Int J Adv Manuf Technol (2012) 62:847–859
DOI 10.1007/s00170-011-3843-z

ORIGINAL ARTICLE

Virtual enterprises partner selection based on reverse auctions

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Received: 30 July 2011 / Accepted: 6 December 2011 / Published online: 6 January 2012

Abstract Partner selection is a key issue in the development of an effective coalition formation mechanism for virtual enterprises (VE). Combinatorial reverse auction can be applied by a firm to select the best partners to minimize the cost in forming VE. The objectives of this paper are to propose architecture for selecting partners based on combinatorial reverse auction mechanism to minimize the cost of VE, develop algorithms to find a near-optimal solution efficiently, and implement a prototype system based on the proposed algorithms. We formulate the partner selection problem based on combinatorial reverse auctions and apply Lagrangian relaxation technique to solve the problem. Our partner selection solution algorithms include an algorithm for solving bidders' subproblems by exploiting their problem structures, a subgradient algorithm for solving the dual problem, and a heuristic algorithm for finding a near-optimal solution. In addition to theoretical development, we also implement a prototype system based on the proposed algorithms and web services technologies to verify the effectiveness of our methodology.

Keywords Virtual enterprise · Partner selection · Coalition formation · Auction · Web service

1 Introduction

The general rationale for forming a virtual enterprise (VE) is to reduce costs and time to market while increasing flexibility and access to new markets and resources. A VE assembles a temporary consortium of partners and services for fulfilling orders or taking advantage of a new resource or market niche [31]. Individual companies in a VE focus on their core competencies and mission critical operations and outsource everything else. Although virtual enterprises make it possible for small flexible enterprises to form a collaborative network to respond to business opportunities through dynamic coalition and sharing of the core competencies and resources, they also pose new challenges and issues. Several projects that focus on the study of VE have been launched. Among them are the NIIIP project in the USA, the PRODNET project, and the VEGA project in Europe. A wide variety of research issues and topics have been studied, including cooperation/coordination [6], formation [18], partner selection [4], planning and control [39], dynamic network process management [15], dynamic process composition [22], and design and implementation of automated procurement systems [24] in virtual enterprises. The special issue on VE in [1] focuses specifically on topics related to methods and approaches for coalition formation. Camarinha-Matos et al. [5] address the need for agility in fast-changing markets as a key requirement for the establishment of dynamic virtual organizations.

Creation of a VE involves dynamically established partnerships between the partners. It relies on an effective information infrastructure such as service-oriented architecture (SOA) [28] to publish, discover partners, and invoke services provided by partners. Jagdev et al. [24] show how emerging semantic web services technologies facilitate the creation of procurement applications. However, several issues remain to be studied to create VE. For example, partner selection [1, 4, 40] is a key issue in the development of an effective coalition formation mechanism. Partner selection has been studied in [3, 4, 7, 8, 33, 37, 38,

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44]. De Boer et al. [10] divided the partner selection process into three stages, including criteria formulation stage, qualification stage, and final selection stage. This paper focuses on final selection stage to select the best partners from the qualified ones. In existing literature, different decision models for the final selection stage have been proposed, including goal programming, multi-objective programming, and analytic/network process (AHP) models. For example, Baldo et al. [3] focus on the critical issue of selecting best fit partners for the creation of virtual organizations. Crispim et al. [8] formulate the partner selection problem for VE as a multi-criteria decision-making problem with both tangible and intangible criteria. Paper [37] presents a framework and reference architecture that describes the activities that must be performed to set up VE. In [44], a multi-objective optimization model of the partner selection problem and its solution with genetic algorithms are proposed. In [38], the authors propose an AHP model to select partners in VE. The study of [7] presents an example on solving the supplier selection problem in the apparel industry by using an AHP model that takes flexibility and delivery cost into account. Each model has its strength and weakness. For example, goal programming and multi-objective programming techniques for the partner selection problem are able to achieve multiple goals for different levels of performance of the corresponding attributes. AHP can be applied to cope with the fuzziness that occurs when a decision maker compares the relative importance of different attributes. However, these methods do not consider the combination of potential partners that may result in better solutions for the whole supply chain. Therefore, combinatorial reverse auction is adopted in this paper. The objectives of this paper are to propose architecture for selecting partners in forming a VE based on combinatorial reverse auction, formulate the partner selection problem to minimize the cost of a VE, develop a solution algorithm to find a near-optimal solution efficiently, and implement a prototype system based on the proposed algorithms.

Creation of a VE is often driven by the lack of capabilities to fulfill the customers' order requirements by a single firm. The requirements of an order are specified by the product demands. In case the requirements of an order cannot be met, a firm may play the role of a buyer to purchase goods or services from the suppliers to respond to the business opportunity. The firm (which acts as the buyer) and the suppliers as a whole form a VE. Procurement of goods or services can be accomplished by holding a reverse auction in which suppliers provide their competitive biddings to a buyer [9, 12]. Each supplier indicates the minimum price at which it is willing to undertake the work or provide the goods/services. Through this, competition auctions appear as an effective way to reduce prices for the buyer. Since the assignment is typically awarded to the supplier providing the lowest bid, each supplier is spurred to provide the lowest possible bid, taking into account the expected level of competition and its expected rate of return.

We propose architecture for forming a VE based on SOA [28] and combinatorial reverse auctions. SOA enables individual firms to provide their services and consume others' services on the Web based on a find–bind–execute paradigm. Combinatorial reverse auctions are popular, distributed, and autonomy-preserving ways of allocating items or tasks among multiple agents to minimize cost. It can be applied to minimize the cost of a VE. Our recent preliminary study [21] indicates that combinatorial reverse auction is a proper business model for VE. Therefore, combinatorial reverse auction is adopted in this paper to determine the best partners in forming a VE.

An excellent survey on combinatorial auctions can be found in [11]. In a combinatorial auction, bidders may place bids on combinations of items or tasks. This allows the bidders to express complementarities between items instead of having to speculate into an item's valuation the impact of possibly getting other complementary items or tasks. Combinatorial auctions have been notoriously difficult to solve from a computational point of view [34] due to the exponential growth of the number of combinations [42]. The combinatorial auction problem can be modeled as a set packing problem (SPP) [2, 13, 19, 36, 41]. Sandholm et al. mention that determining the winners so as to maximize revenue in combinatorial auction is NP-complete ([35, 36]). Many algorithms have been developed for combinatorial auction problems. For example, in [17, 20], the authors proposed a Lagrangian Heuristic for a combinatorial auction problem. Exact algorithms have been developed for the SPP problem, including a branch and bound search, iterative deepening A* search [36]), and the direct application of available CPLEX solver [2]. Ono, Nishiyama, and Horiuchi presented an algorithm to reduce the computational complexity of winner determination for combinatorial ascending auction where bidding agents can place a bid for a combination of items at an arbitrary timing via the Internet [27]. In [25], Kaihara proposed an e-Marketplace server for B2B electronic commerce with multi-agent paradigm that mediates among unspecified various companies in the trade and demonstrated the applicability of the economic analysis to this framework.

