International Journal of Engineering

Journal Homepage: www.ije.ir

Selecting Efficient Service-providers in Electric Power Distribution Industry Using Combinatorial Reverse Auction

R. Alaei, M. Setak*

Faculty of Industrial Engineering, K.N. Toosi University of Technology, Tehran, Iran

PAPER INFO

Paper history:
Received 22 January 2017
Received in revised form 24 April 2017
Accepted 07 July 2017

Keywords:
Supplier Selection
Electric Power Distribution Industry
Combinatorial Reverse Auction
Winner Determination Problem
Multi-Objective Optimization
NSGA-II

ABSTRACT

In this paper, a combinatorial reverse auction mechanism is proposed for selecting the most efficient service-providers for resolving sustained power interruptions in multiple regions of an electric power distribution company's responsibility area. Through this mechanism, supplying the required service in each region is assigned to only one potential service-provider considering two criteria including cost and service time. So, the corresponding winner determination problem of the proposed auction mechanism is formulated as a bi-objective combinatorial optimization problem. However, finding a feasible solution for the formulated problem as well as its solving is NP-complete. Since exact optimization algorithms are failed in solving this kind of problems in a reasonable time, a problem specific metaheuristic called NSGA-II that is an evolutionary algorithm for solving multi-objective optimization problems is developed to estimate the set of Pareto optimal solutions of the formulated bi-objective winner determination problem. In our developed NSGA-II, two problem-specific operators are proposed for creating initial feasible solutions and converting infeasible solutions to feasible ones. Furthermore, a new method for determining the population size based on the size of problem instance is proposed. We conduct a computational experiment in which several randomly generated problem instances are solved using the proposed NSGA-II in different settings. Computational results of proposed algorithm in different settings are compared using a quality measure and statistical hypothesis tests. The results of performance comparison show that the proposed NSGA-II with a population size determined by proposed method and a different form of binary tournament method performs better in finding non-dominated solutions for different instances of formulated bi-objective optimization problem.

***doi**: 10.5829/idosi.ije.2017.30.09c.07*

1. INTRODUCTION

Supplier selection is one of the critical phases of procurement or outsourcing that can be viewed as an allocation problem in which a set of potential suppliers is evaluated in terms of some quantitative and qualitative criteria (such as cost, quality, delivery time, etc.) and the most efficient set of suppliers among them is determined to assign the task of supplying required items [1, 2]. Auctions are used as popular ways for allocating items or tasks to multiple agents for maximizing revenue or minimizing cost. Single-item auctions are the most common auction formats, but they are not always efficient [3]. 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 individual items according to their personal preferences. This kind of auctions are efficient when bidders are interested in multiple items and their valuations for these items are non-additive, particularly when complementary relationships exist between items. For this reason, they have attracted considerable attention in the auction literature. It should be noted that the complementary relationship between some items in a direct (reverse) auction means that the selling price (buying cost) of items together, i.e. in a combination or bundle or subset of items, is more (less) than the sum of their individual selling prices (buying costs) [4]. Excellent surveys on combinatorial auctions have been proposed by Abrache et al. [5], Blumrosen and Nisan [6], Bichler et al. [7], and Hoffman [8]. Various applications for

*Corresponding Author's Email: *setak@kntu.ac.ir* (M. Setak)

Please cite this article as: R. Alaei, M. Setak, Selecting Efficient Service-providers in Electric Power Distribution Industry Using Combinatorial Reverse Auction, International Journal of Engineering (IJE), TRANSACTIONS C: Aspects Vol. 30, No. 9, (September 2017) 1342-1351

combinatorial auctions have been reported in the auction literature such as direct auctioning of airport time slots and resources [9], advertising time slots [10, 11], spectrum licenses [12], timbers [13], reverse auctioning of truckload transportation services [14, 15], and general transportation services [16]. Also, some researchers including Hohner et al. [17], Metty et al. [18], and Sandholm et al. [19] have reported that applying the reverse kind of combinatorial auctions in procurement processes has led to significant savings in time (required for negotiations) and costs of Mars, Motorola, and Procter & Gamble companies, respectively. In all the above-mentioned studies on combinatorial reverse auctions, winners are determined by solving a single-objective problem (minimizing total procurement costs) where the task of supplying each required item can be divisible to multiple potential suppliers. However, Alaei and Setak [20] have proposed a general combinatorial reverse auction mechanism for selecting the most efficient set of suppliers for required items of a company among a set of potential suppliers in which the winner determination process is done in such a way that the task of supplying each required item is assigned to only one potential supplier considering the objective of minimizing total procurement costs. They have developed a scatter search algorithm for solving the formulated single-objective problem in which infeasible solutions are allowed to enter the population of solutions. There are some researches in existing literature of combinatorial reverse auctions in which the winner determination has been done considering multiple objectives. However, in these studies, the task of supplying each required item can be divisible to multiple potential suppliers, as well. Buer and Pankratz [21] have studied the winner determination problem in a combinatorial reverse auction for procurement of transportation contracts. They have modelled the problem as a bi-objective extension to the set covering problem in which the problem's objective functions are minimization of the total procurement costs, and maximization of the service-quality level at which the transportation contracts are executed. Also, Buer and Kopfer [22] have studied the winner determination problem of a combinatorial reverse auction for transport contracts with two objective functions including minimization of total procurement costs, and maximization of total transport quality. They proposed a metaheuristic approach integrates the greedy randomized adaptive search procedure (GRASP) with a two-stage candidate component selection procedure and a neighborhood search in order to find a competitive set of non-dominated solutions.

