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Using announcement options in the bid construction phase for disaster relief procurement

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A B S T R A C T

This paper presents an analysis of the bid construction phase of procurement auctions in disaster relief and humanitarian logistics. Substitution and partial fulfillment options are presented in formulations to allow bidders with fewer inventories to offer substitute item types and partial bids in auctions. During the auction announcement phase, a coordinating platform for disaster locations (i.e., auctioneer) allows substitution and partial fulfillment options to the relief suppliers (i.e., bidders) when acceptable. Thus, suppliers with fewer inventories can offer substitute item types and participate in more auctions by partially bidding. A genetic algorithm, a simulated annealing algorithm and an integer program are used for the analysis of the bid construction phase with different announcement options. Heuristic solution techniques and an IP formulation help understand the dynamics of the bid construction problem. It is shown that the addition of substitution and partial fulfillment options is essential to diversify and increase the usable capacity of the supplier base. Additionally, the partial fulfillment option enables better usage of supplier inventories in an environment with scarce supplies.

1. Introduction

During the last decade, research on disaster planning and disaster relief logistics has received an increasing interest from many disciplines due to the emerging need for effective relief operations. Many studies have investigated disaster planning and relief logistics [1–3] whereas many others have focused on resource allocation and procurement operations in an emergency planning and response context [4–7]. Procurement is necessary to have the required goods readily available for the relief operations. Estimates show that 65% of the total disaster relief budget is dedicated to the procurement of relief supplies and equipment [8], which makes it the step in the disaster relief process where the majority of donor funding is spent. In addition, organization of funding mechanisms, donor expectations, diversity of stakeholders, unpredictability of disasters and resource scarcity/oversupply are some of the factors [9] that contribute to the complexity of the procurement operations. This complexity poses important decisions on the type, quantity, timing, source and destination, as well as the method of delivery procuring relief goods.

Although a few humanitarian organizations have utilized auction-based approaches in procurement by the help of logistics software [10–13], the use of procurement auctions in disaster relief still needs thorough and practical investigations. The practice of Humanitarian Procurement Centres (HPC) of the European Commission (EC) is a practical example for the organized procurement operations when the operations are conducted on behalf of its partners [14]. During a typical procurement operation, first, HPCs receive procurement requests from the partners. Then, they consolidate these requests and conduct the procurement following the principles of ethics, transparency, proportionality, and equal treatment of potential suppliers [15]. This study proposes a procurement auction-based approach for procurement operations in similar environments where a coordinating platform at the disaster location represents the auctioneer and suppliers around the disaster location represent the bidders.

Although the number of studies and publications on procurement auctions has increased in recent years [16], this research area could still benefit from the attention of OR/MS practitioners [17]. Besides, most of the research on this topic is in a commercial context and usually concentrates on the auctioneer's perspective. This study focuses on the bidders' perspective in a disaster relief

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context when there is a coordinating platform which collects needs and conducts the auctions. The motivation for this study is to enable the design of procurement auctions for an effective disaster response. The research question that we seek to answer in this paper is: "What are the specific design parameters for an effective procurement auction in disaster relief setting?" The contribution of this study is that we focus on the suppliers' perspective in a procurement auction and investigate different techniques for the suppliers to construct bids effectively. New procurement auction design parameters are introduced to facilitate following the EC procurement principles and to better utilize suppliers' capacities in a scarce resource environment. Thus, the purpose of the paper is to show that announcement options are beneficial to the suppliers as well as the auctioneer.

2. Literature review

There are a number of factors that necessitate procurement in disaster relief operations. First, pre-positioned inventories are usually insufficient in many disaster relief operations [18]. Second, a demand/supply mismatch and operational problems are frequently observed in practice for gifts-in-kind [19–21]. Third, funding for the disaster is proliferated after the disaster [22] which requires dynamic spending strategies for the available funds. One way to effectively acquire the needs in an environment with scarce resources is procurement auctions. A procurement auction is a mechanism that outlines procedures to establish procurement of supplies based on bids submitted by participants [23]. Two parties are defined for an auction: auctioneer and bidder. A buyer and multiple sellers are present in a procurement auction. In a disaster relief environment the buyer is typically a coordinating platform near the disaster location and acts as the auctioneer whereas the suppliers are bidders that bid on the auctions.

Typically, procurement auction-based models include two main phases: (1) the bid construction phase and (2) the winner determination phase [24,25]. In the bid construction phase, the bidders evaluate the auction and construct a bid price considering a number of objectives and constraints. When the auctioneer has all the bid prices, the winning bid is determined by utilizing a winner determination algorithm [26–28]. To date there is a limited amount of research in the literature that concentrates on the supplier's perspective and focuses on the bid construction phase, which directly affects the auction. Many of the studies in the literature focus on a commercial context [29–31], Trestrail et al. [32] is one of the few studies that analyze the procurement process from the bidders' perspective and illustrate the remote procurement of the world's largest donor of food aid (i.e., United States Department of Agriculture (USDA)). Bagchi et al. [33] proposes an optimal auction mechanism for USDA to deter gaming of suppliers and enhance bid preparation process by combining carrier and supplier bids. On the other hand, Falasca and Zobel [34] present a two-stage stochastic procurement model from the perspective of humanitarian organizations (i.e., auctioneer's perspective).

Equal treatment of potential suppliers is explicitly required from HPCs in real disaster relief operations. Nevertheless, there is usually an imbalance of quality and availability of relief goods between local and global suppliers, which makes it harder for them to follow this principle. Local (i.e., usually smaller) suppliers often do not have the capacity to provide the best quality of relief supplies and to hold inventory of large quantities. On the other hand, procuring from local suppliers is encouraged especially in the recovery phase of disaster relief to support local the economy and contributions of local people [35,36]. Besides, it is logistically cheaper to procure from local suppliers. In order to address this issue, announcement options (i.e., substitution and partial fulfillment) are proposed in procurement auctions to alleviate the imbalance and to create an opportunity for local suppliers to bid. A spillover effect of these announcement options would be in increasing the usable capacity of the supplier base by removing the quantity restriction.

