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Selecting unique suppliers through winner determination in combinatorial reverse auction: Scatter search algorithm

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Abstract. In this paper, a combinatorial reverse auction mechanism is proposed to select suppliers for the required items of a company. As a contribution, it is assumed that the task of supplying each required item is indivisible to multiple suppliers, or the company prefers to select only one supplier for supplying each required item. So, the winner determination process is done in such a way that supplying each tendered item is assigned to only one potential supplier. The corresponding winner determination problem is formulated as a binary integer program which is an NP-complete combinatorial optimization problem. Since exact methods have failed to solve this kind of problems in a reasonable time, a meta-heuristic algorithm called scatter search is proposed to find feasible and near-optimal solutions to the formulated winner determination problem. To evaluate the performance of the proposed algorithm, several instances of the problem with different real-world sizes are randomly generated and solved, using the proposed algorithm with tuned parameters. Computational results show that the proposed scatter search method performs well in solving the problem instances.

1. Introduction

Outsourcing is the action or practice of obtaining required items (goods or services) by contract from outside sources, and it helps companies to perform well in their core competencies and reduce lack of skill or expertise in areas where they want to outsource [1]. Supplier selection is one of the critical phases of outsourcing because a selected supplier will be a close associate of the company for a considerable period of time, during which the two parties will be forced to cooperate and support each other in good and bad times [2]. Selecting suppliers can be viewed as an allocation problem in which a set of potential suppliers is evaluated in terms of some quantitative and qualitative criteria, and the most efficient set of suppliers among potential suppliers is determined to assign the task of supplying required items [3,4].

Auctions are used as popular ways for allocating items or tasks to multiple agents to maximize revenue or minimize cost. Single-item auctions, such as English and Vickrey auctions, are the most common auction formats, but they are not always efficient [5]. Combinatorial auction, as one of multi-item auction formats, enables bidders to place all-or-nothing bids on any subset of items (i.e., bundles of items) rather than just on individual items according to their personal preferences. Combinatorial auctions are efficient when bidders are interested in multiple items

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and their valuations for these items are non-additive, particularly when complementary relationships exist among items. For this reason, they have attracted considerable attention in the auction literature that is reviewed by Abrache et al. [6], Blumrosen and Nisan [7], Bichler et al. [8], and Hoffman [9], to name a few. Combinatorial auctions have various applications, such as auctioning airport time slots and resources [10], truckload transportation [11], bus routes [12], advertising time slots [13,14], spectrum licenses [15], and timber allocation [16]. Some researchers have reported that applying combinatorial auctions to companies' procurement processes can lead to significant savings. Bichler et al. [8] and Hohner et al. [17] studied the use of combinatorial reverse auction in sourcing process of Mars Incorporated in its webpage designed by Mars-IBM team, and they reported significant savings in Mars's procurement costs. Metty et al. [18] studied the Motorola Company's reinvention in its supplier negotiation process which uses an advanced Internet-based negotiation platform for sourcing, and they reported a reduction in the required time and effort for negotiation and significant savings in procurement costs (%3.75, about $600 million in 2005) due to using combinatorial reverse auction in supplier negotiation process. Also, Sandholm et al. [19] studied the changed approach of Procter & Gamble (P&G) in sourcing which puts into practice CombineNet's approach in building sourcing networks by using combinatorial reverse auction in its sourcing processes. They reported significant savings in sourcing costs for P&G (%9.6, about $295 million over a period of two and a half years until March in 2005) as well as a reduction in the required time for sourcing processes from months to weeks.

In a procurement scenario, there is a buyer who wants to buy a set of items efficiently in terms of some special criteria and a set of potential suppliers who can supply the required items. The buyer can hold a reverse auction to buy the required items. If there are complementary relationships between tasks of supplying some tendered items (i.e., synergies in terms of supplying cost), a combinatorial reverse auction can be beneficial in which potential suppliers can express their preferences and submit several bids on combinations of those items that can result in significant savings in procurement costs of companies [8].

In this paper, the problem of selecting suppliers for the required items of a company is considered in which there are complementary relationships between tasks of supplying some required items due to economies of scale in their supplying. Therefore, we propose a combinatorial reverse auction mechanism to select the most efficient set of suppliers among a set of potential suppliers. It is assumed that the task of supplying each required item is indivisible to multiple suppliers, or the company prefers to select only one supplier for supplying each required item. So, the winner determination in our proposed combinatorial reverse auction mechanism is done in such a way that supplying each tendered item is assigned to only one potential supplier. This is the main difference of our research with similar studies in existing literature, such as the research papers of Hsieh [5], Bichler et al. [8], Sandholm et al. [19], and Olivares et al. [20], which have used the combinatorial reverse auction for selecting suppliers. We formulate the corresponding winner determination problem of the proposed combinatorial reverse auction mechanism as a binary integer program with the objective of minimizing the company's procurement costs. The formulated winner determination problem is an NP-complete combinatorial optimization problem. So, the time required to solve this problem, using any currently known algorithm, increases exponentially as the size of the problem grows [21]. Therefore, exact methods will fail to solve the large-scale instances of formulated winner determination problem in a reasonable time. So, we propose a meta-heuristic algorithm called scatter search for finding its feasible and near-optimal solutions.