In this paper, the research is focused on proposing a combinatorial reverse auction mechanism for supplier selection in electric power distribution (EPD) industry in which the problem of selecting efficient service-providers for resolving sustained (not momentary) power interruptions (SPIs) in multiple regions of an EPD company's responsibility area is considered. By assuming the existence of complementary relationships (because of economies of scale) between supplying the required service in some regions for potential service-providers, the EPD company should use combinatorial reverse auction for allowing the potential service-providers to express their preferences on supplying the required service in various combinations of regions. Therefore, our first contribution in this paper is introducing a new application in electric power distribution industry for combinatorial reverse auctions. Also, it is assumed that the task of resolving SPIs in each region is indivisible to multiple service-providers. So, the winner determination in our proposed combinatorial reverse auction mechanism is done in such a way that the task of resolving SPIs in each region is assigned to only one potential service-provider under a contract. Furthermore, we use two criteria for selecting the most efficient service-providers among the set of potential service-providers including (1) the total requested cost, and (2) the average time for supplying the required service in multiple regions by potential service-providers. Therefore, the winner determination problem in our proposed auction mechanism is formulated as a bi-objective combinatorial optimization problem. So, our second contribution in this paper is extending the proposed single-objective winner determination process by Alaei and Setak [20] to a bi-objective one. However, the formulated winner determination problem belongs to NP-complete class of combinatorial optimization problems. The time required to solve this kind of problems using any currently known exact algorithm increases exponentially as the size of the problem grows [23]. Metaheuristics can often find good solutions with less computational effort as compared to exact optimization algorithms, iterative methods, or simple heuristics for combinatorial optimization problems by searching over a large set of feasible solutions [24, 25]. They seem particularly suitable to solve multi-objective optimization problems, because they are less susceptible to the shape or continuity of the Pareto front (e.g., they can easily deal with discontinuous or concave Pareto fronts), whereas this is a real concern for mathematical programming techniques. Additionally, many current metaheuristics such as evolutionary algorithms are population-based, which means that we can aim to generate several elements of the Pareto optimal set in a single run [26]. For these reasons, we propose and use a problem-specific metaheuristic called NSGA-II, a well-known multi-objective evolutionary algorithm, for estimating the set of Pareto optimal solutions of formulated bi-objective optimization problem. The remainder of the paper is organized as follows. In Section 2, the proposed auction mechanism for selecting efficient service-providers for resolving SPIs in multiple regions of an

EPD company's responsibility area is explained. Section 3 formulates the corresponding winner determination problem as a bi-objective combinatorial optimization problem. Some of the major concepts related to multi-objective optimization are described in Section 4 and the solution method which is a problem-specific NSGA-II is explained in detail. In Section 5, the performance of proposed NSGA-II in estimating the set of Pareto optimal solutions of formulated bi-objective optimization problem is evaluated by solving several randomly generated problem instances and the computational results in different settings are presented and compared. Finally, in Section 6, conclusions and future research directions are summarized.

2. AUCTION MECHANISM

Suppose that an EPD company has decided to select a set of efficient service-providers for resolving SPIs resulted from various causes (such as ageing, loading or increased activity, weather, vegetation, animals and pests, human factors, and etc.) in multiple regions of its responsibility area. It is assumed that there are complementary relationships between supplying the required service in some regions for potential service-providers because of economies of scale in their supplying. So, a combinatorial reverse auction mechanism is proposed for determining the most efficient service-providers among the set of potential service-providers. Using this mechanism, the potential service-providers, as bidders, are allowed to express their preferences on supplying the required service in various combinations of regions as well as just individual regions. Also, it is assumed that supplying the required service in each region is indivisible to multiple service-providers or the EPD company, as auctioneer, prefers to select only one service-provider for supplying the required service in each region. Furthermore, the EPD company uses two criteria including cost and service time for selecting efficient service-providers among the set of potential service-providers. In other words, the objectives of the EPD company in winner determination process of combinatorial reverse auction are: (1) minimizing the total requested cost, and (2) minimizing the average time for supplying the required service in multiple regions by potential service-providers. Therefore, the winner determination problem in our proposed auction mechanism will be a bi-objective optimization problem. The EPD company, as auctioneer, reveals the following information about each region for potential service-providers, as bidders, to consider them in bidding process.

- Occurrence probability of a SPI in different sub-regions
- Maximum cost that a potential service-provider can ask for resolving a SPI in different sub-regions
- Maximum average time of resolving a SPI (from discovery moment) in different sub-regions that is expected from potential service-providers the other rules related to bidding and winner determination process in proposed auction mechanism are as follows:
- A combinatorial bid includes a combination of regions, the total cost that a potential service-provider asks for supplying the required service in this combination of regions, and the average time of resolving SPIs in each sub-region.
- Each potential service-provider can submit several bids. However, at most one bid for each potential service-provider will be accepted in winner determination process.

3. WINNER DETERMINATION PROBLEM

After potential service-providers placed several bids on supplying the required service in their desired combinations of regions, the EPD company determines the winners of combinatorial reverse auction by solving a winner determination problem with two objectives including: (1) minimizing the total requested cost, and (2) minimizing the average time for supplying the required service in multiple regions by potential service-providers. The following notation is used to formulate the bi-objective winner determination problem of combinatorial reverse auction mechanism.

- $R = \{1, 2, \ldots, m\}$: Index set of regions
- *r*: index of regions $(r \in R)$
- $I_r = \{1, 2, \ldots, m_r\}$: Index set of sub-regions in region *r*
- *i*: index of sub-regions
- $J = \{1, 2, \ldots, n\}$: Index set of potential service-providers
- *j*: Index of potential service-providers $(j \in J)$
- p_{ri} : Occurrence probability of a SPI in *i*-th sub-region of region *r*
- C_{ri}^{max} : Maximum cost that potential service-providers can ask for resolving a SPI in *i*-th sub-region of region *r*
- T_{ri}^{max} : Maximum average time (from discovery moment) of resolving a SPI in *i*-th sub-region of region *r* that is expected from potential service-providers
- $K_j = \{1, 2, \ldots, n_j\}$: Index set of *j*-th potential service-provider's bids
- *k*: index of potential service-providers' bids
- R_{jk} : The set of regions that potential service-provider *j* includes them in his *k*-th bid