This paper specifically focuses on the bid construction phase for procurement auctions within the context of disaster relief operations. The bid construction phase includes decisions related to quantities and types of items in the bids. The decisions are compared using a Genetic Algorithm (GA), a Simulated Annealing (SA) Algorithm, and an Integer Programming (IP) formulation of the problem. A Linear Programming (LP) relaxation of the IP is used as a benchmark in this comparison. Partial fulfillment and substitution of supplies are two major considerations introduced in this auction process. The impacts of those considerations on bid construction decisions are also analyzed.

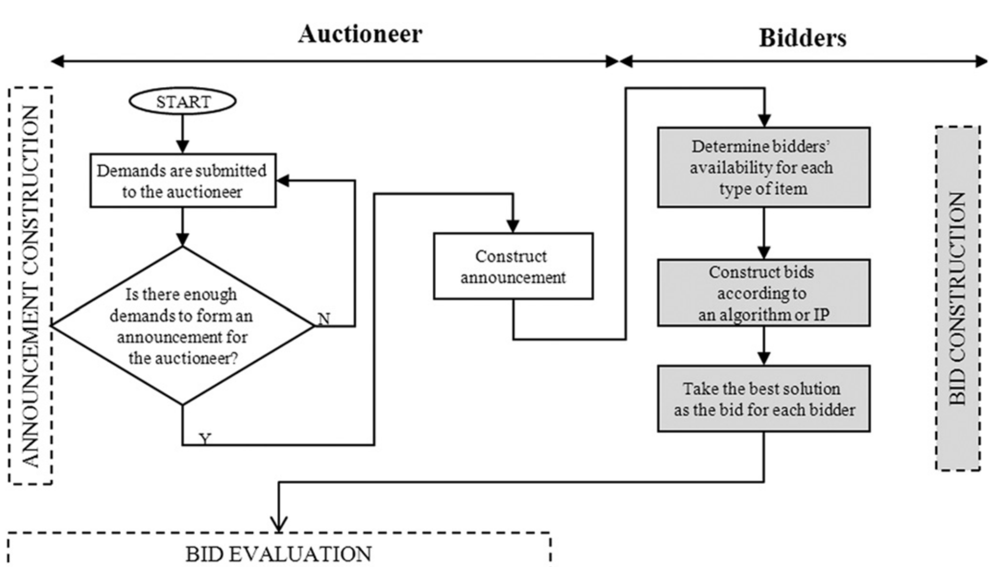

Fig. 1. Procurement auction processes.

3. Methodology

3.1. Auction model

Procurement auctions considered in this study have one auctioneer and multiple bidders. In the process, depicted in Fig. 1, partners of the coordinating platform submit their need for relief supplies to the auctioneer. The auctioneer bundles these needs, creates the auction and announces it. The bidders receive the announcement and construct their bids according to their on-hand inventory. The objective of the auctioneer is to fulfill the needs of the humanitarian organizations as much as possible. On the other hand, the objective of the bidders is to enter into as many auctions as possible and to supply the required items with their available inventory. These objectives are complementary to each other when both parties act on humanitarian grounds such as the disaster relief environment.

Two announcement options are considered in this process, namely substitution and partial fulfillment. *Substitution* is an option that allows bidders to offer substitute supplies if they don't have enough quantity of the needed supply. The *Partial Fulfillment* option, on the other hand, deals with offering only on-hand supplies when bidders don't have enough quantity to meet the entire request.

These options are included in the procurement auction process to fulfill the demand of the auctioneer as much as possible with the on-hand inventories of bidders. Most commercial practices in procurement auctions do not allow the bidders to enter the auction if they do not possess enough quantity for the supplies requested [37]. We hypothesize that inclusion of these options in the auction process would be essential to let local (i.e., lower capacity) suppliers bid and allow them to utilize their on-hand scarce resources better. On the other hand, substitution and partial fulfillment decisions are optional for the auctioneer. Each option may or may not be allowed for different supply types in an announcement.

Shipping and inventory replenishment decisions of the bidders are not considered in this process. Only one substitute for each supply type is considered; two or more order substitutes (i.e., substitute of a substitute) are not allowed. Also, an announcement cannot have the original item and the substitute item at the same time. The substitute item quantity is found by multiplying the original item quantity by a factor. Let Q_j be the original demand quantity for item type j, and F_j be the substitute factor for item type j. Then, B_j, which represents the substitute item quantity for supply type j can be given as:

$$B_j = F_j {}^X Q_j \tag{1}$$

Here, without loss of generality, the range of F_j is assumed to be within [1.0–1.5]. We acknowledge that this range is reasonable only for certain supply types. Nevertheless, it can be applied to many essential ones (e.g., food). An example of substitution can be given for MRE (meals-ready-to-eat) items. A cup of pinto beans (206 kcal) might be a substitute for a cup of chickpeas (286 kcal) [38]. The substitute factor is 1.38 (286/206) for these items. The substitute factor is proposed for products where their substitute quantities can be clearly defined [39] as in the case of calorie comparison.

When an auctioneer releases the announcement data, bidders need to construct bids. A bidder may have choices of satisfying the demand with only original items, only substitute items, or a mix of those depending on their on-hand inventory. Let X_j be the decision variable for original quantity bid and Y_j be the decision variable for the substitute quantity bid of corresponding bidder. Let parameters V_j and W_j be the values of original item type j and its substitute in the inventory of corresponding bidder. The objective function used in bid construction is formulated as:

$$\text{Min} \sum_{j=1}^{n} X_j V_j + \sum_{j=1}^{n} Y_j W_j \tag{2}$$

The value of an item is a function of sales price, condition, and age. The objective function represents the bid value and is minimized to make use of the aged items as soon as possible. The value of each supply in inventory is known by the bidder *a priori*. The challenge in this decision is whether to include substitutes and how much to include when it is allowed by the auctioneer. Since the main aim is to fulfill the demand, registered suppliers are

Table 1
A sample announcement.

