A Simulated Annealing-Based Approach for Aid Distribution in Post-disaster Scenarios

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Abstract. Logistics operations have a direct impact on the effectiveness of the humanitarian relief operations and the survival of the population, supplying all demands in a short period of time using the available limited resources. This work addresses the Emergency k-Location Routing Problem (EkLRP) where humanitarian and relief aid has to be distributed from medical infrastructure to the affected people by routing emergency-aimed vehicles minimizing the time required to provide the humanitarian aid. This work proposes a Simulated Annealing with temperature reset in order to promote diversification as well as for escaping from local optima. The numerical experiments indicate that the metaheuristic approach proposed to solve the EkLRP reports high-quality solutions in reasonable computational times.

Keywords: Humanitarian relief · Metaheuristics · Simulated annealing

1 Introduction

Catastrophes and disasters are undesirable events creating potential losses and impacting societies [9]. They are often categorized as natural, i.e., hurricanes, tsunamis, etc., or as man-made such as those caused by socio-political conflicts, terrorist attacks, among others. A study from the Center for Research on the Epidemiology of Disasters (CRED[1]) between the years 1994 and 2013 indicated that 6873 natural disasters were reported around the world. During that period, each year, an average of 68000 deaths and 218 million people were affected. In addition, there were economic losses valued at 147 billion dollars each year. On the other hand, due to conflicts or wars, the average number of refugees

[1] http://www.cred.be/.

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per year has been 13 million and 20 million internal displacements. However, according to a report from the International Federation of Red Cross Societies (IFRC)[2] conducted after a flood in 2014 in Afghanistan [8], the planning of the distribution of relief resources was one of the most difficult tasks. In that study, it is pointed out that, despite the complexity involved in emergency logistics, many of those processes and planning are still carried out manually, even though they have proven to be inefficient and inadequate [13]. Finally, an improvement in the response mechanisms is required, specifically in the planning, coordination, and delivery of aid resources since the few existing systems are not sufficiently flexible and dynamic for emergency situations where they aim to use them.

The aid distribution networks managed by institutions and organizations seek to mitigate the damage and suffering caused to the population through the distribution of aid in the form of medicines, food, generators of electricity, medical services, etc. The supply chain is planned to take into account that there are limited resources and that each type of demand has a degree of urgency and a window of service time. On the other hand, emergency scenarios are highly dynamic, which forces the operators in charge to make quick decisions under great pressure. Therefore, having supporting tools and fast solution algorithms to help managers during the decision-making process as well as while designing an aid distribution network is crucial for saving lives and alleviating suffering [1,2,7,12].

In this work, we address a humanitarian supply chain planning problem in catastrophe scenarios where aid distribution facilities have to be located and aid have to be distributed from them to the affected people by routing emergency-aimed vehicles. In this context, the catastrophe is considered in a wide area where a part of the population requires humanitarian help distributed by means of vehicles departing from the located depots (i.e., aid distribution centers). The objective of this problem is to provide aid to the people in need of help as soon as possible (i.e. cumulative objective function). Moreover, given the context where this problem arises, solving and planning time is a crucial factor, hence a metaheuristic algorithm based on Simulated Annealing is proposed. To contextualize its contribution and performance, the proposed approach is compared with other well-known metaheuristic approaches.

The remainder of this paper is organized as follows. The Emergency k-Localization Routing Problem is described in Sect. 2. The description of the Simulated Annealing-based approach is presented in Sect. 3. The computational results obtained by our proposal are discussed in Sect. 4. Finally, Sect. 5 presents the conclusions and several lines for further research.

2 Emergency k-Localization Routing Problem

This section is devoted to introducing the Emergency k-Location Routing Problem (EkLRP). Its goal is to provide humanitarian assistance to people after a disaster situation. In this environment we have to tackle the following decisions:

[2] http://www.ifrc.org/.

1. Setting up a well-defined set of medical infrastructures on a ravaged area, where each infrastructure has a fleet of medical vehicles to deliver humanitarian aid and relief.
2. Determining the route that each medical vehicle has to follow in order to provide assistance to the victims.

We are given a set of victims geographically dispersed on a ravaged area and denoted as $N = \{1, 2, \ldots, n\}$. Each victim $c \in N$ requires a strictly positive time to be assisted, $d_c > 0$, and a certain quantity of humanitarian aid, $q_c > 0$.