- a_{rjk} : Indicator of including region *r* in *k*-th bid of potential service-provider *j*.

$$a_{rjk} = \begin{cases} 1 & r \in R_{jk} \\ 0 & otherwise \end{cases} \quad \forall r \in R \tag{1}$$

- C_{jk} : The total cost that potential service-provider *j* asks for supplying the required service in regions which includes them in his *k*-th bid. The following relation should be satisfied:

$$C_{jk} \leq \sum_{r \in R_{jk}} \sum_{i \in I_r} p_{ri} C_{ri}^{\max} \tag{2}$$

- T_{rjk} : Average time (from discovery moment) of resolving a SPI in region *r* that potential service-provider *j* commits to spend in his *k*-th bid. The following relation should be satisfied:

$$T_{rjk} \leq \sum_{i \in I_r} p_{ri} T_{ri}^{\max} \qquad \forall r \in R \tag{3}$$

- w_r : Importance weight of resolving SPIs in region *r*:

$$w_r \in (0,1), \quad \forall r \in R \qquad \sum_{r \in R} w_r = 1 \tag{4}$$

- X_{jk} : Binary decision variable related to acceptance of *k*-th bid of service-provider *j*

Therefore, the bi-objective winner determination problem for selecting the most efficient set of service-providers among the set of potential service-providers, in terms of cost and time of required service, is formulated as follows:

$$\text{Minimize} \quad Cost = \sum_{j \in J} \sum_{k \in K_j} C_{jk} X_{jk} \tag{5}$$

$$\text{Minimize} \quad Time = \sum_{j \in J} \sum_{k \in K_j} \Big(\sum_{r \in R_{jk}} w_r T_{rjk} \Big) X_{jk} \tag{6}$$

subject to

$$\sum_{j \in J} \sum_{k \in K_j} a_{rjk} X_{jk} = 1 \qquad \forall r \in R \tag{7}$$

$$\sum_{k \in K_j} X_{jk} \leq 1 \qquad \forall j \in J \tag{8}$$

$$X_{jk} \in \{0,1\} \qquad \forall j \in J, \ \forall k \in K_j \tag{9}$$

In the formulated problem, the first objective function (5) is written as minimizing the sum of requested costs of potential service-providers for resolving SPIs in regions included in their bids. Also, the second objective function (6) is written as minimizing the weighted sum of average time for resolving a SPI in multiple regions of EPD company's responsibility area. Furthermore, the first constraints (7) guarantee that the task of resolving SPIs in each region is assigned to only one potential service-provider under a contract, and the second constraints (8), i.e. exclusive OR (XOR) constraints, ensure that at most one bid of each potential service-provider is accepted. Sandholm et al. [27] have proved that finding feasible solutions for the winner determination problem with these constraints as well as its solving is NP-complete.

4. SOLUTION METHOD

We propose a problem-specific well-known multi-objective evolutionary algorithm called NSGA-II (the second version of non-dominated sorting genetic algorithm) for estimating the set of Pareto optimal solutions of formulated bi-objective winner determination problem. Before explaining the details of the solution method, some of the major concepts and definitions in multi-objective optimization are described. Multi-objective optimization is concerned with mathematical optimization problems involving more than one objective function to be optimized simultaneously. In a multi-objective optimization problem, solutions are evaluated with respect to conflicting objective functions and for this reason, there is more than one solution that simultaneously optimizes all objective functions [28-31]. The solutions in the search space are compared using the concept of dominance. With reference to a minimization problem, solution X_1 is said to dominate X_2 ($X_1 \prec X_2$), if the following conditions are established.

$$\begin{array}{ll} f_o(X_1) \leq f_o(X_2) & \forall o \in \{1,2,\dots,O\} \\ f_o(X_1) < f_o(X_2) & \exists o \in \{1,2,\dots,O\} \end{array} \tag{10}$$

Also, solution X_1 is said to weakly dominate X_2 ($X_1 \preceq X_2$), if:

$$f_o(X_1) \leq f_o(X_2) \qquad \forall o \in \{1,2,\dots,O\} \tag{11}$$

Solutions which are not dominated by any solution in a given set are called non-dominated with respect to that set, and solutions that are non-dominated within the entire search space are called Pareto optimal. Without additional preference information, all Pareto optimal solutions are considered equally good since they cannot be ordered completely. These solutions constitute the so-called Pareto set, and the projection of Pareto set in the space of objective functions is called Pareto front [28-31]. The NSGA-II is a fast and elitist non-dominated sorting genetic algorithm which has been proposed by Deb et al. [32], and is an extension of genetic algorithm for multi-objective optimization. The objective of NSGA-II is to improve the adaptive fit of a population of candidate solutions to a Pareto front constrained by a set of objective functions. The population is sorted into a hierarchy of subgroups based on dominance, and similarity between members of each subgroup is evaluated. The resulting subgroups and similarities are used to promote a diverse front of non-dominated solutions [26, 28, 32]. In what follows, the proposed NSGA-II for solving the formulated bi-objective winner determination problem is explained in detail.

4. 1. Representation of Solutions For representing a solution in population, a chromosome with integer values is used. The length of this array is equal to the number of potential service-providers (*n*) which participate in combinatorial reverse auction. In other words, solution *X* in the search space is represented as $Y=(y_1, y_2, \ldots, y_n)$ in which y_j is the value of *j*-th gene and $y_j \in ZK_j = \{0\} \bigcup K_j$. A non-zero value for y_j means that the potential service-provider *j* is one of the winners of combinatorial reverse auction, and the value of y_j represents the index of accepted bid among his bids. With this representation scheme, satisfaction of constraints (8) and (9) is ensured.