The rest of the paper is organized as follows. In Section 2, our proposed combinatorial reverse auction mechanism is described for selecting the most efficient set of suppliers among a set of potential suppliers. Section 3 formulates the corresponding winner determination problem of the proposed combinatorial reverse auction mechanism as a single-objective binary integer program. In Section 4, a problem-specific scatter search algorithm is proposed to solve the formulated winner determination problem. Section 5 presents the computational results and the performance of the proposed scatter search algorithm evaluated by solving several randomly generated instances of winner determination problem with different real-world sizes. Finally, in Section 6, conclusions and future research directions are summarized.

2. Combinatorial reverse auction mechanism

Suppose that a company has decided to supply some of its required items (goods or services) from external sources. It is assumed that there are complementary relationships between tasks of supplying some required items due to economies of scale in their supplying. The complementary relationship between supplying two items means that the supplying cost of items together is less than the sum of their individual supplying costs. So, to select the most efficient suppliers among a set of potential suppliers, the company conducts a combinatorial reverse auction. As mentioned in the previous section, the combinatorial reverse auction establishes an environment in which potential suppliers can compete and express their preferences about tendered items by submitting bids on any combination of tendered items that exhibit synergies in terms of supplying cost. This provides an opportunity for the company to have significant savings in procurement costs [8]. Before conducting the combinatorial reverse auction, the company determines the acceptable characteristics for each required item and the maximum cost that potential suppliers can ask for its supplying. Since a combinatorial auction mechanism is defined by a set of rules related to bidding and winner determination process [9], the company must determine the rules of combinatorial reverse auction mechanism. The bidding rules for potential suppliers that participate as bidders in our proposed combinatorial reverse auction mechanism are as follows:

- Each potential supplier can submit bids on various combinations of tendered items rather than on just individual items. In other words, the task of supplying multiple items rather than just individual items can be assigned to each potential supplier;
- Each combinatorial bid includes a subset of tendered items that a potential supplier wants to supply and the total cost that the potential supplier asks for its supplying;
- Potential suppliers should consider the maximum costs of tendered items when submitting combinatorial bids.

Also, the rules that are related to winner determination process in our proposed combinatorial reverse auction mechanism are as follows:

- The task of supplying each tendered item is done under a contract with only one supplier. This can mean that each tendered item is single-unit. Therefore, selecting multiple suppliers for supplying a required item will have extra cost, i.e. it will not be done with free disposal. So, the proposed auction mechanism is a single-unit combinatorial reverse auction mechanism without free disposal;
- Although each potential supplier can submit several bids in combinatorial reverse auction, at most one of his bids will be accepted in winner determination process.

3. Winner determination problem

After potential suppliers submit several bids on their desired combinations of tendered items, the most efficient set of suppliers is selected among them through winner determination process. As mentioned in Section 2, the winner determination in our proposed combinatorial reverse auction mechanism is done in such a way that the task of supplying each tendered item is assigned to only one potential supplier. Consider the following notations for problem formulation:

m :	Number of tendered items
i :	Index of tendered items
n :	Number of potential suppliers
j :	Index of potential suppliers
b_j :	Number of bids that potential supplier j submits
k :	Index of bids
I_{jk} :	A subset of tendered items that potential supplier j includes them in his kth bid
a_{ijk} :	A number that is equal to 1 if $i \in I_{jk}$, else it is equal to 0
c_{jk} :	The cost that potential supplier j asks for supplying items in his kth bid
x_{jk} :	Binary decision variable related to the acceptance of kth bid of potential supplier j
$I = \{1, 2, ..., m\}$:	Index set of tendered items
$J = \{1, 2, ..., n\}$:	Index set of potential suppliers
$K_j = \{1, 2, ..., b_j\}$:	Index set of bids of potential supplier j

The winner determination problem for selecting the most efficient set of suppliers among the set of potential suppliers, with the objective of minimizing the company's procurement costs, is formulated as follows which consists of $\sum_{j \in J} b_j$ decision variables and $m + n$ constraints:

$$\min \qquad \text{Cost} = \sum_{j \in J} \sum_{k \in K_j} c_{jk} x_{jk}, \tag{1}$$