Index for item type (j)	Original quantity (Q_j)	Substitute factor (F_j)	Substitute quantity (B_j)	Substitution option (S_j)	Partial fulfillment option (P_j)
1	62	1.25	78	0	1
2	38	1.40	54	1	1
3	82	1.30	107	1	0
4	98	1.20	118	1	0
5	50	1.10	55	1	1

```
procedure genetic algorithm
begin
    t ← 0
    initialize P(t)
    evaluate P(t)
    while (not termination condition) do
    begin
        t ← t + 1
        select P(t) from P(t - 1)
        alter P(t)
        evaluate P(t)
    end
end
```

Fig. 2. Pseudo code of implemented GA.

```
procedure simulated annealing
begin
    t ← 0
    initialize T
    select a random feasible bid v_c
    evaluate v_c
    repeat
      repeat
        select a new feasible bid v_n in the neighborhood of v_c
        if eval(v_c) > eval(v_n)
          then v_c ← v_n
          else if random[0,1) < e^((eval(v_c)−eval(v_n))/T)
            then v_c ← v_n
      until (termination-condition)
      T ← αT
      t ← t + 1
    until (halting-criterion)
end
```

Fig. 3. Pseudo code of implemented SA.

Table 2
Inventory situation of a bidder.

Index for item type (j)	Original		Substitute	
	Asset value (V_j)	Inventory on-hand (I_j)	Asset value (W_j)	Inventory on-hand (H_j)
1	16	77	39	79
2	73	20	92	74
3	12	72	15	58
4	73	66	20	80
5	6	78	27	73

Table 4
Bidder on-hand inventories.

Bidder index	Parameters $U(a,b)$
1	$U(0,50)$
2	$U(50,100)$
3	$U(50,100)$
4	$U(50,100)$
5	$U(50,100)$
6	$U(100,150)$
7	$U(100,150)$
8	$U(100,150)$
9	$U(100,150)$
10	$U(150,200)$

required to bid for the announcement if they can satisfy the announcement (e.g., mixing substitute supplies with the originals). This consideration is practical in disaster relief logistics where only limited supply is available and the bidder needs to satisfy the requirements in a short time with these supplies and can be included in the contractual agreements with coordinating platforms and their registered suppliers. Inventory status of each bidder is also defined by the original and substitute item inventory on hand quantity, represented by I_j for original item type j and H_j for substitute item type j, respectively. A sample announcement constructed by the auctioneer is given in Table 1 to illustrate the substitution and partial fulfillment concepts. Announcement options are represented by S_j and P_j, substitution and partial fulfillment options respectively, where 1 represents allowing this option and 0 represents otherwise.

3.2. Solution approaches

In this study, three solution approaches are tested for the bid construction decisions: Genetic Algorithm (GA), Simulated Annealing (SA) Algorithm, and Integer Programming (IP).

3.2.1. Genetic algorithm

Let $P(t)$ denote a population of n individuals for iteration t. In this definition, individuals represent a possible solution to the problem. They are compared with each other using some fitness criteria. Fitter individuals are selected by some selection criteria to serve as parents. These parents are mated to form the next generation [40]. The structure of the GA is given in Figs. 2 and 3.

A dynamic real encoding scheme is used to represent the bid quantities. Here, an individual of a possible solution is defined by original and substitute bid quantities, represented by X_j and Y_j respectively for item type j where each item type represents a different relief supply. Samples from various solutions are represented in the initial population. The fitness of individual i from a population is found as follows:

$$fitness(i) = 1/[objective(i) - Best + 1] \quad (3)$$

where $objective(i)$ is calculated with equation (2) for individual i and $Best$ is the smallest objective function value found up to that iteration. One is added to the denominator to avoid division by zero for the best individual. These fitness values are then mapped to a percentage fitness to facilitate comparison.

The process of selecting the fittest individual will be illustrated with an example. On-hand inventory and values for a bidder are given in Table 2. Table 3 represents the initial population (i.e., $P(0)$) for the inventory status in Table 2 and the sample announcement in Table 1. Here, five original item types and five substitute item types are considered. The encoding scheme is dynamic because the chromosome length is 2^x(Number of Item Types) for each announcement. Since this is the initial population, the smallest objective function value (i.e., $Best$) of all individuals up to that iteration is computed as 10,385. Note that each individual in Table 3 is feasible (i.e., has bid quantities less than or equal to the inventory on-hand) with respect to the inventory situation in Table 2 and announcement data in Table 1.

Three methods [41] are used in the GA to create diversity in the next generation. Parents are selected 75 percent of the time using tournament selection, 23 percent of the time using a roulette wheel, and two percent of the time with an elitist strategy. The elitist strategy preserves the best two individuals from previous generations for the next generation. Parents are selected for the next generation based on their fitness values in the roulette wheel selection method. The smaller the objective function of an individual, the greater the chance of being selected. Tournament selection works as follows: It starts with selecting two individuals randomly. The individual with the smallest objective function is selected as a parent among the two. Then two other individuals are selected randomly and the best is picked. Then, the two selected individuals are used to mate. After selecting the parents, the next population is generated by using a uniform crossover operator where one X_j–Y_j pair is changed between individuals. Utilizing this approach results in feasibility being preserved and more alternatives are being considered, which were not in the initial population.

After initial experimentation, the following GA parameters are used in the model: Population size of 100, number of generations as

Table 3
Initial population of size seven.

Individual	Original					Substitute					Objective value	Fitness (%)
	X_1	X_2	X_3	X_4	X_5	Y_1	Y_2	Y_3	Y_4	Y_5		
1	62	8	50	66	48	0	42	42	39	3	12,637	0.04
2	62	20	40	32	50	0	26	55	80	0	10,385	92.95
3	62	20	72	32	8	0	26	13	80	47	11,156	0.12
4	62	20	38	32	48	0	26	58	80	3	10,475	1.02
5	62	20	38	32	50	0	26	58	80	0	10,406	4.22
6	62	10	66	44	36	0	40	0	65	16	11,354	0.10
7	62	18	38	32	50	0	28	58	80	0	10,444	1.55

Table 5
Demand vs. inventory match.