4. 2. Population Size For determining the population size, the Reeves method for binary (0-1) representation [33] is extended for the representation scheme used here as a contribution. According to this method, in order to have an appropriate level of diversity, the size of population (*N*) is chosen in such a way that every possible point in the search space is reachable from the initial population by crossover only. This requirement can only be satisfied if for every $j \in J$, at least one instance of each member of ZK_j ($|ZK_j| = n_j + 1$) exist in the *j*-th gene column of initial population's matrix. Given the number of gene columns ($|J| = n$), the corresponding probability (*p*) is calculated as follows:

$$p = \prod_{j \in J} \frac{Str_2(N, n_j+1)(n_j+1)!}{(n_j+1)^N} \tag{12}$$

where $Str_2(N,b)$ is the Stirling number of the second kind which is the number of ways for partitioning a set with *N* members into *b* nonempty subsets.

$$Str_2(N,b) = \frac{1}{b!}\sum_{k=0}^{b}(-1)^{b-k}\binom{b}{k}k^N \tag{13}$$

It is now possible to determine a value for *N* such that *p* exceeds a desired value (e.g., 0.95).

4. 3. Initialization The initial population including *N* non-duplicate feasible solutions is randomly generated using our proposed problem-specific procedure which is another contribution in this paper. For generating a feasible solution, a potential service-provider is randomly selected and one of his bids is accepted at random. Then, all bids of remained potential service-providers that include at least a region in recently accepted bid are removed. This process is repeated until all regions are assigned to potential service-providers. Figure 1 shows the steps of generating a random feasible solution (*Y*) for the formulated problem in which $LHS_r(Y)$ is the left hand side of equality constraints (7) for solution *Y* that is defined as follows:

$$LHS_r(Y) = \sum_{j \in J | y_j \neq 0} a_{rj, y_j} \qquad \forall r \in R \tag{14}$$

4. 4. Evaluation of Solutions After generating initial random feasible solutions, each solution is evaluated in order to determine its objective function values. These values for solution Y are calculated as follows:

$$f_1(Y) = \sum_{j \in J | y_j \neq 0} C_{j, y_j} \tag{15}$$

$$f_2(Y) = \sum_{j \in J | y_j \neq 0} \Big(\sum_{r \in R_{j, y_j}} w_r T_{rj, y_j}\Big) \tag{16}$$

4. 5. Ranking the Population After evaluating the solutions in population, they are ranked based on dominance using the fast non-dominated sorting procedure of NSGA-II that is summarized in Figure 2.

Step 1. Set $S := J$ and for all $j \in S$, set $B_j := K_j$.
Step 2. Generate a uniformly distributed random number, s, from S and set $S := S \setminus \{s\}$.
Step 3. Determine the value of y_s by generating a uniformly distributed random number from B_s.
Step 4. For all $j \in S$ and all $k \in B_j$, if $R_{jk} \cap R_{s,y_s} \neq \varnothing$ set $B_j := B_j \setminus \{k\}$.
Step 5. For all $j \in S$, if $B_j = \varnothing$ set $S := S \setminus \{j\}$.
Step 6. For all $r \in R$, if $LHS_r(Y) = 1$, stop, else go to Step 2.

Figure 1. Initialization procedure

Step 1. Set $l := 1$, and for each solution Y, calculate/find: • $d(Y)$: the number of solutions that dominate the solution Y • $D(Y)$: the set of solutions that the solution Y dominates
Step 2. Move all solutions with $d(Y) = 0$ to the l-th non-dominated front.
Step 3. For each solution Y in l-th front, visit each $Y' \in D(Y)$ and reduce $d(Y')$ by one and move it to the $(l+1)$-th non-dominated front if $d(Y') = 0$.
Step 4. Set $l := l + 1$, and go to step 3 until all fronts are identified.

Figure 2. Non-dominated sorting procedure of NSGA-II

This procedure ranks the solutions in different non-dominated fronts and assigns a rank for each solution in population that is equal to its non-domination level (1 is the best rank). These assigned ranks will be used in parent selection process.

4. 6. Parent Selection A popular technique called binary tournament method is used for parent selection. In conventional form of this method, for selecting each parent, two solutions are randomly chosen from the population as members of a tournament and a reproductive chance is allocated to the winner of tournament. As well as conventional form, another form of binary tournament method is used in which the members of first tournament are chosen from the first quartile of population and the second tournament's members are chosen from other quartiles [24, 25]. In NSGA-II, the non-domination rank is used as criterion for determining the tournament's winner. If the solutions in a tournament have equal non-domination ranks, the less crowded one is selected as winner in order to preserve the population diversity. To do this, the crowding-distance of each solution is calculated as the average distance of its two neighbor solutions and the reproductive chance is allocated to the solution with more crowding-distance value (i.e. the less crowded one) [32]. Figure 3 represents the crowding-distance computation procedure of NSGA-II for solutions in a non-dominated front. In this procedure, $cd(Y)$ is the crowding-distance value of solution Y.

4. 7. Reproduction The reproduction phase includes crossover and mutation operators for creating new solutions [24, 25]. The uniform crossover is used to create a child solution using selected parents. Suppose $Y' = (y'_1, y'_2, \ldots, y'_n)$ and $Y'' = (y''_1, y''_2, \ldots, y''_n)$ are the selected parent solutions. The child solution, $Y = (y_1, y_2, \ldots, y_n)$, is created by generating a uniformly distributed random number (between 0 and 1) for each $j \in J$ as follows:

Step 1. Normalize the objective function values of solutions in population $(f_o \to \varphi_o)$.
Step 2. Set $cd(Y) := 0$ for each $Y \in Front$, and $o := 1$.
Step 3. Sort solutions in *Front* based on *o*-th objective function value in ascending order.
Step 4. Set $cd(Y_{(1)}) := \infty$ and $cd(Y_{(|Front|)}) := \infty$.
Step 5. For $s = 2$ to $|Front|-1$:
- Set $cd(Y_{(s)}) := cd(Y_{(s)}) + \dfrac{\varphi_o(Y_{(s+1)}) - \varphi_o(Y_{(s-1)})}{\varphi_o^{\max} - \varphi_o^{\min}}$.