S.t.

$$\sum_{j \in J} \sum_{k \in K_j} a_{ijk} x_{jk} = 1 \qquad \forall\, i \in I, \tag{2}$$

$$\sum_{k \in K_j} x_{jk} \leq 1 \qquad \forall\, j \in J, \tag{3}$$

$$x_{jk} \in \{0, 1\} \qquad \forall\, j \in J, \quad \forall\, k \in K_j. \tag{4}$$

In the formulated problem, the first constraints, i.e. equality constraints, ensure that the task of supplying each tendered item is assigned to only one potential supplier, and the second constraints guarantee that at most one bid of each potential supplier is accepted. The second constraints are called XOR constraints in the context of combinatorial auctions [22]. Without XOR constraints, the remained constraints are as the same as those of set packing problem that is a well-known NP-complete combinatorial optimization problem [23]. So, we can easily say that the formulated winner determination problem is NP-hard. But, Sandholm et al. [24] proved that the winner determination problem of single-unit combinatorial reverse auction with/without free disposal is NP-complete. Also, they proved that finding feasible solutions to winner determination problem of single-unit combinatorial reverse auction without free disposal by considering XOR constraints (i.e., formulated winner determination problem) is NP-complete. Therefore, finding feasible solutions to the formulated winner determination problem as well as its solving is NP-complete. Although any given solution to an NP-complete problem can be verified quickly (in polynomial time), there is no known efficient way to locate a solution in the first place. Indeed, the most notable characteristic of NP-complete problems is that no fast solution to them is known. That is, the time required to solve the problem using any currently known algorithm increases exponentially as the size of the problem grows [21].

Therefore, exact methods will fail to solve the large-scale instances of formulated winner determination problem in a reasonable time. So, we propose a meta-heuristic algorithm called scatter search to find its feasible and near-optimal solutions.

4. Scatter search

Scatter search is a population-based meta-heuristic which exploits the knowledge of the problem to create new and thus better solutions from the combination of existing ones. The fact that the relevant information regarding the optimal solution is embedded in a diversified subset of elite solutions is one of the fundamentals of scatter search. Scatter search takes multiple solutions into account as a foundation for creating new ones, and it uses heuristics which combine them through mechanisms that promote diversity and quality. So, scatter search enhances the exploration of the information not contained in each solution individually. The usual process for solving a problem by means of creating progressively better solutions is divided into the following components [25-27]:

- *Diversification generation method:* Creates a collection of trial solutions;
- *Improvement method:* Transforms the trial solutions into enhanced ones and usually restores feasibility;
- *Reference set update method:* Maintains the reference set with the best solutions according to certain criteria;
- *Subset generation method:* Creates subsets of solutions from the reference set;
- *Solution combination method:* Combines solutions from each subset, thus creating new ones.

In what follows, the proposed problem-specific scatter search method that is used to find feasible and near-optimal solutions to winner determination problem is explained in detail.

4.1. Representation of solutions

Before explaining the details of solution procedure, the scheme that is used to represent the solutions in the search space is described. A solution in the search space is represented with $Y = (y_1, y_2, \cdots, y_n)$ in which $y_j \in ZK_j = \{0\} \cup K_j$. A non-zero value for y_j means that potential supplier j is one of the winners of combinatorial reverse auction, and the value of y_j represents the index of his accepted bid. With this representation scheme, satisfaction of XOR constraints is ensured.

4.2. Generating a population of diverse solutions

For creating a population, POP, including N non-duplicate solutions, a random generation method is used. Solution Y in POP is constructed by generating y_j as a uniformly distributed random number in ZK_j, for all $j \in J$. Since finding a feasible solution to the formulated winner determination problem is NP-complete, infeasible solutions are allowed to enter the population of solutions.

4.3. Improving the solutions in population

Since infeasible solutions allow entering the population of solutions, we use an improvement procedure to adjust the solutions in population with the aim of decreasing their infeasibility. For this purpose, we first define the left-hand side value of ith equality constraint for solution Y as follows:

$$\mathrm{LHS}_i(Y) = \sum_{j \in J | y_j \neq 0} a_{ij,y_j} \qquad \forall\, i \in I. \tag{5}$$

Also, we define $\delta_i(Y)$ as inclusion state of ith tendered item in at least one accepted bid of solution Y:

$$\delta_i(Y) = \begin{cases} 1 & \mathrm{LHS}_i(Y) \geq 1 \\ 0 & \mathrm{LHS}_i(Y) = 0 \end{cases} \qquad \forall\, i \in I. \tag{6}$$

Then, we use the following necessary conditions for solution Y to determine if it is a candidate of improvement or not:

(a) $\sum_{i \in I} \delta_i(Y) = m$,

(b) $\exists i \in I$, $\mathrm{LHS}_i(Y) > 1$.