Percentage of all announcements (%)	Satisfying proportion of all bidders (%)
35.4	90
79.5	50
86.3	10
92.4	0

100 and a crossover ratio of 0.7. Since the GA converges to one good solution when using the three parent selection methods, all individuals in the last generation remain unchanged. One of the individuals from the last generation is selected as the bid for that bidder.

3.2.2. Simulated annealing algorithm

SA is a stochastic local search algorithm, which enables the search to escape from local optima in the solution space [42]. At each iteration of the algorithm, the current objective function value (v_c) and newly selected solution (v_n) from the neighborhood of the current one are evaluated. If the new solution is promising, then the search jumps to that solution. Even if v_n is non-improving, it is undertaken with some probability. The probability of accepting an inferior solution decreases in consecutive iterations using a temperature parameter (T) using a cooling schedule (α). In this way, SA searches the current neighborhood extensively to converge the best value in later iterations of the algorithm [40,41]. The pseudo code of the implemented SA algorithm is given in Fig. 3.

The algorithm starts with finding a random feasible bid, which is determined using the availability of the bidders. The objective function used in *eval*(v) is given in equation (2). There are several parameters in the SA that affect the goodness of the solution, namely the neighborhood of a solution, the cooling schedule (α), the initial temperature (T), the halting criterion and termination condition. These SA parameters are experimented to find the best combination of parameters specifically for the bid construction problem.

For the cooling schedule, a geometric schedule is used where T is updated by αT. Here, α is the cooling parameter and is changed to three levels: 0.95, 0.9, and 0.85. To find an estimate for the range of the initial temperature, a formula from Gonzales et al. [43] is used ($T = -\Delta f^*/\ln(p_a)$). In this formula, Δf^* is the average objective increase observed in a random change, and p_a is the initial acceptance probability (0.8 is usually used). Approximately 10,000 random functions are observed and the average value was 400. To find an initial value for T, values of 800, 500, and 300 are analyzed. Similarly, 50 and 100 iterations are used to initiate the termination criterion and 100 and 250 are used for halting criterion. Along with these levels, a minimum temperature of 0.0001 is used to halt the algorithm (i.e. when the temperature reaches 0.0001).

Results of the initial experiments are compared with each other using convergence criteria as well as whether the best bid is found for a sample announcement. When the results from these experiments are examined, one item neighbor, 0.85 for α in the cooling schedule, 300 for T, 100 iterations for halting criterion, and 100 iterations for termination criterion are the best combination.

3.2.3. Integer programming formulation

The objective function, parameters and decision variables definitions in the following IP formulation are the same as Section 3.1 with an addition of M (i.e., Big-M) and z_j. Big-M is a sufficiently large integer and z_j represents the availability of the bidder for the announcement, and is calculated using the parameters given in the announcement and on-hand inventory. The formula ($F_jI_j + S_jH_j \geq F_jQ_j$) is used to compute z_j for each item in the announcement. If this inequality is valid (i.e., the bidder has enough inventory to satisfy this item in the announcement), then $z_j = 0$; else $z_j = 1$. The IP formulation uses the objective function in equation (2) and the constraints are as follows:

$$F_jX_j + S_jY_j \geq F_jQ_j - \mathrm{M}z_j \quad \forall j \tag{c.1}$$

$$Y_j \leq \mathrm{M}S_j \quad \forall j \tag{c.2}$$

$$X_j \leq I_j \quad \forall j \tag{c.3}$$

$$Y_j \leq H_j \quad \forall j \tag{c.4}$$

$$X_j \geq P_jI_j - \mathrm{M}(1 - z_j) \quad \forall j \tag{c.5}$$

$$Y_j \geq S_j\,P_j\,H_j - \mathrm{M}(1 - z_j) \quad \forall j \tag{c.6}$$

$$X_j \geq 0 \text{ and integer} \quad \forall j \tag{c.7}$$

$$Y_j \geq 0 \text{ and integer} \quad \forall j \tag{c.8}$$

The first two constraints are the announcement fulfillment constraints. In constraint (c.1), the first term on the left hand side represents the original quantity and the second term on the left hand side is present only when substitutes are allowed (i.e., $S_j = 1$). The right hand side is the original quantity in the announcement. If there is not enough inventory (i.e. $z_j = 1$), then this constraint is redundant by the use of the Big-M. Constraint (c.2) forces substitute bids to be 0 when substitution is not allowed. Constraints (c.3) and (c.4) prohibit the supplier from bidding more than the on-hand

Table 6
Results of experiments.

Number of items	Average comp time (sec)				Average min objective value				Average objective value			
	GA	SA	IP	LP bound	GA	SA	IP	LP bound	GA	SA	IP	LP bound
1	117.3	86.2	50.0	45.2	771.9	767.4	767.1	766.1	2123.5	2104.9	2104.1	2102.2
2	152.0	100.1	51.1	47.0	5109.4	5107.6	5106.2	5099.0	6011.1	6008.7	6007.8	5990.8
3	195.2	110.5	50.0	45.4	5243.2	5240.1	5237.4	5228.6	8192.4	8173.6	8169.8	8160.1
4	222.3	120.5	51.6	45.3	9200.2	9196.2	9191.5	9121.4	10,935.2	10,911.5	10,906.9	10,874.7
5	257.8	133.3	46.6	45.6	11,585.5	11,566.8	11,560.1	11,469.5	14,060.7	14,016.8	14,010.1	13,974.9
6	292.5	151.0	50.8	45.4	14,184.7	14,094.0	14,089.1	14,072.4	17,008.0	16,923.8	16,916.6	16,899.9
7	330.6	164.0	47.9	45.3	18,067.7	17,927.3	17,919.1	17,883.1	19,990.9	19,864.5	19,857.1	19,834.1
8	367.4	179.2	50.6	45.3	21,273.4	21,110.1	21,101.8	20,984.3	23,306.7	23,135.5	23,124.8	23,079.8
9	403.5	192.0	50.0	44.8	23,209.2	22,914.5	22,905.4	22,882.1	25,996.0	25,793.0	25,779.1	25,757.1
10	436.1	206.2	47.5	45.2	25,470.2	25,153.0	25,146.1	25,121.2	28,558.0	28,315.6	28,299.6	28,276.1