Step 6. If $o < O$ then set $o := o + 1$ and go to Step 3, else stop.

Figure 3. Crowding-distance computation procedure

$$y_j = \begin{cases} y'_j & rand_j \le 0.5 \\ y''_j & \text{otherwise} \end{cases} \quad \forall j \in J \tag{17}$$

After crossover, a simple mutation operator is applied on resulting child solution. For each $j \in J$, a uniformly distributed random number in (0,1) is generated and if it is not greater than $1/n$, then the value of *j*-th gene is replaced with a uniformly distributed random number in $ZK_j \setminus \{y_j\}$.

4. 8. Repairing Infeasible Child Solutions Since the created child solutions may be infeasible, a problem-specific repair operator is proposed to convert them to feasible ones. Let we define the assignment status of *r*-th region, $\delta_r(Y)$, as follows:

$$\delta_r(Y) = \begin{cases} 1 & LHS_r(Y) \ge 1 \\ 0 & LHS_r(Y) = 0 \end{cases} \quad \forall r \in R \tag{18}$$

Step 1. Set $S := J$.
Step 2. Generate a uniformly distributed random number, s, from S and set $S := S \setminus \{s\}$.
Step 3. If $y_s \neq 0$ and the value of $\sum_{r \in R} \delta_r(Y)$ remained unchanged by changing the value of y_s to 0, set $y_s := 0$.
Step 4. If $S \neq \varnothing$ go to Step 2.
Step 5. For all $r \in R$, set $E_r := \varnothing$
Step 6. For all $j \in J$ that $y_j \neq 0$, set $E_r := E_r \cup \{(j, y_j)\}$ for all $r \in R_{j,y_j}$.
Step 7. Set $L := \varnothing$ and for all $r \in R$, if $LHS_r(Y) > 1$ set $L := L \cup \{r\}$.
Step 8. If $L = \varnothing$ go to Step 11, else generate a uniformly distributed random number $l \in L$.
Step 9. Assuming that (s, y_s) is a randomly selected member of E_l, set $y_s := 0$ and update $LHS_r(Y)$ for all $r \in R_{s,y_s}$.
Step 10. For all $r \in R_{s,y_s}$, set $E_r := E_r \setminus \{(s, y_s)\}$ and go to Step 7.
Step 11. Stop if for all $r \in R$, $LHS_r(Y) = 1$, else set $A := \varnothing$.
Step 12. For all $j \in J$ that $y_j = 0$ and all $k \in K_j$, if the left hand side values of equality constraints remained less than or equal to 1 by changing the value of y_j to k, set $A := A \cup \{(j, k)\}$.
Step 13. Sort the members of A based on $(c_{jk} / \sum_{r \in R_{jk}} c_r^{\max}, \sum_{r \in R_{jk}} w_r T_{rjk} / \sum_{r \in R_{jk}} w_r T_r^{\max})$ using the fast non-dominated sorting procedure.
Step 14. Randomly select a member of A among members with best rank, $(\bar{j}, \bar{k})$.
Step 15. Set $y_{\bar{j}} := \bar{k}$, update $LHS_r(Y)$ for all $r \in R_{\bar{j}\bar{k}}$ and go to Step 11.

Figure 4. Procedure of repairing infeasible child solutions

For repairing an infeasible child solution, each winner is removed from a random permutation of winners if it does not result in changing the assignment status of regions. Then, the following process is repeated until no region with over-assignment status ($LHS_r(Y) > 1$) is remained:

- Regions with over-assignment status as well as accepted bids related to each of these regions are identified.
- One of these regions is randomly selected and one of its related accepted bids is removed.

After all, if there are unassigned regions, then potential service-providers with no accepted bid are considered and all of their bids that do not result to over-assignment of regions are identified. The identified bids are sorted based on cost and service time using the fast non-dominated sorting procedure and a random bid among the most promising ones is selected to be accepted. This process is repeated until all regions are assigned to potential service-providers. This is our last contribution in this paper. Figure 4 shows the steps of converting an infeasible child solution (Y) to a feasible one.

4. 9. Elitist Replacement In each generation, the size of non-dominated front, N_1, is calculated and $N - N_1$ non-duplicate feasible child solutions through parent selection, reproduction, and repairing phases are created and together with solutions in non-dominated front constitute the members of population in next generation.

4. 10. Stopping Condition The proposed NSGA-II's search terminates after a given number of generations.

4. 11. NSGA-II's Outline Figure 5 explains the outline of NSGA-II's procedure for estimating the Pareto front of bi-objective winner determination problem in combinatorial reverse auction mechanism.

```
Step 1. Set g := 1 and generate an initial
population (POP_1) including N non-duplicate random
feasible solutions.
Step 2. Calculate the objective function values
of new solutions in POP_g .
Step 3. Rank the solutions in POP_g based on
objective function values using the fast non-
dominated sorting procedure.
Step 4. If g = G , stop and report the estimated
set of Pareto optimal solutions and estimated
Pareto front.
Step 5. Repeat the following sub-steps until a
population including N − N_1 non-duplicate
feasible child solutions (POP_Children) are
generated:
•    Select two parents from population using
     parent selection method.
•    Create a child solution by applying crossover
     and mutation operators on selected parents.
•    Convert the infeasible child solution to a
     feasible one using repair operator.
Step 6. Set:
   g := g + 1
   POP_g := NDSet_{g−1} ∪ POP_Children
and then go to Step 2.
```

Figure 5. Outline of NSGA-II's procedure

5. COMPUTATIONAL RESULTS

For evaluating the performance of proposed NSGA-II in estimating the set of Pareto optimal solutions of the problem, it is tested with a set of randomly generated problem instances with different sizes listed in Table 1. It is assumed that in the first set of problem instances (I), potential service-providers can include at most three regions in their combinatorial bids. This upper bound in the second and third sets of problem instances (II and III) is equal to four and five, respectively.