The first condition (a) means that all tendered items should be included in accepted bids of solution Y, and the second condition (b) means that there should be at least one tendered item that is included more than one time in accepted bids of solution Y. Therefore, all

Step 1: Create a random permutation of $(1, 2, \cdots, n)$, P.
Step 2: For $j = 1$ to n:
If $y_{P(j)} \neq 0$ and setting $y_{P(j)} := 0$ do not change the value of $\sum_{i\in I} \delta_i(Y)$, set $y_{P(j)} := 0$.

Figure 1. Improving solutions in population.

solutions in population are checked and if a solution has these conditions, the improvement procedure that is described in Figure 1 is run M times for decreasing its infeasibility. A solution that has these conditions may be improved using this procedure, and if the result is a non-duplicate solution, it is added to the population of solutions, i.e., POP.

4.4. Evaluation of solutions

To evaluate the solutions in population, two criteria are used. The first criterion is the value of objective function, i.e. the total procurement cost of tendered items. This criterion for solution Y is calculated as follows:

$$\text{Cost}(Y) = \sum_{j\in J|y_j\neq 0} c_{j,y_j}. \tag{7}$$

Furthermore, since infeasible solutions are allowed to enter the population of solutions, infeasibility is considered as the second criterion which is defined for solution Y as follows:

$$\text{Inf}(Y) = \begin{cases} \sum_{i\in I} \alpha_i(Y) + \frac{\sum_{i\in I}\beta_i(Y)}{\sum_{i\in I}\alpha_i(Y)} & \sum_{i\in I} \alpha_i(Y) > 0 \\ 0 & \sum_{i\in I} \alpha_i(Y) = 0 \end{cases} \tag{8}$$

in which $\alpha_i(Y)$ and $\beta_i(Y)$ are defined as violation state and violation severity of ith equality constraint, respectively:

$$\alpha_i(Y) = \begin{cases} 1 & \text{LHS}_i(Y) \neq 1 \\ 0 & \text{LHS}_i(Y) = 1 \end{cases} \quad \forall\, i \in I, \tag{9}$$

$$\beta_i(Y) = \begin{cases} \frac{\text{LHS}_i(Y)-1}{\sum_{j\in J}\sum_{k\in K_j} a_{ijk}-1} & \text{LHS}_i(Y) \geq 1 \\ 1 & \text{LHS}_i(Y) = 0 \end{cases} \quad \forall\, i \in I. \tag{10}$$

4.5. Building reference set

After improving a population of solutions, a reference set, including B solutions, from the population is selected for combining and creating new solutions. The reference set, *RefSet*, has two parts: $RefSet_1$ and $RefSet_2$. In other words, we have the following equation:

$$RefSet = RefSet_1 \cup RefSet_2. \tag{11}$$

Step 1: Set $f := 1$, and for each solution Y, calculate/find:
- $d(Y)$: The number of solutions that dominate the solution Y
- $S(Y)$: The set of solutions that the solution Y dominates

Step 2: Move all solutions with $d(Y) = 0$ to the fth non-dominated front.
Step 3: For each solution Y in fth front, visit each $Y' \in S(Y)$ and reduce $d(Y')$ by one and move it to the $(f+1)$th non-dominated front if $d(Y') = 0$.
Step 4: Set $f := f + 1$, and go to Step 3 until all fronts are identified.

Figure 2. Non-dominated sorting of solutions in population.

The first part, i.e. $RefSet_1$, consists of B_1 high-quality solutions from the population. The criterion for selecting the members of $RefSet_1$ can be based on objective function value or infeasibility of solutions. The difficulty with these criteria for a minimization problem is that the solutions with less objective function value generally have higher infeasibility, and vice versa. Thus, if the selection is favored on the solutions with less objective function value, choosing solutions, mostly infeasible, is likely. This will not help scatter search in finding feasible solutions to winner determination problem. On the other hand, if the selection is favored on less infeasible solutions, selecting solutions with higher objective function value is likely. Therefore, selection should be done in such a way that both of these criteria are improved. To do this, the solutions in population are sorted based on these criteria using a fast non-dominated sorting procedure proposed by Deb et al. [28] that is described in Figure 2. It should be noted that solution Y dominates solution Y' if:

$$[Cost(Y), Inf(Y)] \neq [Cost(Y'), Inf(Y')]$$

and:

$$[Cost(Y), Inf(Y)] \leq [Cost(Y'), Inf(Y')].$$

The non-dominated sorting procedure ranks the solutions in different non-dominated fronts, and then B_1 solutions from the best non-dominated fronts are selected as members of $RefSet_1$. The second part of reference set, i.e. $RefSet_2$, includes B_2 diverse solutions from the remained population, i.e. $POP\backslash RefSet$. To select the first member of $RefSet_2$, for all $Y \in POP\backslash RefSet$, the minimum distance of solution Y from the members of *RefSet* is calculated as follows:

$$D(Y, RefSet) = \min_{Y'\in RefSet} \left(\sum_{j\in J} D_j(Y, Y') \right), \tag{12}$$

in which:

$$D_j(Y, Y') = \begin{cases} 1 & y_j \neq y'_j \\ 0 & y_j = y'_j \end{cases} \quad \forall\, j \in J. \tag{13}$$

Then, solution $\hat{Y}$ that is determined by Eq. (14) is removed from $POP\backslash\ RefSet$ and added to $RefSet_2$. This process is repeated B_2 times by updating the value of $D(Y, RefSet)$ for all $Y \in POP\backslash\ RefSet$:

$$\hat{Y} = \underset{Y \in POP\backslash RefSet}{\arg\max}\ D(Y, RefSet). \tag{14}$$

4.6. Combining solutions in reference set

To create new non-duplicate solutions, $NewYs$, all pairs of solutions in the reference set are combined. So, the number of new solutions created in this phase is equal to $B(B-1)/2$. Let Y' and Y'' be two members of the reference set. To create new solution Y, a uniformly distributed random number in $[0,1]$, r_j, is generated for all $j \in J$ and the value of y_j is determined as follows:

$$y_j = \begin{cases} y'_j & r_j \in [0, 0.4] \\ y''_j & r_j \in (0.4, 0.8] \\ 0 & r_j \in (0.8, 0.9] \\ Bid_j & r_j \in (0.9, 1] \end{cases} \qquad \forall\ j \in J, \tag{15}$$

where Bid_j is a random number in ZK_j that is calculated as a function of r_j and b_j:

$$Bid_j = \left\lceil \frac{r_j - 0.9}{1 - 0.9} \times b_j \right\rceil \qquad \forall\ j \in J. \tag{16}$$

Example 1. Suppose that:

$n = 10$,

$\mathbf{b} = (5, 6, 5, 7, 4, 5, 9, 5, 5, 8)$,

$Y' = (0, 5, 3, 0, 1, 1, 2, 0, 4, 7)$,

$Y'' = (5, 1, 4, 5, 0, 0, 0, 3, 2, 0)$.

New solution $Y = (0, 1, 4, 0, 0, 5, 0, 3, 0, 7)$ is created by combining Y' and Y'' as illustrated in Figure 3.

4.7. Updating the reference set

After combining the solutions in the reference set and creating new solutions, $RefSet \cup NewYs$ is considered as the population of solutions and the improvement procedure is applied to its members. Then, the objective function value and infeasibility of solutions in improved population are evaluated and the new reference set is constructed using the reference set building method, explained in Subsection 4.5.

b_j	5	6	5	7	4	5	9	5	5	8
Y'	0	5	3	0	1	1	2	0	4	7
Y''	5	1	4	5	0	0	0	3	2	0
r_j	0.14	0.91	0.54	0.23	0.79	0.99	0.47	0.66	0.84	0.39
Y	0	1	4	0	0	5	0	3	0	7

Figure 3. Combining two solutions to create a new one.

4.8. Stopping condition

Creating new solutions and updating the reference set continue if at least one better solution is found in each iteration, or else another population, including solutions in $RefSet_1$ and $N-B/2$ numbers of randomly generated diverse solutions, is used to continue the search procedure. If the number of iterations is equal to a given number, T, the scatter search stops and the results are reported.

4.9. Outline of scatter search procedure

The outline of the proposed scatter search method for finding feasible and near-optimal solutions of winner determination problem in the combinatorial reverse auction is described in Figure 4.

5. Computational experiments

To evaluate the performance of the proposed scatter search method in finding feasible and near-optimal solutions to winner determination problem, it is tested with several randomly generated problem instances with different sizes. The size of a problem instance is determined by the number of tendered items (m), the number of potential suppliers (n), and the number of their bids (b_j). In Table 1, we have listed different sizes of problem instances used to evaluate the performance of the proposed scatter search algorithm. The problem instance generation procedure in the Appendix is used to generate 3 instances for each problem size.