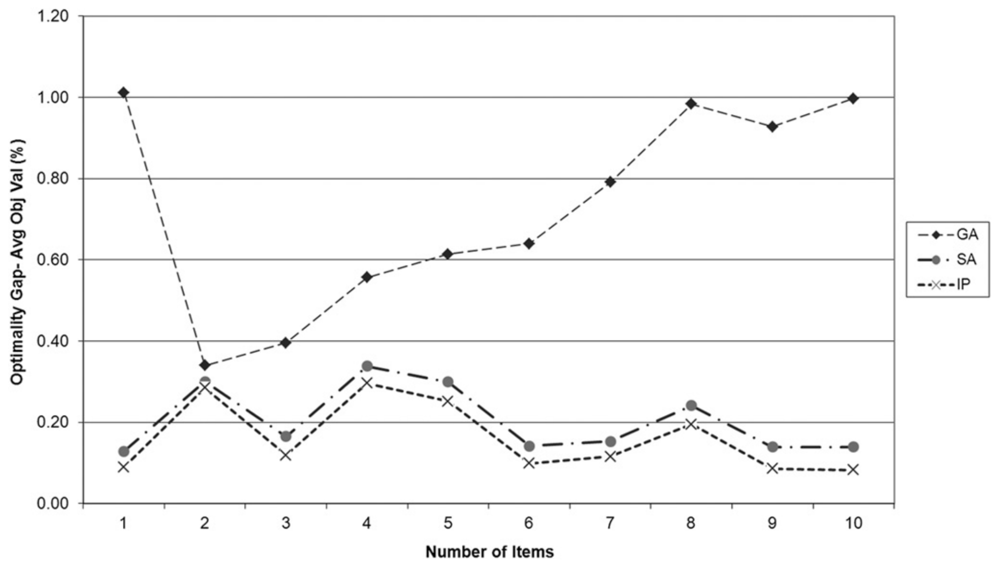

Fig. 4. Optimality gap of average objective values from LP lower bound.

inventory. Constraints (c.5) and (c.6) oblige bidders to provide whatever they possess as a bid if they do not have enough inventory to fully satisfy the announcement. Constraints (c.7) and (c.8) are integrality constraints.

3.3. Experimental study

In this section, an experimental study is conducted to compare the performances of the GA, SA and IP formulations in bid construction and analyze the impacts of substitution and partial fulfillment options. Demands for different supply types are constructed using a Poisson distribution with a mean of 100 demands/day for a week long period. Poisson distribution has been used in estimating the disaster relief demand [44] and inventory models with emergency orders [45]. Each supply type is equally likely to be demanded. The number of different supplies in an announcement is altered from one to ten for different experiments. The number of items in an announcement relates to the maximum number of supply types allowed to be auctioned together.

Ten bidders with different capacities are used to simulate system behavior with diverse suppliers. Studies on the commercial context report that an advantage of procurement auctions is the opportunity to find new diverse suppliers [46] and a diverse supply base positively affects bundle performance [47]. The bidders have different on-hand inventory levels with varying values to satisfy the auctioneer's demand. Capacity (i.e., on-hand inventory) is one of the attributes of supply base heterogeneity in procurement auctions [48]. Bidder inventory levels of all items are determined by drawing from uniformly distributed random variables with different parameters. The parameters of these uniform distributions for the bidders are given in Table 4.

While determining inventory levels for bidders, the values are set to satisfy some portion of all announcements. This logic stems from a practical figure of a previously studied transportation services auctions [49]. The demand and on-hand inventory match is given in Table 5. For example, approximately 90% of bidders can bid on about 35% of all announcements and only 10% of bidders can bid on about 86% of all announcements.

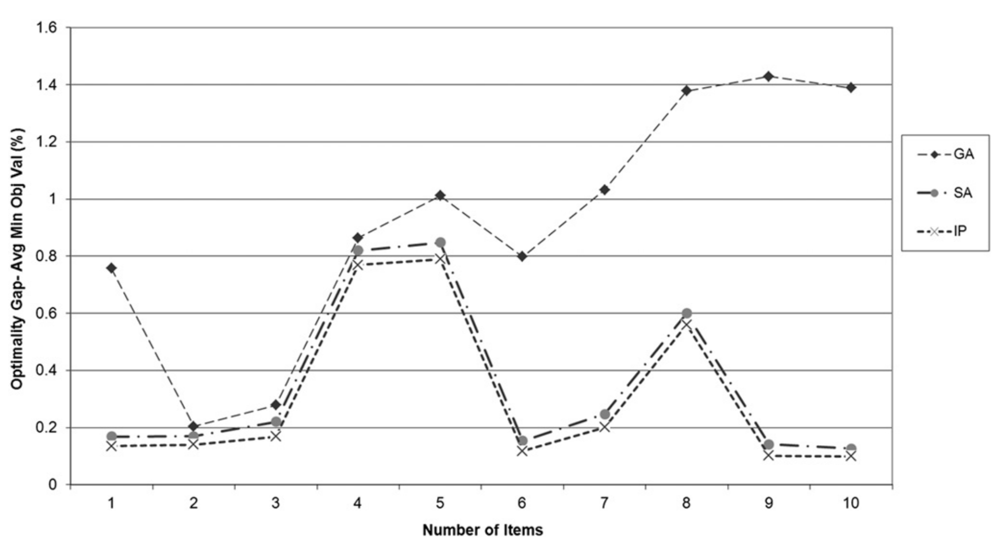

Fig. 5. Optimality gap of average of minimum objective values from LP lower bound.