One way to reduce the computational complexity in solving the partner selection problem based on combinatorial reverse auction is to set up a fictitious market to determine an allocation and prices to adapt to dynamic environments. In this paper, we apply Lagrangian relaxation [26, 29] technique to develop a solution algorithm for the partner selection problem. Lagrangian relaxation provides a systematic approach to determine an allocation and prices based on the introduction of Lagrange multipliers, which set prices for each item to be purchased by the buyer. It should be emphasized that Lagrangian relaxation is not guaranteed to find the optimal solution to the underlying problem. Furthermore, it is not guaranteed to produce a feasible solution by applying Lagrangian relaxation technique. In case the resulting solution is not feasible, a heuristic algorithm must be applied to adjust the infeasible solution to a feasible one. We develop a heuristic algorithm for finding a near-optimal, feasible solution based on the solution of the relaxed problem.

Based on the proposed partner selection algorithms, we design and implement a prototype system based on Web Services technologies. The core of the Web Services consists of several functions, including request for tender, submission of bids, and determination of winners. To demonstrate the effectiveness of our prototype system, we study the performance and efficiency of our algorithms through numerical examples. We evaluate the quality of the solutions obtained by applying Lagrangian relaxation based on the duality gap, which makes it possible to evaluate the optimality of the solution obtained without knowing the optimal solution. To assess the efficiency and the scalability of our algorithm, we study the growth of the computational time with respect to the problem size parameters. This study is different from paper [17] in that this paper focuses on combinatorial reverse auction problem whereas paper [17] concentrates on combinatorial auction problem. Although combinatorial auction and combinatorial reverse auction are related, the problem structures and application scenarios are different as combinatorial auction is applied by a seller to maximize the revenue via selection of the best bids placed by the potential buyers while combinatorial reverse auction is applied by a buyer to minimize the procurement cost by selecting the best bids placed by the potential sellers. Despite their differences, the subgradient algorithm proposed in this paper exhibits advantage over the CPLEX solver [23] in computational efficiency and performance similar to those of paper [17].

The remainder of this paper is organized as follows. In Section 2, we present architecture for formation of a VE based on combinatorial reverse auctions. In Section 3, we formulate the partner selection problem. In Section 4, we propose a partner selection algorithm based on Lagrange relaxation. In Section 5, we detail the design of our prototype system and present our experimental results and analysis. We conclude this paper in Section 6.

2 Virtual enterprises formation based on auctions

Given an order with specific product demands, the problem is to form a VE for fulfilling the order. Consider a scenario in which a customer places an order to a manufacturer. Suppose the order requirements include a bundle of items and the manufacturer is not able to provide all the items on its own. In this case, the manufacturer will try to acquire the required items from the suppliers or partners. Service-oriented architecture (SOA) provides an infrastructure to discover partners and services to process an order. However, SOA does not provide the mechanism to determine the best partners. An effective approach to determine the best partners is based on auctions. Auctions are popular, distributed, and autonomy-preserving ways of allocating items or tasks among multiple agents to maximize revenue or minimize cost. In economics, different types of auctions have been proposed and extensively studied, including English Auction (open ascending price auction), Dutch auction (open descending price auction), sealed first-price auction, etc. Single-item auctions are by far the most common auction format, but they are not always efficient. Combinatorial auctions [30, 35, 43] enable several bidders to bid on different combination of goods according to personal preferences in the auction process. Allowing bids for bundles of items is the foundation of combinatorial auctions. Bidders can select multiple items at one time and offer those items a price. It enables bidders to decide combinations of auction according to personal preferences of bidders. Combinatorial auctions are beneficial if complementarities exist between the items to be auctioned.

To endow the SOA infrastructure with the capability to determine the best partners, we propose architecture based on combinatorial reverse auction as shown in Fig. 1 in which four steps are involved to form a VE.

Step 1: The manufacturer acts a buyer and issues a request for tender to solicit the potential sellers to place bids.

Step 2: Each seller registers his/her products/services in the registry. Based on the registry, the system generates a list of request for tenders for the sellers to place bids.

Step 3: The manufacturer determines the winners and notifies them.

Step 4: The manufacturer establishes the contracts with the winners.

Combinatorial reverse auction can be applied in procurement to purchase goods at the lowest possible cost. A buyer can hold a reverse auction to try to obtain the goods from a set of sellers who can provide the goods. Each seller places bids for each bundle of goods he can provide. From the viewpoint of a buyer, an important issue is to design an effective algorithm to collectively minimize the overall cost. To minimize the cost in forming a VE, the manufacturer holds a combinatorial reverse auction. Figure 2 illustrates a scenario in which a manufacturer requests to purchase at least a bundle of items 2A, 3B, 2C, and 1D from the market. There are three bidders, supplier 1, supplier 2, and supplier 3, who place bids in the system. Suppose supplier 1 places

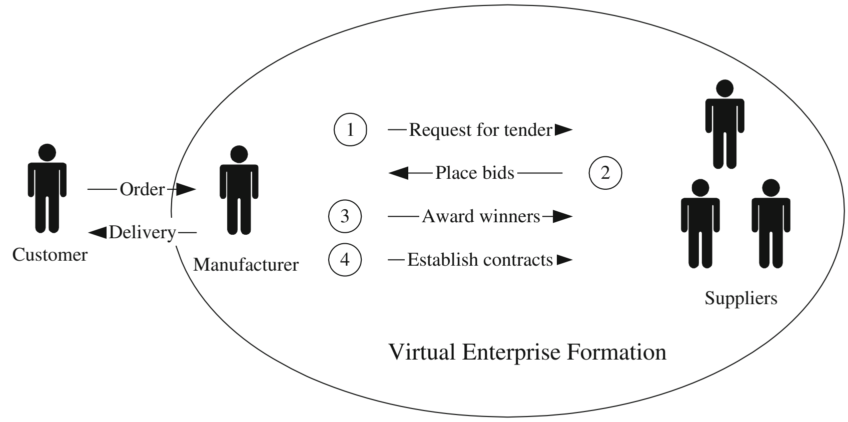


Fig. 1 Formation of a VE based on reverse auction

the bid: (2A, 2B, p1), where p1 denotes the price of the bid. Supplier 2 places the bid: (1B, 2C, 1D, p2), where p2 denotes the price of the bid. Supplier 3 places the bid: (1C, 1D, p3), where p3 denotes the price of the bid. We assume that all the bids entered in the auction are recorded. A bid is said to be active if it is in the solution. We assume that there is only one bid active for all the bids placed by the same bidder. For this example, the solution for this reverse auction problem is supplier 1: (2A, 2B, p1) and supplier 2: (1B, 2C, 1D, p2). The total price of the solution is p1+p2.

To propose a systematic methodology to solve the partner selection problem, a problem formulation is required. The problem formulation is detailed in the next section.

3 Partner selection problem formulation

In this section, we first formulate the partner selection problem based on combinatorial reverse auction as an integer programming problem. We then develop solution algorithms based on Lagrangian relaxation.