5.1. Tuning parameters

Meta-heuristics show different performances when various values of their parameters are used. Therefore, the use of a calibration method is necessary to achieve better performances. Taguchi has developed a fractional factorial design based on different factors and their levels that uses a reduced number of experiments. This method can be used for tuning the parameters of meta-heuristics (e.g., see [29,30]). Taguchi has classified the factors affecting a response into two categories, including controllable factors and noise factors. Considering orthogonal arrays, he has suggested a method to reduce the change around the target so that the best design is the one that is impressed less by noise factors. In the Taguchi method, there are two approaches to analyze the results. The first one is the analysis of variance that is applied to experiments with one replication, and the

Table 1. Different sizes of problem instances.

Size #	m	n	b_j
I	10	25	≤ 10
II	10	50	≤ 10
III	20	50	≤ 10
IV	20	75	≤ 10

Step 1: Set $t := 0$ and generate a random population of N non-duplicate solutions, POP.
Step 2: Set $t := t + 1$, improve the solutions in POP, and add the resulted improved solutions to POP.
Step 3: Evaluate the objective function value and infeasibility of solutions in POP.
Step 4: Build the first part of reference set, i.e. $RefSet_1$, and update the best solution found.
Step 5: If $t = T$, go to Step 10.
Step 6: If $t > 1$, check the changes in the best solution found. If there is no change, go to Step 9.
Step 7: Build the second part of reference set, i.e. $RefSet_2$.
Step 8: Combine all pairs of solutions in $RefSet$ to create a set of new solutions ($NewYs$), set $POP := RefSet \cup NewYs$, and go to Step 2.
Step 9: Generate a random population of $N - B/2$ non-duplicate solutions (POP'), set $POP := RefSet_1 \cup POP'$, and go to Step 2.
Step 10: Stop and report the best solution found.

Figure 4. Outline of the proposed scatter search procedure.

second one is the signal-to-noise ratio analysis which is suggested for experiments with multiple runs [31]. Since meta-heuristics run several times in order to achieve high-quality solutions to problems, the signal-to-noise ratio analysis is used here to analyze the results and tune the parameters of proposed scatter search method. To do this, first, the parameters (factors) that affect the performance of scatter search method as well as their values (levels) are determined in Table 2. Note that the values of parameters in Taguchi method are defined based on a trial and error procedure on a problem instance [31]. Here, the first instance in Table A.1 (in Appendix), i.e. I-1, is used for defining the values of scatter search parameters. The aim of the Taguchi method for a minimization problem is to find a combination of parameters' values such that the signal-to-noise ratio is maximized. The signal-to-noise ratio is defined as follows in which z_r is the target (response) in the Taguchi method and R is the number of replications [31]. Here, the response is the objective function value of winner determination problem:

$$\mathrm{SN} = -10 \log \left(\frac{1}{R} \sum_{r=1}^{R} z_r^2 \right). \tag{17}$$

Table 2. Parameters of scatter search method and their values.

Parameters	**Values**			
$\boldsymbol{N}$	50	100	150	200
$\boldsymbol{B}$	10	20		
$\boldsymbol{M}$	$m/2$	m	$3m/2$	$2m$

The Taguchi method for tuning the parameters of scatter search is implemented in Minitab® 17.1. Assuming that $T = 100$ and $R = 30$, the experimental results of scatter search method using L^{16} orthogonal arrays from the Taguchi method for the first instance of each problem size, i.e., I-1, II-1, III-1, and IV-1, are shown in Table 3. Based on the information in Table 3, the mean of signal-to-noise ratios for different values of parameters is calculated and listed in Table 4. Now, the best values of parameters that maximize the mean of signal-to-noise ratios can be determined for solving different problem sizes. These values are listed in Table 5.