Table 7
Bid content where substitution is an option.

Bidder	X (%)		Y (%)		XY (%)		None (%)	
	IP	SA	IP	SA	IP	SA	IP	SA
1st	13.7	10.9	3.2	3.2	50.0	52.4	33.1	33.5
Avg. 2nd–5th	34.1	33.2	17.7	17.2	40.6	42.1	7.6	7.5
(stdev)	(5.9)	(6.2)	(4.6)	(4.3)	(1.9)	(2.8)	(0.9)	(0.2)
Avg. 6th–9th	52.7	51.8	23.7	23.0	20.9	22.6	2.6	2.5
(stdev)	(7.5)	(7.2)	(4.5)	(3.8)	(3.5)	(4.1)	(0.2)	(0.1)
10th	62.7	61.3	25.0	25.0	11.1	12.5	1.2	1.2

The GA, SA, and IP are compared using three performance metrics: (a) average computation time in seconds, (b) average minimum objective value (given by the ten bidders), and (c) average objective value. The GA and SA are coded in Visual Basic™. The IP and LP are coded in AMPL™ using the CPLEX 9.1.2™ solver. All experiments are conducted in a PC having an Intel Pentium D 3.2 GHz CPU and 2 GB RAM. The results of experiments are summarized in Table 6. These average values are for problem instances where bidders satisfy all of the announced items.

The IP model consistently outperforms the GA and SA models in average computation time; however, the performance difference of models in terms of average minimum objective value and average objective value are much smaller. For further analysis the optimality gaps between the three approaches and the LP lower bound are calculated. The LP formulation relaxes the integrality constraint for the decision variables in the IP formulation; therefore, non-integer bids are allowed in the LP formulation, and the rest of the constraints are kept the same as the IP formulation. Average computation time, average minimum objective value, and average objective value for the LP lower bound are calculated and the results are also given in Table 6. The following formula is used to calculate the optimality gap:

$$\text{Optimality Gap} = 100^{x}(\text{corresponding obj.val.} - \text{LP obj.val.})/\text{LP obj.val.} \tag{4}$$

The optimality gap for the average objective values are given in Fig. 4. As seen in the figure, SA and IP outperform GA; they are more stable as the number of items in an announcement increases. The SA has a maximum optimality gap of 0.34% and the same value for the IP is 0.30%.

The optimality gap between the averages of the minimum objective values of all bidders is given in Fig. 5. It is observed that GA performs worse with increasing number of items. The IP and the SA both vary approximately between 0.10% and 0.40%. The optimality gap tends to decrease both in SA and IP with increasing number of items.

After comparing different solution approaches, two sets of experiments are conducted to study the impacts of substitution (i.e., the first set) and partial fulfillment options (i.e., the second set). The SA and IP models are selected for this study due to their steady performance compared to the GA. Individual bid quantities for ten supply types are considered for this analysis since they incorporate other problem instances. The ten bidders are divided into four categories with the same parameters. These categories include the 1st bidder, the bidders 2nd–5th, the bidders 6th–9th, and the 10th bidder from Table 4. The values for the second and third category are averaged.

Table 8
Bid content where substitution is not an option.

Bidder	X (%)		Y (%)		XY (%)		None (%)	
	IP	SA	IP	SA	IP	SA	IP	SA
1st	58.7	58.7	0.0	0.0	0.0	0.0	41.3	41.3
Avg. 2nd–5th	81.4	81.0	0.0	0.0	0.0	0.0	18.6	19.0
(stdev)	(2.5)	(2.0)	(0.0)	(0.0)	(0.0)	(0.0)	(2.5)	(2.0)
Avg. 6th–9th	92.3	92.2	0.0	0.0	(0.0)	(0.0)	7.7	7.8
(stdev)	(0.5)	(0.5)	(0.0)	(0.0)	(0.0)	(0.0)	(0.5)	(0.5)
10th	94.8	94.6	0.0	0.0	0.0	0.0	5.2	5.4

Table 9
Bid content for partial fulfillment option.

Bidder	Substitution allowed				Substitution not allowed			
	Full (%)		Partial (%)		Full (%)		Partial (%)	
	IP	SA	IP	SA	IP	SA	IP	SA
1st	31.1	31.1	68.9	68.9	13.7	13.7	86.3	86.3
Avg. 2nd–5th	84.6	85.5	15.4	14.5	51.9	52.5	48.1	47.5
(stdev)	(1.9)	(0.4)	(1.9)	(0.4)	(5.0)	(4.5)	(5.0)	(4.5)
Avg. 6th–9th	93.4	93.1	6.6	6.9	77.9	79.0	22.1	21.0
(stdev)	(0.7)	(1.0)	(0.7)	(1.0)	(1.4)	(0.5)	(1.4)	(0.5)
10th	98.4	98.4	1.6	1.6	84.8	84.8	15.2	15.2

The impact of substitution option is analyzed in the first set of experiments. Bid content is classified as follows: (1) bids where only original item types (X) are used, (2) bids where only substitute item types (Y) are used, (3) bids where both original and substitute item types (XY) are used and (4) bids where no supply can be offered with the on-hand inventory. The results for bids where substitution is allowed are depicted in Table 7, the results for bids where substitution is not allowed are given in Table 8.

Tables 7and 8 illustrate that if substitution is allowed, regardless of their inventory level category, the number of demands, which bidders can bid on, increases. Standard deviation figures for original item types decrease in Table 7 compared to Table 6, since there is no flexibility of using substitute types. Bidders with fewer inventories are allowed to bid with the inclusion of a substitution option.

In the second set of experiments, the partial fulfillment option for the bids is also enabled. Here, the bidders with fewer inventories than the announced quantity are allowed to offer whatever they have in their inventory. Bid content is classified into two categories: full demand fulfillment and partial demand fulfillment. The results for these categories where substitution is allowed and not allowed are depicted in Table 9.