Furthermore, in all problem instances, it is assumed that there are four/five sub-regions in each region and the SPI occurrence probabilities in sub-regions are set to be a random permutation of (0.1,0.2,0.3,0.4) or (0.1, 0.15,0.2,0.25,0.3), respectively. Each problem instance is solved using the proposed NSGA-II which is coded in MATLAB in a computer with 2.13GHz CPU and 4GB RAM. The number of generations in each run is set to be G = 500. After running the algorithm 10 times for each problem instance, the resulted populations are combined and duplicate solutions are removed. Then solutions in combined population are ranked using the fast non-dominated sorting procedure to determine the estimated set of Pareto optimal solutions and estimated Pareto front. Figure 6 shows the estimated Pareto front of a problem instance (III-2).

TABLE 1. Different sizes for problem instances

Set of problem instances	Number of regions (m)	Number of potential service-providers (n)
I	10	50, 100, 150, 200
II	15	50, 100, 150, 200
III	20	50, 100, 150, 200

Computational results including average runtime and the number of non-dominated solutions resulted from running the proposed NSGA-II in four different settings are shown in Table 2. There are four estimated Pareto sets resulting from proposed NSGA-II in four different settings. For comparing the performance of proposed NSGA-II in these settings, a quality measure called coverage of two sets (CS) proposed by Zitzler and Thiele [34] is used.

$$CS_i = \frac{\left|x' \in U_i : \exists x \in X_i\ ,\ x \preceq x'\right|}{|U_i|}$$
$$U_i = \bigcup_{j \in \{1,2,3,4\} \setminus i} X_j\ ,\quad i \in \{1,2,3,4\} \qquad (19)$$

Using the concept of weak dominance, the coverage strength ratio of each estimated Pareto set over the union of remaining ones is calculated for different problem instances and shown in Table 3.

We conduct hypothesis tests for comparing the means of coverage ratios in four different settings of NSGA-II using paired T-test. For this test to be valid it is only required that the differences between the means of coverage ratios to be approximately normally distributed.

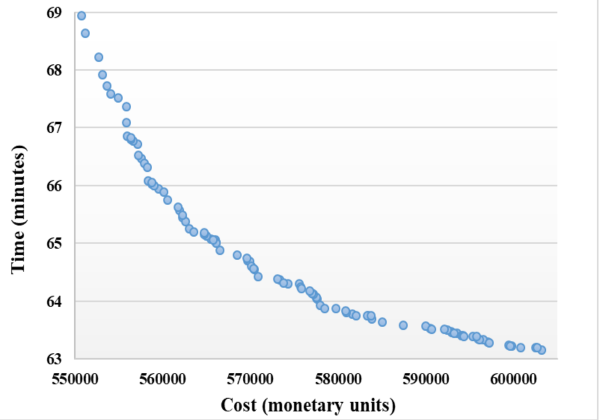

Figure 6. Estimated Pareto front of a problem instance

TABLE 2. Computational results of proposed NSGA-II in four different settings

Problem instance ID	No. of decision variables	Setting 1: *CBT* [a] & $N = N_p$			Setting 2: *NCBT* [b] & $N = N_p$			Setting 3: *CBT* & *N* = 100		Setting 4: *NCBT* & *N* = 100	
		N_p [c]	*ART* [d]	*NDS* [e]	N_p	*ART*	*NDS*	*ART*	*NDS*	*ART*	*NDS*
I-1	237	54	11	42	54	11	37	67	38	70	38
I-2	447	58	28	52	58	23	56	163	58	170	56
I-3	702	61	41	44	61	30	41	186	47	204	47
I-4	903	62	52	58	62	36	56	234	59	240	59
II-1	332	88	65	88	88	61	90	82	91	91	88
II-2	687	96	152	79	96	165	70	187	72	193	72
II-3	934	97	192	68	97	200	70	205	71	223	72
II-4	1246	99	273	84	99	259	79	292	78	278	75
III-1	413	129	133	97	129	146	99	105	88	97	88
III-2	932	142	250	112	142	281	101	213	77	202	91
III-3	1182	142	393	149	142	344	147	265	116	249	112
III-4	1688	151	517	135	151	488	109	347	101	322	96

[a] Conventional binary tournament method, [b] Non-conventional binary tournament method,
[c] Population size determined by our proposed method (p = 0.95), [d] Average runtime (seconds), [e] No. of non-dominated solutions

TABLE 3. Coverage ratios in different settings

Instance No.	Setting 1	Setting 2	Setting 3	Setting 4
I-1	0.1400	0.2400	0.2400	0.2400
I-2	0.1129	0.1656	0.1687	0.1538
I-3	0.0741	0.1741	0.0980	0.1667
I-4	0.1286	0.1351	0.1840	0.1840
II-1	0.0900	0.1909	0.1200	0.1143
II-2	0.0723	0.1205	0.1206	0.1732
II-3	0.1875	0.2500	0.1867	0.1800
II-4	0.1687	0.2379	0.1379	0.1494
III-1	0.2018	0.1982	0.1795	0.1250
III-2	0.1379	0.1757	0.0744	0.1157
III-3	0.3022	0.3054	0.1909	0.1659
III-4	0.2164	0.3148	0.2168	0.2218
Average	**0.1527**	**0.2090**	**0.1544**	**0.1658**

TABLE 4. The results of paired T-test

(i,j)	*Q*	H_0 (Null hypothesis)		
		$d_{ij} = 0$	$d_{ij} > 0$	$d_{ij} < 0$
(1,2)	-5.17	-	-	Not Rejected
(1,3)	-0.44	Not Rejected	-	-
(1,4)	-0.66	Not Rejected	-	-
(2,3)	3.33	-	Not Rejected	-
(2,4)	2.64	-	Not Rejected	-
(3,4)	-0.64	Not Rejected	-	-

$t_{11,0.975} = 2.201$, $t_{11,0.95} = 1.796$

The results of Kolmogorov-Smirnov's normality tests in Minitab do not reject the normality of differences between means of coverage ratios.