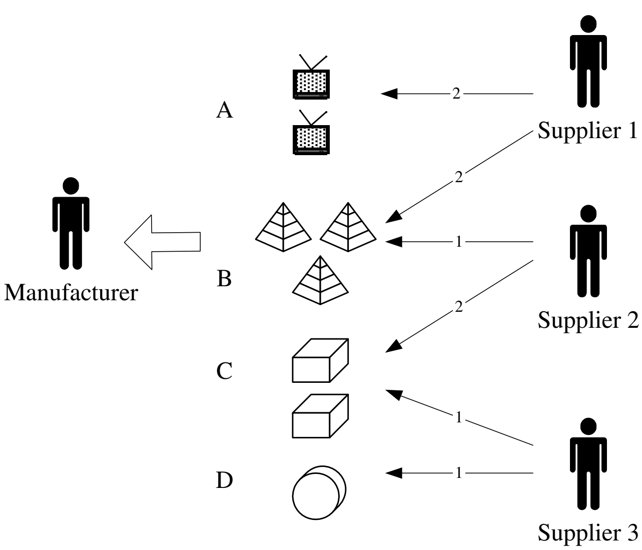


Fig. 2 Combinatorial reverse auction

In a combinatorial auction, there are many bidders to submit a tender. To model the combinatorial auction problem, we define the following notation.

K	the number of items requested by the buyer who requests a set of items to be purchased.
d_k	the desired units of the kth items, where $k \in \{1,2,3....,K\}$.
S	the set of bidders in a combinatorial reverse auction. Each $s \in S$ represents a bidder.
$b_{sj}=(q_{sj1}, q_{sj}, q_{sj3},\ldots,q_{sjK}, p_{sj})$	a vector to represent the jth bid submitted by bidder $s \in S$, where q_{sjk} is a nonnegative integer that denotes the quantity of the kth items and p_{sj} is a real positive number that denotes the price of the bundle.
n_s	the number of bids placed by bidder $s \in S$.
x_{sj}	the variable to indicate the jth bid placed by bidder s is selected ($x_{sj}=1$) or not selected ($x_{sj}=0$).

As the quantity of the kth items cannot exceed the quantity d_k, it follows that the constraint $0 \le q_{sjk} \le d_k$ must be satisfied. The jth bid b_{sj} is actually an offer to deliver q_{sjk} units of items for each $k \in \{1,2,3,....,K\}$ a total price of p_{sj}. The partner selection problem can be formulated as an Integer Programming problem as follows.

Partner selection problem

$$\min \sum_{s \in S} \sum_{j=1}^{n_s} x_{sj} p_{sj}$$

$$s.t. \sum_{s \in S} \sum_{j=1}^{n_s} x_{sj} q_{sjk} \ge d_k \ \forall k = 1, 2, \ldots, K \tag{3–1}$$

$$\sum_{j=1}^{n_s} x_{sj} \leq 1 \forall s \in S \qquad (3\text{–}2)$$

$$x_{sj} \in \{0,1\} \forall s,j \qquad (3\text{–}3)$$

In partner selection problem (PSP), we observe that the coupling among different operations is caused by the contention for the items through the minimal requirement constraints (3–1). To find a solution to PSP requires the development of combinatorial reverse auction algorithms. By applying an effective combinatorial reverse auction algorithm, the reseller will be able to optimize the overall costs.

Development of an effective combinatorial reverse auction algorithm to solve PSP is a key issue. Combinatorial auctions have attracted considerable attention in the existing literature. An excellent survey on combinatorial auctions can be found in [11] and [30]. Combinatorial auctions have been notoriously difficult to solve from a computational point of view [34] due to the exponential growth of the number of combinations [42]. One way to reduce the computational complexity in solving the PSP is to set up a fictitious market to determine an allocation and prices in a decentralized way to adapt to dynamic environments where bidders and items may change from time to time. In this paper, we apply Lagrangian relaxation technique to develop a solution algorithm for PSP.

Lagrangian relaxation provides a systematic approach to determine an allocation and prices based on the introduction of Lagrange multipliers, which set prices for each item to be purchased by the buyer. If two or more sellers compete for the same item, the price will be adjusted. This saves bidders from specifying their bids for every possible combination and the buyer from having to process each bid function. Based on the price for the individual items, bidders submit bids. The bundle associated with a bid is tentatively assigned to that bidder only if the price of the bid is the lowest. Based on the iterative price adjustment mechanism, a solution will be obtained. It should be emphasized that Lagrangian relaxation is not guaranteed to find the optimal solution to the underlying problem. Furthermore, it is not guaranteed to produce a feasible solution by applying Lagrangian relaxation technique. In case the resulting solution is not feasible, a heuristic algorithm must be applied to adjust the infeasible solution to a feasible one. We develop a heuristic algorithm for finding a near-optimal, feasible solution based on the solution of the relaxed problem.

4 Partner selection algorithm

The partner selection algorithm proposed in this paper is developed by applying the Lagrangian relaxation technique. Figure 3 details the flow chart of our partner selection algorithms, which consists of the algorithm for solving the dual problem described in Fig. 4 and the heuristic algorithm to find feasible solution detailed in Fig. 5.

(1) Subgradient algorithm for solving dual problem

The dual problem of PSP is as follows.

$\max_{\lambda \geq 0} L(\lambda)$, where

$$\begin{aligned} L(\lambda) = \min & \sum_{k=1}^{K} \lambda_k d_k + \sum_{s\in S} \sum_{j=1}^{n_s} x_{sj}\left(p_{sj} - \sum_{k=1}^{K} \lambda_k q_{sjk}\right) \\ s.t. & \sum_{j=1}^{n_s} x_{sj} \leq 1 \ \forall s \in S \\ & x_{sj} \in \{0,1\} \\ = & \sum_{k=1}^{K} \lambda_k d_k + L_s(\lambda), \text{ with} \end{aligned}$$

$$\begin{aligned} L_s(\lambda) = \min & \sum_{j=1}^{n_s} x_{sj}\left(p_{sj} - \sum_{k=1}^{K} \lambda_k q_{sjk}\right) \\ s.t. & \sum_{j=1}^{n_s} x_{sj} \leq 1 \\ & x_{sj} \in \{0,1\} \end{aligned}$$

$L_s(\lambda)$ defines a bidder's subproblems.

For a given Lagrange multiplier λ, the relaxation of constraints (3–1) decomposes the original problem into a number of bidder's subproblems. These subproblems can be solved independently. Given λ, the optimal solution to subproblem $L_s \lambda()$ can be solved as follows.

Let $j^* = \arg \min_{j\in\{1,2,\ldots,n_i\}} \left(p_{sj} - \sum_{k=1}^{K} \lambda_k q_{sjk}\right)$. The optimal solution to $L_s(\lambda)$ is as follows.