It can be concluded from Table 9 that when the bidders have fewer inventories, the ratio of partial fulfillment increases. If substitute items are allowed, all bidders have more chance of bidding than in the prohibited case. The impact of the substitution option is more substantial for bidders with fewer inventories than for bidders with more inventories.

4. Conclusion and discussion

Humanitarian and disaster relief logistics involve control, planning, and management of cumbersome operations in a disaster relief environment where short-term crisis management strategies are used to push products out in parallel systems. In order to accomplish these tasks immediately and supply the demand at the disaster locations effectively, the use of procurement auction-based methods has a potential to increase. Coordinating platforms require effective auction models designed specifically for procurement in disaster relief environment. Bid construction and winner determination are the two major phases in typical procurement auctions. In this paper, the bid construction phase is analyzed with a Genetic Algorithm (GA), a Simulated Annealing (SA) Algorithm and an Integer Program (IP). Substitution and partial fulfillment options are presented in formulations to allow bidders with fewer inventories (i.e., local suppliers) to offer substitute types and partially bid in auctions.

The results illustrate that inclusion of these options allows local suppliers (i.e., the ones with less on-hand inventory) to bid in procurement auctions, which in return helps the coordinating platform (i.e., auctioneer) attain better diversity and higher capacity in its supplier base. Heuristic solution techniques help understand the dynamics of the bid construction problem and the IP formulation gives a more structured and precise solution. It can be concluded that the number of supply types in an announcement affects the success of the auction positively, because the optimality gap tends to decrease with an increasing number of item types. This result is complementary with case studies in Beall et al. [36], where researchers report that if more items are auctioned together, this gives suppliers more flexibility in determining bid content. Computation time results depict that if there are too many supplies in the auction to manage, the bid construction problem becomes complex.

The use of substitution is beneficial both for relief suppliers and the coordinating platform. In this way, suppliers can offer substitute items in place of original supplies and better utilize their on-hand inventory. The auctioneer makes use of this option in cases when a more diverse and higher capacity supply base is desired. It is shown with the proposed quantitative modeling approach that the substitution option is more auspicious for the lower capacity suppliers than the higher capacity suppliers. It is also noted that the determination of a substitute factor is essential in converting the original supply types to substitute types. This factor is for quantities, and if intangible specifications are considered, a substitute factor needs to incorporate those specifications as well. A partial fulfillment option enables better usage of supplier inventories. Relief suppliers are allowed to bid less than the announced quantity, which provides them the opportunity to offer their inventory more quickly rather than waiting for an auction that fits their specific inventory level. If partial fulfillment is not allowed, higher capacity suppliers are more likely to be awarded an auction than lower capacity suppliers.

One limitation of using procurement auctions might stem from varying quality of relief supplies that are procured from different bidders. If beneficiaries are exposed to different levels of supply quality, it would be a clear violation of the equity principle. Thus, coordinating platforms should clearly specify the product specifications when announcing the demand.

References

[1] van Wassenhove L. Humanitarian aid logistics: supply chain management in high gear. Journal of Operational Research Society 2006;57:475–89.

[2] Kovacs G, Spens KM. Humanitarian logistics in disaster relief operations. International Journal of Physical Distribution and Logistics Management 2007;37(2):99–114.

[3] Kovacs G, Spens KM. Identifying challenges in humanitarian logistics. International Journal of Physical Distribution and Logistics Management 2009;39(6):506–28.

[4] Zaki AS, Cheng HK, Parker BR. A simulation model for the analysis and management of an emergency service system. Socio-Economic Planning Sciences 1997;31(3):173–89.

[5] Fiedrich F, Gehbauer F, Rickers U. Optimized resource allocation for emergency response after earthquake disasters. Safety Science 2000;35(1–3):41–57.

[6] Jotshi A, Gong Q, Batta R. Dispatching and routing of emergency vehicles in disaster mitigation using data fusion. Socio-Economic Planning Sciences 2009;43:1–24.

[7] Yi P, George SK, Paul JA, Lin L. Hospital capacity planning for disaster emergency management. Socio-Economic Planning Sciences 2010;44:151–60.

[8] Schulz SF. Disaster relief logistics: benefits of and impediments to cooperation between humanitarian organizations. Switzerland: Haupt Verlag AG; 2009. p. 95.

[9] Balcik B, Beamon B, Krejci C, Muramatsu K, Ramirez M. Coordination in humanitarian relief chains: practices, challenges and opportunities. International Journal of Production Economics 2010;126(1):22–34.

[10] Fritz Institute [Internet]. Helios on-demand software: tactical visibility for the humanitarian supply chain; [updated 2007; cited 2010 Dec 29]. Available from: www.fritzinstitute.org/PDFs/HELIOS/HELIOS%20OVERVIEW.pdf.

[11] Aidmatrix Foundation [Internet]. Supply chain management suite; [updated 2009; cited 2010 Dec 29]. Available from: www.aidmatrix.org/technology/scm.htm.

[12] FEMA [Internet]. Aidmatrix donations management system designed for FEMA; [updated 2009; cited 2010 Dec 29]. Available from: www.aidmatrixnetwork.org/fema/PublicPortal/ListOfNeeds.aspx?PortalID=0.

[13] FedBid [Internet]. FEMA's extended testing of reverse auctions leads to FedBid contract; [updated 2009 Sep 27; cited 2010 Dec 29]. Available from: www.fedbid.com/news/124/.

[14] Humanitarian Procurement Centres [Internet]. Fact Sheet; [updated 2009 Jul 14; cited 2010 Dec 29]. Available from: http://ec.europa.eu/echo/files/about/actors/Fact_Sheet_D4_140709.pdf.

[15] Humanitarian Procurement Centres [Internet]. Charter; [updated 2009 Oct 26; cited 2010 Dec 29]. Available from: http://ec.europa.eu/echo/files/about/actors/HPC_Charter_26-10-09_%20EN.pdf.

[16] Natarajarathinam M, Capar I, Narayanan A. Managing supply chains in times of crisis: a review of literature and insights. International Journal of Physical Distribution and Logistics Management 2009;39(7):535–73.

