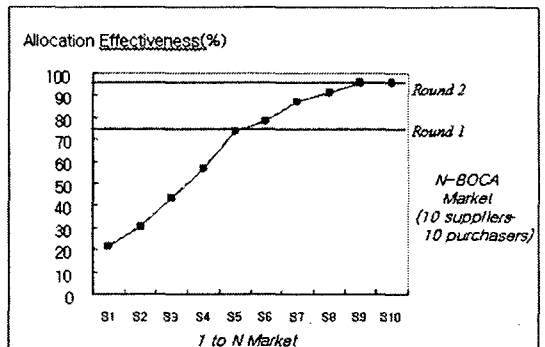
auction market. It means that five independent general marketplaces should be opened for the same allocation efficiency. [Fig. 10] is the simulation result of the test market in which 10 suppliers and 10 purchasers participate. The overall tendency of the results is the same as in [Fig. 9]. In particular, the accumulated allocation efficiency of two rounds in one N-BOCA market is the same as the accumulated efficiency of independent nine 1-to-10 general combinatorial auction market.

The results of both experiments appear to provide compelling evidence that N-BOCA outperforms the general combinatorial auction approach. In addition, the overall performance of N-BOCA significantly increases as more suppliers participate in the market.

[Fig. 11] and [Fig. 12] give the comparison results of N-BOCA and 1-to-N general combinatorial auction from the perspective of the allocation effectiveness. The allocation effectiveness



[Fig. 11] Comparison of the Allocation Effectiveness: N-BOCA vs. General Combinatorial Auction Market (5 supplier and 10 purchasers)



[Fig. 12] Comparison of the Allocation Effectiveness: N-BOCA vs. General Combinatorial Auction Market (10 supplier and 10 purchasers)

of the auction mechanism is the ratio of the number of accepted items to the number of total bid items by all bidders. The overall tendency of the simulation result on allocation effectiveness is similar to that on allocation efficiency. There are totally 23 bid items which bidders want to buy. The allocation effectiveness of N-BOCA changes from 56.5% (1st round), 73.9% (2nd round) to 78.2% (3rd round) under N-BOCA mechanism, while the allocation effectiveness of 1 to 5 general combinatorial auction mechanism changes from 21.7% to 73.9% gradually. Similarly, the allocation effectiveness of N-BOCA where 10 suppliers and 10 purchasers join is 73.9% (1st round) and 95.6% (2nd round).

The above experimental test results show that N-BOCA mechanism yields higher performance. The difference of performance will be increased in proportion to the number of participants and bids when it compared to the general combinatorial auction mechanism.

7. CONCLUSION AND ROADS AHEAD

We have proposed a web-based N-bilateral Combinatorial Auction mechanism with dynamic combinatorial auction - N-BOCA - to overcome the deficiency of traditional 1-to-N general Combinatorial Auction. N-BOCA is a flexible iterative combinatorial auction model that offers optimized solution for multi-purchasers and multi-sellers in the supply chain.

We have designed N-BOCA model from the perspective of architecture, protocol, and trading strategy. N-BOCA, in particular, needs the capability to automatic model formulation to cope with diverse trading strategies of bidders and auctioneers. Hence, we have proposed rule-based optimization modeling agent with automatic model formulation for Integer Programming modeling.

In addition, we have shown the viability of N-BOCA through prototype and experiments. The results yield both higher allocation efficiency and effectiveness compared with 1-to-N general combinatorial auction mechanisms.

Although it seems that N-BOCA model would be a useful auction mechanism for multiple suppliers and purchasers in its current form, additional study is needed to extend the results for a more rigorous and practical mechanism.

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요약

공급사슬에서의 새로운 동적 경매 메커니즘: 다자간 최적화 조합경매 모형

최진호* · 장용식** · 한인구*

본 논문에서는 새로운 조합경매(combination auction)모형인 다자간 최적화 경매모형(N-Bilateral Optimized Combinatorial Auction; N-BOCA)을 제시하였다. N-BOCA는 다수의 공급자 및 다수의 구매자간 최적화된 거래를 지원하는 조합경매모형이다. 특히 아키텍처, 거래규약, 거래전략 세가지 관점에서 N-BOCA 시스템을 설계하였다. 경매시장 참여자인 경매자들과 입찰자들은 특정 아키텍처 및 거래규약하에서 최적 거래 대상자 선정을 위한 다양한 전략을 가지게 되며 이러한 거래전략에 따른 유연한 의사결정 모델링 지원을 필요로 한다. 이에 본 논문에서는 최적의 입찰 및 경매자 선정을 위한 Integer Programming 모형 기반의 에이전트 시스템을 제시하였다. 아울러 N-BOCA 모형의 유용성을 입증하기 위해 프로토타입과 실험결과를 제시하였다. 실험결과, 기존의 일대다 조합경매 모형 대비 높은 거래 성과를 나타내었다.

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