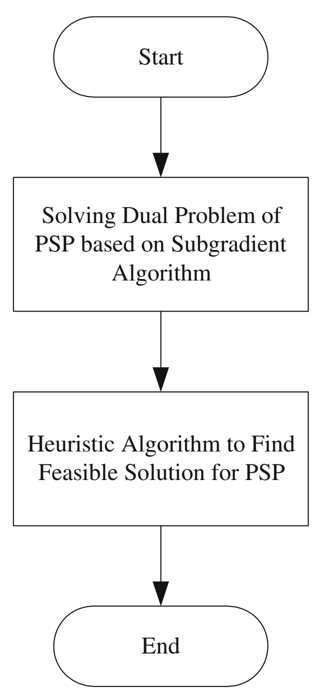


Fig. 3 Flow chart of the solution algorithm

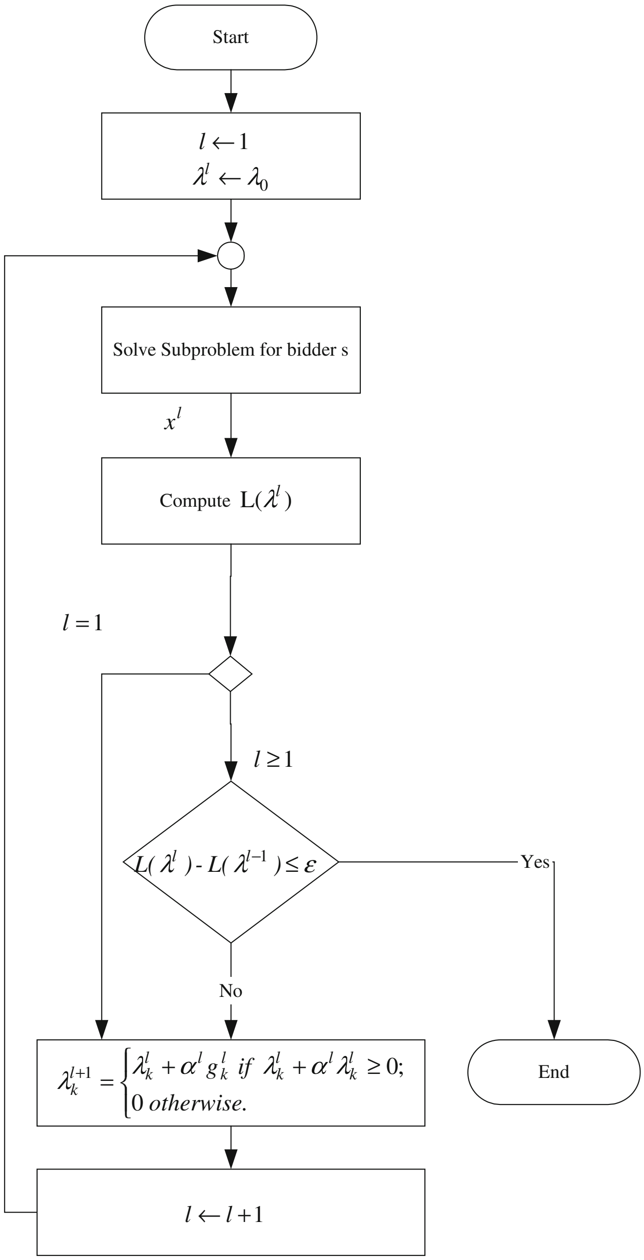


Fig. 4 Flow chart for solving the dual problem

$$x_{sj} = \begin{cases} 0 \ \forall j \in \{1, 2, \ldots, n_s\} \backslash \{j^*\} \\ 1 \text{ if } P_{sj^*} - \sum_{k=1}^{K} \lambda_k q_{sj^*k} < 0 \\ 0 \text{ if } P_{sj^*} - \sum_{k=1}^{K} \lambda_k q_{sj^*k} >= 0 \end{cases}$$

The subgradient method to iteratively solve the dual problem $\max_{\lambda \geq 0} L(\lambda)$ is outlined as follows.

Let x^l be the optimal solution to the subproblems for given Lagrange multipliers λ^l of iteration l. We define the subgradient of $L(\lambda)$ as

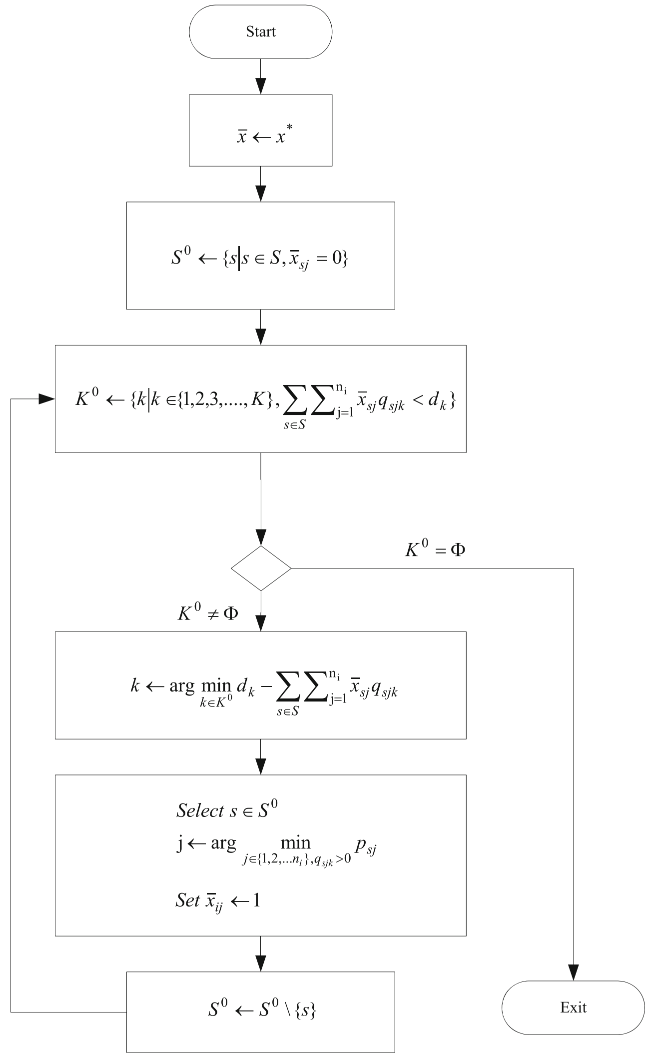


Fig. 5 Heuristic algorithm for finding a feasible solution

$$g_k^l = \frac{\partial L(\lambda)}{\partial \lambda_k} \bigg|_{\lambda_k^l} = d_k - \sum_{s \in S} \sum_{j=1}^{n_s} x_{sj} q_{sjk},$$

where $k \in \{1,2,\ldots,K\}$.

The subgradient method proposed by Polak [32] is adopted to update λ as follows

$$\lambda_k^{l+1} = \begin{cases} \lambda_k^l + \alpha^l g_k^l \ if \ \lambda_k^l + \alpha^l \lambda_k^l \geq 0; \\ 0 \text{ otherwise} \end{cases}, \text{where } \alpha^l = c \frac{\overline{L} - L(\lambda)}{\sum_k \left(g_k^l\right)^2},$$

$0 \leq c \leq 2$ and $\overline{L}$is an estimate of the optimal dual cost. The iteration step terminates if α^l is smaller than a threshold. This method has a linear convergence rate.