[17] Altay N, Green WG. OR/MS research in disaster operations management. European Journal of Operational Research 2006;175:475–93.

[18] Whybark DC. Issues in managing disaster relief inventories. International Journal of Production Economics 2007;108:228–35.

[19] Tomasini R, van Wassenhove L. Genetically modified food donations and the cost of neutrality: logistics response to the 2002 Southern Africa food crisis; 2004. INSEAD Case 03/2004-5169.

[20] Thomas A, Fritz L. Harvard business review. Disaster Relief, Inc.; 2006; Nov. pp. 1–11.

[21] Murray S. How to deliver on the promises: supply chain logistics: humanitarian agencies are learning lessons from business in bringing essential supplies to regions hit by the tsunami. The Financial Times; 2005; Jan 7:9.

[22] Tatham PH, Pettit SJ. Transforming humanitarian logistics: the journey to supply network management. International Journal of Physical Distribution and Logistics Management 2010;40(8/9):609–22.

[23] Beil DR. Procurement auctions. In: Tutorials in operations research 2010. INFORMS; 2010. p. 248–59.

[24] de Vries S, Vohra RV. Combinatorial auctions: a survey. INFORMS Journal on Computing 2003;15(3):284–309.

[25] de Vries S, Vohra RV. Design of combinatorial auctions. In: Handbook of quantitative supply chain analysis: modeling in the e-business era. New York: Kluwer Academic Publishers; 2004. p. 247–87.

[26] Ledyard JO, Olson M, Porter D, Swanson JA, Torma DP. The first use of a combined-value auction for transportation services. Interfaces 2002;32(5):4–12.

[27] Bichler M, Kalagnanam J. Bidding languages and winner determination in multi-attribute auctions. IBM Research Report RC 22478; 2002.

[28] Kalagnanam J, Parkes DC. Auctions, bidding and exchange design. In: Handbook of quantitative supply chain analysis: modeling in the e-business era. New York: Kluwer Academic Publishers; 2004. p. 143–212.

[29] Song JJ, Regan A. Approximation algorithms for the bid construction problem in combinatorial auctions for the procurement of freight transportation contracts. Transportation Research Part B-Methodology 2005;39:914–33.

[30] Veeramani D, Wang KJ. Bid construction scheme for job flow time reduction in auction-based fully-distributed manufacturing systems. International Journal of Advanced Manufacturing Technology 2006;28:541–50.

[31] Günlük O, Ladányi L, de Vries S. A branch-and-price algorithm and new test problems for spectrum auctions. Management Science 2005;51(3):391–406.

[32] Trestrail J, Paul J, Maloni M. Improving bid pricing for humanitarian logistics. International Journal of Physical Distribution and Logistics Management 2009;39(5):428–41.

[33] Bagchi A, Paul JA, Maloni M. Improving bid efficiency for humanitarian food aid procurement. International Journal of Production Economics 2011;134:238–45.

[34] Falasca M, Zobel CW. A two-stage procurement model for humanitarian relief supply chains. Journal of Humanitarian Logistics and Supply Chain Management 2011;1(2):151–9.

[35] Gong W. Post-crisis domestic procurement network to facilitate humanitarian assistance (a case of Sudan). In: ICEC '03 proceedings of the 5th international conference on electronic commerce. NY: ACM Press New York; 2003. p. 505–9.

[36] Coulter J, Walker D, Hodges R. Local and regional procurement of food aid in Africa: impact and policy issues [Internet]. Journal of Humanitarian Assistance; [updated 2007 Oct 28; cited 2011 Aug 13]. Available from: http://jha.ac/2007/10/28/local-and-regional-procurement-of-food-aid-in-africa-impact-and-policy-issues.

[37] Beall S, Carter CC, Carter PL, Germer T, Hendrick TE, Kaufman L, et al. The role of reverse auctions in strategic sourcing. CAPS Research Report; 2003.

[38] National Agricultural Library [Internet]; [updated 2010 Feb 02; cited 2010 Dec 29]. Available from: http://www.nal.usda.gov/fnic/foodcomp/search/index.html.

[39] Smeltzer LR, Carr AS. Electronic reverse auctions promises, risks and conditions for success. Industrial Marketing Management 2003;32:481–8.

[40] Silver EA. An overview of heuristic solution methods. Journal of the Operational Research Society 2004;55:936–56.
[41] Michalewicz Z, Fogel DB. How to solve it: modern heuristics. 2nd ed. Germany: Springer-Verlag; 2004.
[42] Henderson D, Jacobson SH, Johnson AW. The theory and practice of simulated annealing. In: Glover F, Kochenberger GA, editors. Handbook of metaheuristics. Boston: Kluwer Academic Publishers; 2003. p. 287–320.
[43] Gonzales J, Rojas I, Pomares H, Salmeron M, Merelo JJ. Web newspaper layout optimization using simulated annealing. IEEE Transactions on Systems, Man, and Cybernetics. Part B Cybernetics 2002;32(5):686–91.
[44] Sheu JB. An emergency logistics distribution approach for quick response to urgent relief demand in disasters. Transportation Research Part E 2007;43: 687–709.
[45] Johansen SG, Thorstenson A. An inventory model with poisson demand and emergency orders. International Journal of Production Economics 1998; 56–57:275–89.
[46] Cullen AJ, Webster M. A model of B2B e-commerce, based on connectivity and purpose. International Journal of Operations and Production Management 2007;27(2):205–25.
[47] Schoenherr T, Mabert VA. The use of bundling in B2B online reverse auctions. Journal of Operations Management 2008;26(1):81–95.
[48] Hazra J, Mahadevan B. Impact of supply base heterogeneity in electronic markets. European Journal of Operational Research 2006;174:1580–94.
[49] Elmaghraby W, Keskinocak P. Combinatorial auctions in procurement. In: Harrison TP, Lee HL, Neale JJ, editors. The practice of supply chain management: where theory and application converge. New York: Springer; 2006. p. 245–58.

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