5.2. Results and comparison

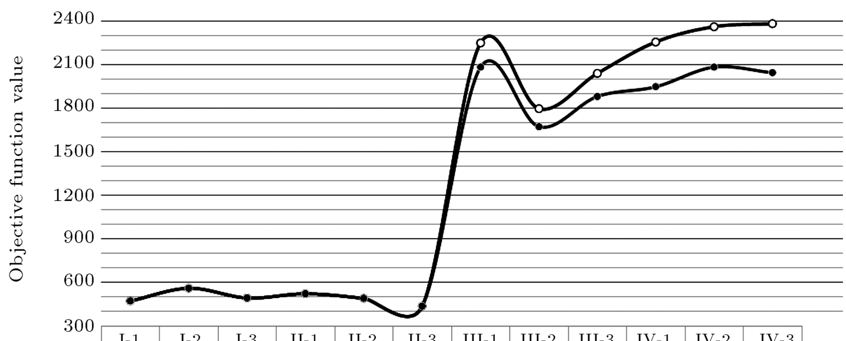
The proposed scatter search method, with $T = 2$ mn and the best values of parameters, is run 10 times for each problem instance using MATLAB® 7.6 in a computer with Intel® Core™ i5 (2.53 GHz) CPU and 4 GB RAM. Computational results of different problem instances, including the best feasible solution found by scatter search and its average runtime as well as the results of using LINGO® 8.0 for solving the problem instances, are summarized in Table 6. In Figure 5, performance of the proposed scatter search in solving different instances of winner determination problem is compared with LINGO® software. As illustrated in Figure 5, the proposed scatter search performs better than the used software in finding feasible and near-optimal solutions to the problem instances with larger sizes. Also, Figure 6 compares the average runtime of the proposed scatter search method with LINGO® software and shows a significant difference between their average runtime in solving different instances of winner determination problem, especially instances with larger sizes.

Table 3. Experimental results of scatter search using Taguchi method for different problem sizes.

Parameters & values			Signal to noise ratios			
N	B	M	I-1	II-1	III-1	IV-1
50	10	$m/2$	−53.6768	−55.1309	−68.2404	−67.4761
50	10	m	−53.6204	−55.0990	−68.2435	−67.5454
50	20	$3m/2$	−53.5930	−54.7381	−67.6144	−67.3838
50	20	$2m$	−53.5664	−54.7376	−67.7082	−67.3549
100	10	$m/2$	−53.6497	−55.0612	−67.9354	−67.4732
100	10	m	−53.6238	−54.9884	−67.8690	−67.4302
100	20	$3m/2$	−53.5889	−54.6328	−67.7745	−67.1794
100	20	$2m$	−53.5741	−54.7128	−67.7235	−67.1636
150	20	$m/2$	−53.5611	−54.6501	−67.6017	−67.2584
150	20	m	−53.5723	−54.7387	−67.6783	−67.2087
150	10	$3m/2$	−53.5976	−54.9599	−67.9714	−67.3310
150	10	$2m$	−53.5902	−55.0376	−67.9243	−67.3843
200	20	$m/2$	−53.5604	−54.7261	−67.6029	−67.1597
200	20	m	−53.5832	−54.6916	−67.6354	−67.1643
200	10	$3m/2$	−53.5623	−54.9610	−68.0290	−67.3077
200	10	$2m$	−53.5980	−55.0080	−67.9769	−67.2995

Table 4. Mean of signal-to-noise ratios for different problem sizes.

Parameters	Values	Mean of SN ratios			
		I-1	II-1	III-1	IV-1
N	50	−53.614	−54.926	−67.952	−67.440
	100	−53.609	−54.849	−67.826	−67.312
	150	−53.580	$\underline{-54.846}$	$\underline{-67.794}$	−67.296
	200	$\underline{-53.576}$	−54.847	−67.811	$\underline{-67.233}$
B	10	−53.615	−55.031	−68.024	−67.406
	20	$\underline{-53.575}$	$\underline{-54.703}$	$\underline{-67.667}$	$\underline{-67.234}$
M	$m/2$	−53.612	−54.892	−67.845	−67.342
	m	−53.600	−54.879	−67.857	−67.337
	$3m/2$	−53.585	$\underline{-54.823}$	−67.847	$\underline{-67.300}$
	$2m$	$\underline{-53.582}$	−54.874	$\underline{-67.833}$	−67.301



	I-1	I-2	I-3	II-1	II-2	II-3	III-1	III-2	III-3	IV-1	IV-2	IV-3
LINGO	472	560	493	522	490	437	2247	1795	2038	2254	2359	2380
Scatter search	472	560	493	522	490	437	2081	1671	1879	1946	2081	2043

Figure 5. Comparing the performances of scatter search and LINGO®.

Table 5. The best values of scatter search parameters for different problem sizes.

Parameters	Best values			
	I	II	III	IV
$\boldsymbol{N}$	200	150	150	200
$\boldsymbol{B}$	20	20	20	20
$\boldsymbol{M}$	20	15	40	30

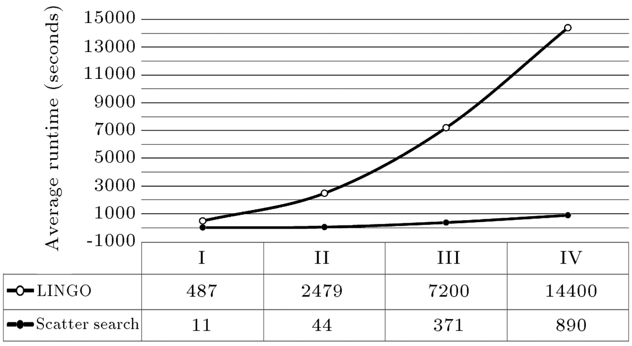


Figure 6. Comparing the average runtime of scatter search and LINGO®.