The flow chart of our algorithm for solving the dual problem is depicted in Fig. 4. By iteratively applying the algorithm, the solution will converge to an optimal dual solution (x^*, λ^*).

(2) A heuristic algorithm to find a near-optimal feasible solution

The solution (x^*, λ^*) may result in one type of constraint violation due to relaxation: assignment of the quantity of items less than the demand of the items. We propose the following heuristic algorithm in Fig. 5 to adjust the solution (x^*, λ^*) of the dual problem to obtain a feasible solution.

Our heuristic scheme first checks the demand constraints (3–1) that are not satisfied. The set of demand constraints violated is $K^0 =$

$$\left\{k|k \in \{1,2,3,....,K\}, \sum_{s\in S}\sum_{\mathrm{j}=1}^{n_s} x^*_{sj}q_{sjk} < d_k\right\}.$$

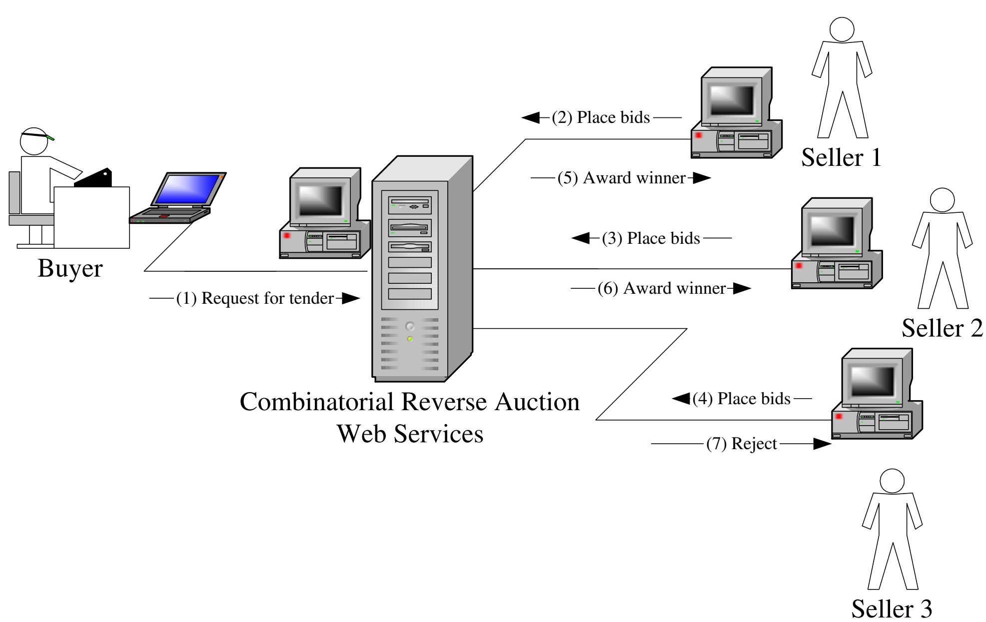
The set of bidders that is not a winner in solution x^* is $S^0 = \{s|s \in S\}, x^*_{sj} = 0\}$. To make the set of constraints K^0 satisfied, the algorithm first picks $k \in K^0$ with $k = \arg\min_{k\in K^0} d_k - \sum_{s\in S}\sum_{j=1}^{n_s} x^*_{sj}q_{sjk}$, selects $s \in S^0$ and $j \in \{1,2,\ldots,n_s\}$ with $j = \arg\min_{j\in\{1,2,\ldots n_s\}, q_{sjk}>0} p_{sj}$ and sets $x^*_{sj} = 1$. After performing the above operation, we set $S^0 \leftarrow S^0 \backslash \{s\}$. The same procedure repeats if the violation of the kth constraint cannot be completely resolved. Eventually, all the constraints will be satisfied.

5 Design of prototype system and experimental results

Based on the proposed algorithms for combinatorial reverse auction, we design and implement a prototype system to verify the effectiveness of our solution methodology. In this section, we focus on the design and implementation of our prototype system. Experimental results and analysis based on the prototype system will be detailed in the next section.

Figure 6 shows a scenario in which one buyer issues a request for tender to the potential sellers based on our prototype system. In Fig. 6, three potential sellers place bids, but only seller 1 and seller 2 are awarded the contracts. We implement our algorithms based on Web Services technologies. The core of the Web Services consists of several functions, including request for tender, submission of bids, and determination of winners. The prototype system provides several functions for buyers and sellers to request for tender and submit the proposals. Specifications of the prototype system requirements with UML are shown in Figs. 7, 8, and 9. Figure 7 shows the class diagram of the prototype system. There are nine classes that define the entities in our prototype, including Member, Buyer, Bidder, Requirement, Item, Bid, Bid_Details, Contract, and Solver. Buyer and Bidder inherit the properties and methods of the Member class and are subclasses of the Member classes. A Buyer object can add, update (before submission), remove, and query the requirements, whereas a Bidder object can create, update (before submission), and submit bids. A requirement often consists of multiple items in combinatorial reverse auctions. The Requirement class provides addItem, updateItem, updateItem, and queryItem to specify the items and quantities. A bid is made of multiple items and the bundle price for the items offered in combinatorial reverse auctions. The Bid_Details class provides the specifyBidDetails method to specify the quantities of the items offered and the bundle price. The Solver class has two methods, solve_dual problem and find_feasible_solution, defined to find a