The values of paired T-test statistic (Q) as well as the results of hypothesis tests in significance level of %5 are summarized in Table 4. As shown in Table 4, the means of coverage ratios of proposed NSGA-II in first, third and fourth settings are approximately equal in significance level of %5. Also, in this significance level, the mean of coverage ratio of proposed NSGA-II in second setting is greater than the means of coverage ratios in other settings.

6. CONCLUSIONS

In this paper, a combinatorial reverse auction mechanism was proposed for selecting the most efficient service-providers for resolving sustained power interruptions in multiple regions of an electric power distribution company's responsibility area. Through this mechanism, supplying the required service in each region is assigned to only one potential service-provider considering two criteria including cost and service time. So, the corresponding winner determination problem was formulated as a combinatorial optimization problem with two objectives including: (1) minimizing the total requested cost, and (2) minimizing the average time for supplying the required service by potential service-providers. Because of NP-completeness of finding a feasible solution for the formulated problem as well as its solving and weakness of exact optimization algorithms in solving this kind of problems, a problem-specific NSGA-II was developed to estimate the set of Pareto optimal solutions of the formulated bi-objective problem. In proposed NSGA-II, two problem-specific operators were proposed for creating initial feasible solutions and converting infeasible solutions to feasible ones. Furthermore, a new method for determining the population size based on problem instance's size was proposed. Computational results of running the proposed algorithm in different settings on several randomly generated problem instances were compared using a quality measure and statistical hypothesis tests. The results of performance comparison demonstrate that the proposed NSGA-II with a population size determined by proposed method and a different form of binary tournament method performs better in finding non-dominated solutions for different instances of formulated bi-objective winner determination problem. As a future research direction, researchers can use other algorithms for solving the formulated problem and compare them with our proposed NSGA-II. Also, they can change the formulation of winner determination problem by introducing other objective functions or constraints and develop our proposed algorithm or other algorithms for solving their own models.

7. REFERENCES

1. Setak, M., Sharifi, S. and Alimohammadian, A., "Supplier selection and order allocation models in supply chain management: A review", ***World Applied Sciences Journal***, Vol. 18, No. 1, (2012), 55-72.
2. Azadnia, A., "A multi-objective mathematical model for sustainable supplier selection and order lot-sizing under inflation", ***International Journal of Engineering-Transactions B: Applications***, Vol. 29, No. 8, (2016), 1141.
3. Hsieh, F.-S., "Combinatorial reverse auction based on revelation of lagrangian multipliers", ***Decision Support Systems***, Vol. 48, No. 2, (2010), 323-330.
4. Cramton, P., Shoham, Y. and Steinberg, R., "Introduction to combinatorial auctions", in, MIT Press., (2010).
5. Abrache, J., Crainic, T.G., Gendreau, M. and Rekik, M., "Combinatorial auctions", ***Annals of Operations Research***, Vol. 153, No. 1, (2007), 131-164.
6. Blumrosen, L. and Nisan, N., "Combinatorial auctions", ***Algorithmic Game Theory***, Vol. 267, (2007), 300-308.
7. Bichler, M., Davenport, A., Hohner, G. and Kalagnanam, J., "Industrial procurement auctions", ***Combinatorial Auctions***, (2006), 593-612.
8. Hoffman, K.L., "Combinatorial auctions", ***Encyclopedia of Operations Research and Management Science***, (2013), 181-192.
9. Ball, M., Donohue, G. and Hoffman, K., "Auctions for the safe, efficient, and equitable allocation of airspace system resources", ***Combinatorial Auctions***, Vol. 1, (2006).
10. Alaei, R. and Ghassemi-Tari, F., "Development of a genetic algorithm for advertising time allocation problems", ***Journal of Industrial and Systems Engineering***, Vol. 4, No. 4, (2011), 245-255.
11. Ghassemi Tari, F. and Alaei, R., "Scheduling tv commercials using genetic algorithms", ***International Journal of Production Research***, Vol. 51, No. 16, (2013), 4921-4929.
12. Cramton, P., "Spectrum auction design", ***Review of Industrial Organization***, Vol. 42, No. 2, (2013), 161-190.
13. Farnia, F., Frayret, J.-M., Lebel, L. and Beaudry, C., "Agent-based simulation of multiple-round timber combinatorial auction", ***Canadian Journal of Forest Research***, Vol. 47, No. 1, (2016), 1-9.
14. Caplice, C. and Sheffi, Y., "Combinatorial auctions for truckload transportation", ***Combinatorial Auctions***, Vol. 21, (2006), 539-571.
15. Triki, C., "Location-based techniques for the synergy approximation in combinatorial transportation auctions", ***Optimization Letters***, Vol. 10, No. 5, (2016), 1125-1139.
16. Cantillon, E. and Pesendorfer, M., "Auctioning bus routes: The london experience", (2006).
17. Hohner, G., Rich, J., Ng, E., Reid, G., Davenport, A.J., Kalagnanam, J.R., Lee, H.S. and An, C., "Combinatorial and quantity-discount procurement auctions benefit mars, incorporated and its suppliers", ***Interfaces***, Vol. 33, No. 1, (2003), 23-35.
18. Metty, T., Harlan, R., Samelson, Q., Moore, T., Morris, T., Sorensen, R., Schneur, A., Raskina, O., Schneur, R. and Kanner, J., "Reinventing the supplier negotiation process at motorola", ***Interfaces***, Vol. 35, No. 1, (2005), 7-23.
19. Sandholm, T., Levine, D., Concordia, M., Martyn, P., Hughes, R., Jacobs, J. and Begg, D., "Changing the game in strategic sourcing at procter & gamble: Expressive competition enabled by optimization", ***Interfaces***, Vol. 36, No. 1, (2006), 55-68.