6. Conclusions

In this research, we proposed a combinatorial reverse auction mechanism for selecting the most efficient suppliers for required items of a company. As a contribution, it was assumed that the task of supplying each required item is indivisible to multiple suppliers, or the company prefers to select only one supplier for supplying each required item. So, the winner determination process was done in such a way that supplying each tendered item is assigned to only one potential supplier. Development of a meta-heuristic algorithm called scatter search with problem-specific components for solving the corresponding winner determination problem was another contribution in this research. The experimental results of evaluating the performance of the proposed algorithm show that the proposed scatter search with parameters tuned by Taguchi method performs well in solving different sizes of problem instances with respect to solution quality and runtime. Some of directions for the future research are as follows:

- Formulating the winner determination problem with either more or other decision criteria such as quality and delivery time;
- Formulating the winner determination problem by introducing other constraints, e.g., lower and upper bounds for the number of winners (i.e., selected suppliers);
- Developing other meta-heuristic algorithms to target the resulted winner determination problems;
- Developing exact methods for solving the resulted winner determination problems and using the output of meta-heuristics as the initial solutions for exact methods;
- Applying the proposed combinatorial reverse auction mechanism in selecting unique suppliers for providing the following services in multiple regions of an electric power distribution company's responsibility area:
  - Repairing some or all parts of distribution network including distribution lines and substations;

Table 6. Computational results for different problem instances.

Instance #	LINGO®			Scatter search		
	Obj. value	Optimal	Runtime	Best obj. value	Optimal	Average runtime
I-1	472	Yes	528	472	Yes	9
I-2	560	Yes	436	560	Yes	12
I-3	493	Yes	496	493	Yes	11
II-1	522	Yes	2431	522	Yes	44
II-2	490	Yes	2380	490	Yes	41
II-3	437	Yes	2626	437	Yes	47
III-1	2247	No	7200	2081	Unknown	371
III-2	1795	No	7200	1671	Unknown	348
III-3	2038	No	7200	1879	Unknown	395
IV-1	2254	No	14400	1946	Unknown	887
IV-2	2359	No	14400	2081	Unknown	894
IV-3	2380	No	14400	2043	Unknown	890

– Repairing some or all types of sustained power interruptions that occur in distribution network.

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Appendix

Generating problem instances

As mentioned in Section 5, we use a procedure to generate several problem instances for evaluating the performance of our proposed scatter search algorithm in solving the winner determination problem of single-unit combinatorial reverse auction mechanism without free disposal. The procedure in Figure A.1 is used for generating 3 instances for all problem sizes listed in Table 1 (Section 5). Also, the number of decision variables for each generated problem instance is listed in Table A.1.

Table A.1. Different instances of winner determination problem.

Problem size: (m, n)	Instance #	Variables
	I-1	148
I: (10,25)	I-2	150
	I-3	143
	II-1	271
II: (10,50)	II-2	290
	II-3	276
	III-1	290
III: (20,50)	III-2	293
	III-3	293
	IV-1	429
IV: (20,75)	IV-2	421
	IV-3	429

Step 1: Generating b_j for all $j \in J$:

- m_j: random number in $\{2,3,4\}$
- $b_j = \begin{cases} 3 & m_j = 2 \\ \text{random number in } \{4, \cdots, 7\} & m_j = 3 \\ \text{random number in } \{5, \cdots, 10\} & m_j = 4 \end{cases}$

Step 2: Generating I_{jk} for all $j \in J$ and $k \in K_j$:

- I_j: a random subset of I with size m_j
- $I_{jk} = \begin{cases} \text{random subset of } I_j (|I_j| < m_j), & k = 1, \cdots, b_j - 1 \\ I_j & k = b_j \end{cases}$

(I_{jk}s are sorted based on their size in ascending order.)

Step 3: Generating c_{jk} for all $j \in J$ and $k \in K_j$:

- CMAX: random permutation of $10 \times (1, 2, \cdots, 2m)$
- c_{jk}: random number that is less than $\sum_{i \in I_{jk}} \text{CMAX}_i$

(If $I_{jk} = I_{jk'} \cup I_{jk''}$, and $I_{jk'} \cap I_{jk''} = \phi$ then c_{jk} should be less than $c_{jk'} + c_{jk''}$).

Figure A.1. Procedure of generating problem instances.

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