Fig. 6 A scenario of combinatorial reverse auction



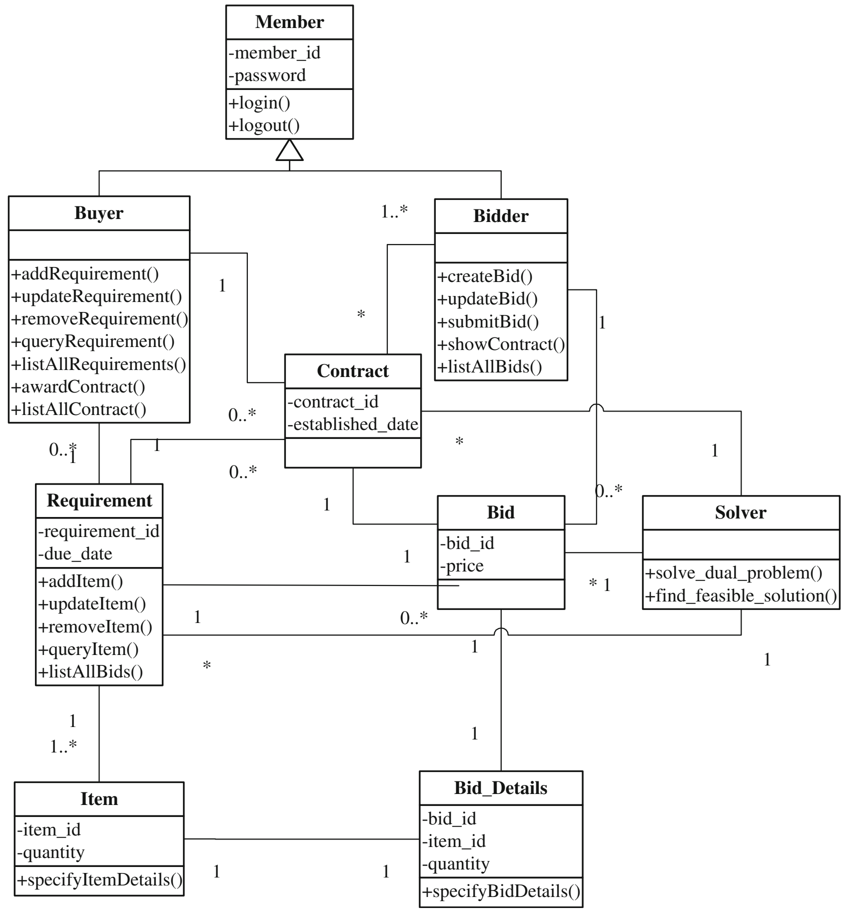


Fig. 7 Class diagram

feasible solution for PSP based on the object of the Requirement class and the objects of the Bid class. The solution obtained by the Solver class is represented by the objects of the Contract class.

Figure 8 illustrates the sequence diagram detailing the interaction between a buyer and the system. The methods provided to a buyer include: (1) login method to verify users, (2) addRequirement method to create a requirement for combinatorial reverse auction, (3) addItem method to add items to the requirement, and (4) specifyItemDetails method to detail each item specified in the requirement. Our prototype system is implemented based on the platforms that support Java 2 Enterprise Edition.

Figure 9 shows the sequence of operations performed by the sellers to take part in the activities involved in the combinatorial reverse auction. The methods provided to a

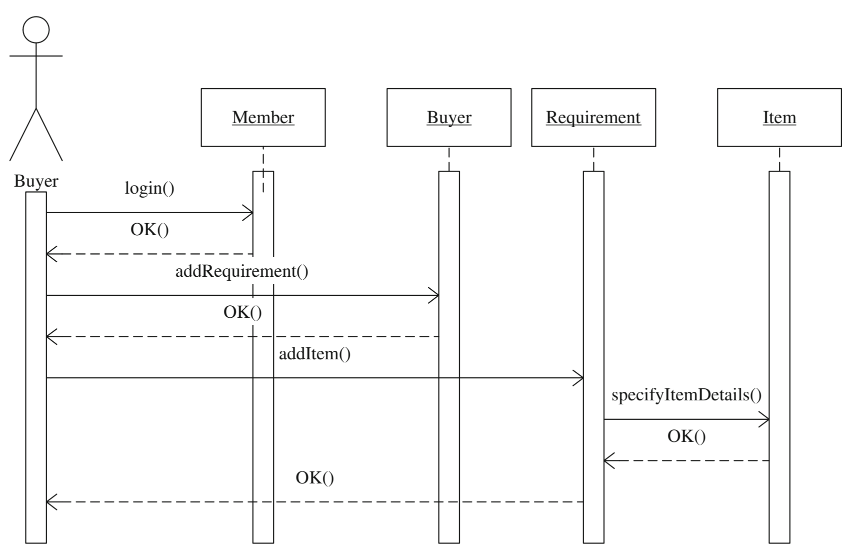
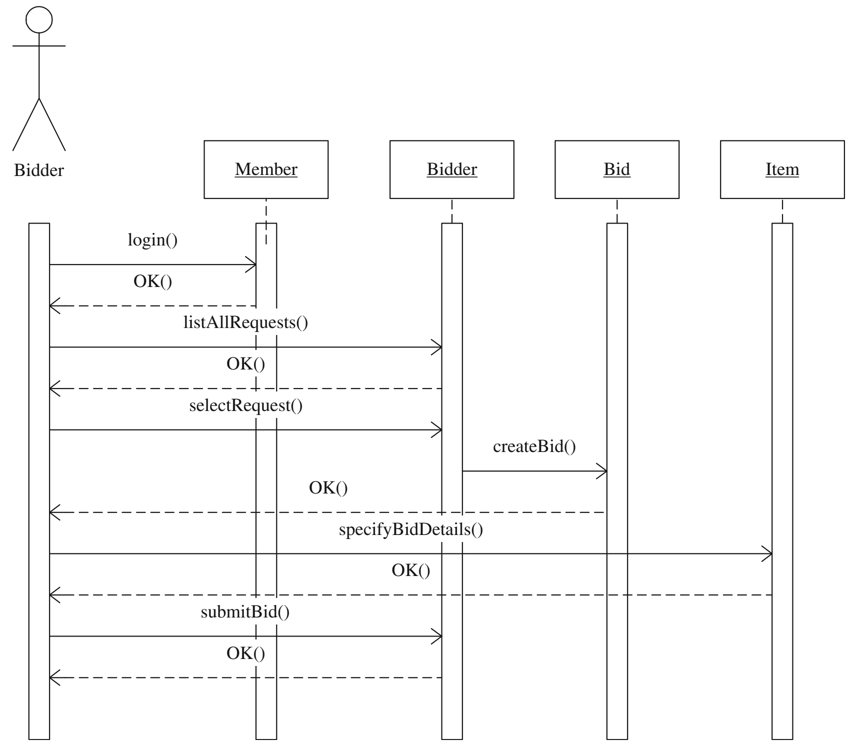


Fig. 8 Interaction between a buyer and the system

Fig. 9 Interactions between a bidder and the system



bidder include:(1) login method to verify users, (2) listAllRequests method to browse all the available combinatorial reverse auctions, (3) selectRequest method to select the requirement to place bid, (4) createBid method to create the bid, (5) specifyBidDetails to specify the details of the bid for the selected combinatorial reverse auction, and (6) submitBid to upload the bid to the database.

In addition to the nine classes that define the entities in our prototype, we also define two methods for the proposed algorithm: the Subgradient method and the Heuristics method. The subgradient algorithm for solving the dual problem is implemented in the Subgradient method, whereas the heuristic algorithm is implemented in the Heuristics method. The subgradient algorithm and the heuristic algorithm are triggered by the due date of the combinatorial reverse auction. Figure 10 shows the interactions between a buyer and the problem solver developed based on the proposed algorithm.

Based on the proposed algorithms for combinatorial reverse auction, we conduct simulation of several examples to illustrate the effectiveness of our method. To demonstrate the effectiveness of our prototype system, we study the performance and efficiency of our algorithms through numerical examples. The performance issue focuses on the optimality of the solutions obtained through our algorithm, whereas the efficiency issue concentrates on the scalability of our proposed algorithm. In optimization theory, the quality of a solution obtained by applying Lagrangian relaxation can be assessed based on the duality gap. Duality gap is the ratio of the difference between primal and dual objective values divided by the primal objective value. Duality gap makes it possible to evaluate the optimality of the solution obtained without knowing the optimal solution. For our problem formulation, the duality gap is defined by $\frac{f(\overline{x})-L(\lambda^*)}{f(\overline{x})}$ with $f(\overline{x}) = \sum\limits_{s\in S} \sum_{j=1}^{n_s} \overline{x}_{sj} p_{sj}$.