20. Alaei, R. and Setak, M., "Selecting unique suppliers through winner determination in combinatorial reverse auction: Scatter search algorithm", ***Scientia Iranica, Transactions E: Industrial Engineering***, (2017).
21. Buer, T. and Pankratz, G., "Solving a bi-objective winner determination problem in a transportation procurement auction", ***Logistics Research***, Vol. 2, No. 2, (2010), 65-78.
22. Buer, T. and Kopfer, H., "A pareto-metaheuristic for a bi-objective winner determination problem in a combinatorial reverse auction", ***Computers & Operations Research***, Vol. 41, (2014), 208-220.
23. Cormen, T.H., "Introduction to algorithms, MIT press, (2009).
24. Blum, C. and Roli, A., "Metaheuristics in combinatorial optimization: Overview and conceptual comparison", ***ACM Computing Surveys (CSUR)***, Vol. 35, No. 3, (2003), 268-308.
25. Talbi, E.-G., "Metaheuristics: From design to implementation, John Wiley & Sons, Vol. 74, (2009).
26. Sharma, A.K., Datta, R., Elarbi, M., Bhattacharya, B. and Bechikh, S., Practical applications in constrained evolutionary multi-objective optimization, in Recent advances in evolutionary multi-objective optimization. (2017), Springer.159-179.
27. Sandholm, T., Suri, S., Gilpin, A. and Levine, D., "Winner determination in combinatorial auction generalizations", in Proceedings of the first international joint conference on Autonomous agents and multiagent systems: part 1, ACM. , (2002), 69-76.
28. Deb, K., Multi-objective optimization, in Search methodologies. (2014), Springer.403-449.
29. Tavakkoli-Moghaddam, R., Makui, A., Khazaei, M. and Ghodratnama, A., "Solving a new bi-objective model for a cell formation problem considering labor allocation by multi-objective particle swarm optimization", ***International Journal of Engineering-Transactions A: Basics***, Vol. 24, No. 3, (2011), 249-256.
30. Fakhrzad, M., Sadeghieh, A. and Emami, L., "A new multi-objective job shop scheduling with setup times using a hybrid genetic algorithm", ***International Journal of Engineering-Transactions B: Applications***, Vol. 26, No. 2, (2012), 207-216.
31. Bashiri, M. and Rezanezhad, M., "A reliable multi-objective p-hub covering location problem considering of hubs capabilities", ***International Journal of Engineering-Transactions B: Applications***, Vol. 28, No. 5, (2015), 717-126.
32. Deb, K., Pratap, A., Agarwal, S. and Meyarivan, T., "A fast and elitist multiobjective genetic algorithm: NSGA-ii", ***IEEE Transactions on Evolutionary computation***, Vol. 6, No. 2, (2002), 182-197.
33. Reeves, C.R., "Using genetic algorithms with small populations", in ICGA. Vol. 590, (1993), 92-100.
34. Zitzler, E. and Thiele, L., "Multiobjective optimization using evolutionary algorithms—a comparative case study", in international conference on parallel problem solving from nature, Springer., (1998), 292-301.

Selecting Efficient Service-providers in Electric Power Distribution Industry Using Combinatorial Reverse Auction

R. Alaei, M. Setak

Faculty of Industrial Engineering, K.N. Toosi University of Technology, Tehran, Iran

PAPER INFO

Paper history:
Received 22 January 2017
Received in revised form 24 April 2017
Accepted 07 July 2017

Keywords:
Supplier Selection
Electric Power Distribution Industry
Combinatorial Reverse Auction
Winner Determination Problem
Multi-Objective Optimization
NSGA-II

چکیده

در این مقاله، یک مکانیزم مناقصه ترکیبی برای انتخاب بهترین تأمین‌کنندگان خدمات رفع خاموشی‌ها در مناطق چندگانه محدوده مسئولیت یک شرکت توزیع نیروی برق ارائه می‌شود که با استفاده از این مکانیزم، تأمین خدمات مورد نیاز در هر منطقه تنها به یک تأمین‌کننده بالقوه با در نظر گرفتن دو معیار هزینه و مدت زمان تأمین خدمات تخصیص داده می‌شود. بنابراین، مسئله تعیین برندگان متناظر با مکانیزم مناقصه ترکیبی به صورت یک مسئله بهینه‌سازی ترکیبی دو هدفه فرموله می‌شود. اما یافتن جواب موجه برای مسئله فرموله شده و نیز حل آن خیلی پیچیده است و الگوریتم‌های بهینه‌سازی دقیق قادر به حل این نوع از مسائل در مدت زمان معقول نمی‌باشند. به این دلیل، از نسخه دوم الگوریتم ژنتیک با مرتب‌سازی ناچیرگی که یک روش فراابتکاری برای حل مسائل بهینه‌سازی چند هدفه است، برای تخمین مجموعه جواب‌های پارتو مسئله دو هدفه فرموله شده استفاده می‌شود. در این الگوریتم، دو عمل‌گر خاص مسئله برای ایجاد جواب‌های موجه اولیه و تبدیل جواب‌های غیرموجه به موجه و همچنین روش جدیدی برای تعیین اندازه جمعیت بر اساس اندازه مسئله ارائه شده است. عملکرد الگوریتم ارائه شده در تنظیمات مختلف با حل مجموعه‌ای از مسائل نمونه که به صورت تصادفی ایجاد شده‌اند، ارزیابی می‌شود. کیفیت نتایج الگوریتم ارائه شده در تنظیمات مختلف با استفاده از یک سنجه مناسب و آزمون فرض‌های آماری مقایسه می‌شود. نتایج حاصل از مقایسه عملکرد نشان می‌دهد که الگوریتم ارائه شده با اندازه جمعیت تعیین شده با روش جدید و با شکل متفاوتی از روش تورنمنت دودویی، عملکرد بهتری در یافتن جواب‌های ناچیره مسئله دو هدفه فرموله شده دارد.

***doi**: 10.5829/idosi.ije.2017.30.09c.07*