Figure 11a, b shows two screen shots of our prototype system.

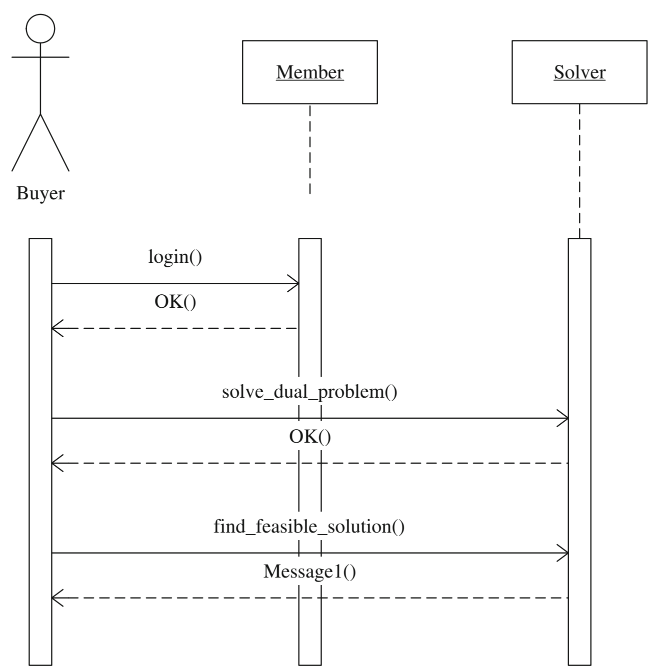
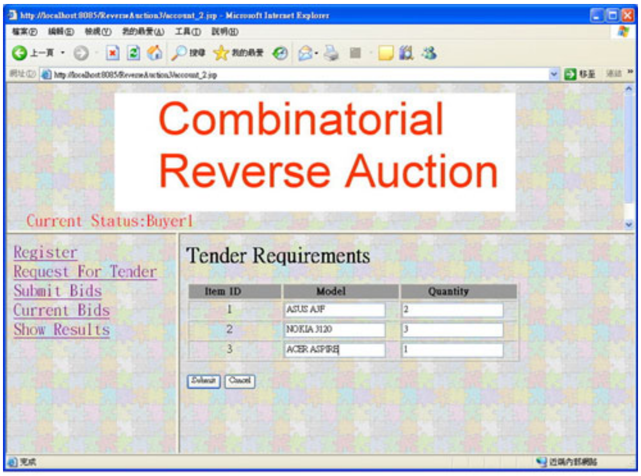
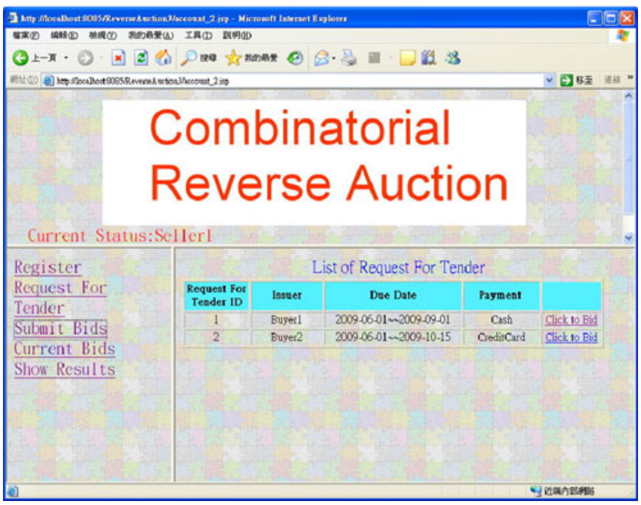


Fig. 10 Interactions between a buyer and the solver



(a) Specification of Tender Requirements



(b) A screenshot of combinatorial reverse auction system

Fig. 11 **a** Specification of tender requirements. **b** A screenshot of combinatorial reverse auction system

Example: Consider a buyer who will purchase a set of four items. The desired quantity of each type of items is listed in Table 1. Suppose there are 14 bidders. Suppose each seller only places one bid. The bids placed by the bidders are listed in Table 2.

For this example, we have

$$|S| = 14, \quad J = 1, \quad K = 4,$$
$$d_1 = 4, d_2 = 5, d_3 = 5, d_4 = 7.$$

Table 1 A buyer's requirement

Goods	Item1	Item2	Item3	Item4
Quantity	4	5	5	7

Table 2 Bids placed by bidders

	Item1	Item2	Item3	Item4	Price
Bid 1	2	3	1	0	48
Bid 2	0	0	3	2	85
Bid 3	1	2	0	4	100
Bid 4	0	0	0	1	23
Bid 5	1	0	0	0	6
Bid 6	0	0	1	0	16
Bid 7	1	1	1	1	61
Bid 8	0	0	1	1	50
Bid 9	1	0	0	2	60
Bid 10	1	0	1	0	30
Bid 11	0	2	2	0	55
Bid 12	3	1	0	0	35
Bid 13	0	0	1	2	60
Bid 14	0	2	2	0	60

$$q_{111} = 2, q_{112} = 3, q_{113} = 1, q_{114} = 0$$
$$q_{211} = 0, q_{212} = 0, q_{213} = 3, q_{221} = 2$$
$$q_{311} = 1, q_{312} = 2, q_{313} = 0, q_{314} = 4$$
$$q_{411} = 0, q_{412} = 0, q_{413} = 0, q_{414} = 1$$
$$q_{511} = 1, q_{512} = 0, q_{513} = 0, q_{514} = 0$$
$$q_{611} = 0, q_{612} = 0, q_{613} = 1, q_{614} = 0$$
$$q_{711} = 1, q_{712} = 1, q_{713} = 1, q_{714} = 1$$
$$q_{811} = 0, q_{812} = 0, q_{813} = 1, q_{814} = 1$$
$$q_{911} = 1, q_{912} = 0, q_{913} = 0, q_{914} = 2$$
$$q_{10,11} = 1, q_{10,12} = 0, q_{10,13} = 1, q_{10,14} = 0$$
$$q_{11,11} = 0, q_{11,12} = 2, q_{11,13} = 2, q_{11,14} = 0$$
$$q_{12,11} = 3, q_{12,12} = 1, q_{12,13} = 0, q_{12,14} = 0$$
$$q_{13,11} = 0, q_{13,12} = 0, q_{13,13} = 1, q_{13,14} = 2$$
$$q_{14,11} = 0, q_{14,12} = 2, q_{14,13} = 2, q_{14,14} = 0$$

Suppose the prices of the bids are:

$$p_{11} = 48, p_{21} = 85, p_{31} = 100, p_{41} = 23, p_{51} = 6, p_{61}$$
$$= 16, p_{71} = 61, p_{81} = 50, p_{91} = 60, p_{10,1} = 30, p_{11,1}$$
$$= 55, p_{12,1} = 35, p_{13,1} = 60, p_{14,1} = 60.$$

Suppose we initialize the Lagrange multipliers as follows: $\lambda(1) = 5.0, \lambda(2) = 10.0, \lambda(3) = 15.0, \lambda(4) = 20.0$. Our algorithm generates the solution: $\bar{x}_{31} = 1, \bar{x}_{11} = 1, \bar{x}_{21} = 1, \bar{x}_{11,1} = 1, \bar{x}_{12,1} = 1, \bar{x}_{13,1} = 1$. The solution indicates that the complementarity between the bids placed by bidder 1, bidder 2, bidder 3, bidder 11, bidder 12, and bidder 13 makes it possible for them to form a virtual enterprise to fulfill the buyer's requirements. This result is consistent with the fact that there exists complementarity between the bids placed by the winners of most combinatorial reverse auctions. For the current example, the duality gap of the solution is 0.7%.

In addition to the above example, Table 3 illustrates the duality gap of several cases based on the problem size (|*S*|, *J*, *K*). According to the results, the duality gaps are within 2.5%. This means the solution methodology generates near-optimal solutions.

In addition to the examples above, we also conduct several experiments to study the performance and computational efficiency of our proposed algorithm. Our algorithm always leads to optimal or near-optimal solutions much more efficiently than the CPLEX integer programming solver (IBM ILOG CPLEX Optimizer) [23]. For all the 40 test cases that have been tested in this paper, our algorithm generates optimal solutions for 92% of the test cases and generates solutions within 3% of the optimal solutions for the remaining 8% of the test cases often in less than 10% of the time required by CPLEX. These results illustrate that our algorithm leads to near-optimal solutions more efficiently than CPLEX. To study the computational efficiency of our proposed algorithm, we conduct the following experiments to compare the computational time of our algorithm with that of the CPLEX integer programming solver with respect to |*S*|, the number of bidders.

Figure 12 shows the CPU time for a number of problems in which all other parameters are fixed while the number of bidders |*S*| is increased. The increase in the CPU time is not significant with respect to the number of bidders. Figure 12 shows the growth of CPU time with respect to |*S*| for the CPLEX integer programming solver and our algorithm. Figure 12 also indicates that the CPU time required for the CPLEX integer programming solver is significantly longer than our algorithm. Table 4 shows the detail results for a number of problems in which all other parameters are fixed (J=1, K=10) as the number of bidders |*S*| is increased. Table 4 indicates our method leads to near-optimal solutions as the duality gap is within 3%, which means that the cost of our solution is within 3% the optimal solution. In summary, the quality of the solutions generated by our algorithm is comparable to those generated by the CPLEX integer programming solver and our algorithm is more efficient than the CPLEX integer programming solver.

Table 3 Duality gap of several cases

|*S*|	*J*	*K*	Duality gap (%)
7	2	4	0.73
10	5	10	2.2
30	10	20	2.4
70	2	5	0.9

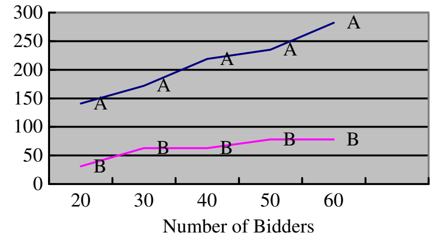


Fig. 12 CPU time (in milliseconds) with respect to the number of bidders. **a** CPLEX, **b** our algorithm

6 Conclusion

Creation of a virtual enterprise (VE) relies on an effective partner selection method to determine the best partners. We propose architecture for forming a VE based on service-oriented architecture and combinatorial reverse auctions. Combinatorial reverse auction is a popular, distributed, and autonomy-preserving way to minimize the cost of a VE. It enables several bidders to bid on different combination of goods efficiently with a combined price according to their available goods and capabilities and makes it possible for a buyer to arrange bid winners more effectively. Despite the aforementioned advantages, combinatorial reverse auction problems are notoriously difficult to solve from a computational point of view due to the exponential growth of the number of combinations. We formulate the partner selection problem based on combinatorial reverse auctions and propose a partner selection algorithm. By applying Lagrangian relaxation technique, the original optimization problem can be decomposed into a number of bidders' subproblems. Our solution algorithm consists of three parts: (1) an algorithm for solving bidders' subproblems by exploiting their individual structures, (2) a subgradient algorithm for solving the dual problem, and (3) a heuristic algorithm for finding a near-optimal solution. We design and implement a prototype system based on Web Services technologies. To demonstrate the effectiveness of our prototype system, we study the performance and efficiency of our algorithms. Numerical results indicate that our proposed algorithms yield near-optimal solutions. We also conduct several experiments to study the computational efficiency of our proposed

Table 4 Comparison of CPU time (in milliseconds) and performance

|*S*|	CPU time (CPLEX)	CPU time(our algorithm)	Duality gap (%)
20	141	31	0.2
30	172	63	1.5
40	219	63	2.9
50	235	78	0.5
60	282	78	2.6
120	1,154	160	0.7

algorithms. These experiments show that the growth of CPU time with respect to the number of bidders is polynomial. Our algorithm is scalable as the problem grows.

We compare the difference between the method proposed in this paper with those proposed in existing literature. This paper is differentiated from the work proposed by Camarinha-Matos et al. [5], which proposes a framework to assist organizations, the virtual organizations (VO) broker, and the VO planner with finding suitable collaboration opportunities and finding the best fit partners to meet the requirements. This paper is different from [5] as we concentrate on the partner selection problem in forming VE based on combinatorial reverse auctions. This paper narrows the scope and select cost as the performance indicator for forming VE. The goal is to determine the best partners with complementary capabilities based on computationally efficient algorithms. Our methodology is therefore differentiated from those proposed in [4, 6, 8, 18, 39] in that we focus on the optimization aspect in formation of VE.

Our approach to solving the partner selection problem based on combinatorial reverse auction is also different from the one proposed by Sandholm [36] to find the optimal solution in that we adopt the Lagrangian relaxation approach to find approximate solutions. The advantage of our Lagrangian relaxation approach is to find approximate solutions efficiently. Our proposed algorithm is different from the one proposed by Guo et al. [17] based on Lagrangian heuristic in existing literature as our algorithm is based on the subgradient algorithm to adjust Lagrangian multipliers in combinatorial reverse auctions. The prototype system proposed in this paper is different from the Auction Advisor system proposed by Gregg and Walczak [16], which is designed to collect data from online auctions to help improve the decision making of auction participants. Our approach is different from iBundler [14]. iBundler is an agent-aware service offered to buying agents to help them determine the optimal bundle of received offers based on their business rules [14]. Although our algorithm does not guarantee generation of optimal solutions, it often leads to optimal or near-optimal solutions more efficiently than the CPLEX integer programming solver.

Acknowledgment This paper is currently supported in part by NSC under grant NSC100-2410-H-324-006-MY2.

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