On the other hand, we are also given a set of locations on the ravaged area denoted as $L = \{1, 2, \ldots, m\}$ in which a medical infrastructure could be set up. Setting up a medical infrastructure at location $l \in L$ involves a positive time, $t_l > 0$, stemming from moving the infrastructure to its destination and deploy it. The first goal is to select a subset of locations, denoted as $L' \subseteq L$ with $|L'| = k$. k is a parameter of the problem which determines the number of locations to select and whose value is selected by the user.

The EkLRP can be modelled by means of a complete graph $G = (H, A)$ with $n + m$ vertices, split into two sets, $H = N \cup L$. Each vertex $v \in H$ is located in a given location (x_v, y_v). Arcs $a_{ij} \in A, \forall i, j \in H$ represent the possibility of moving between the nodes i and j with positive travel time $t_{ij} > 0$. It is worth mentioning that we consider that the travel times are asymmetric for each pair of vertices.

Each medical infrastructure, $l \in L'$, has a fleet of heterogeneous medical vehicles denoted as $V_l = \{1, 2, \ldots, v_l\}$, where each vehicle $v \in V_l$ has a positive capacity, $Q_v > 0$, to carry humanitarian aid. The vehicles are used to assist the victims in such a way that the waiting time of the victims is as short as possible. Therefore, we pursue to determine a set of routes for each selected location, denoted as R_l. Each route r is used by a vehicle $v_r \in V_l$, starts from a medical infrastructure $\sigma_0^r \in L'$, visits a sequence of n_r victims, $\sigma_1^r, \sigma_2^r, \ldots, \sigma_{n_r}^r \in N$, and returns to the same medical infrastructure, that is, $\sigma_{n_r+1}^r = \sigma_0^r$. Additionally, the duration time of the route r is denoted as

$$d(r) = t_{\sigma_0^r \sigma_1^r} + \sum_{i=0}^{n_r} (t_{\sigma_i^r \sigma_{i+1}^r} + d_{\sigma_i^r}) \tag{1}$$

Where:

- Set of selected locations, L'.
- Set of routes of the medical vehicles in the infrastructure $l \in L'$, R_l.
- Number of victims visited by route r, n_r.
- Waiting time of a victim σ_i^r served by a medical vehicle along the route r, $w(\sigma_i^r)$.

The waiting time of a victim σ_i^r served by a medical vehicle along the route r is computed as follows:

$$w(\sigma_i^r) = \begin{cases} t_{\sigma_i^r, r(0)} + d_{\sigma_i^r} & if\, i = 0 \\ w(\sigma_{i-1}^r) + t_{\sigma_{i-1}^r \sigma_i^r} + d_{\sigma_i^r} & if\, i > 0 \end{cases} \tag{2}$$

Where:

- Waiting time of a victim σ_i^r along the route r, $w(\sigma_i^r)$.
- Travel time required to move between i and j, t_{ij}.
- Time required to set up a medical infrastructure $l \in L'$, t_l.
- Time to assist victim $d_{\sigma_i^r}$.
- σ_i^r i-th vertex visited by the vehicle associated to the route r.

The optimization objective of the EkLRP is to minimize the time required to provide humanitarian aid to all the victims. This time is composed of the time required to set up the k medical infrastructures and deliver the aid to the victims:

$$f(s) = minimize \sum_{l \in L'} \sum_{r \in R_l} \sum_{i=1}^{n_r} w(\sigma_i^r) \tag{3}$$

3 Metaheuristic Approach

Since EkLRP is an $\mathcal{NP}$-hard problem an efficient heuristic algorithm is required in order to provide high-quality solutions within small computational times. In order to achieve these goals a metaheuristic approach based on Simulated Annealing (SA, [3]) is proposed.

3.1 Constructive Heuristic

In order to properly start the SA-based approach, a starting solution is required. In this sense, we propose the Greedy Randomized Algorithm (GRA, [10]) that splits the EkLRP into two interconnected subproblems.

- High-level Problem: Determining the subset of locations to set up medical infrastructures aimed at serving all the victims.
- Low-level Problem: Determining the route that each medical vehicle has to follow in order to provide assistance to the victims.

GRA is used in the generation of initial solutions and in the repair process within Simulated Annealing. Thus, it is used along with a restricted list of candidates (RLC) that contains a subset of the best k candidates to add to the solution constructed so far. By means of this method, we are able to generate a fast initial and feasible solution. Firstly, we use an elitist selection using the average distance of all victims to the medical infrastructure. It tries to insert every victim between each pair of nodes in the routes of the solution. All feasible and possible positions in which non-assigned victims can be placed are included in a restricted candidate list (RCL). Finally, it selects one movement between the best candidates in the RCL with a roulette wheel selection. A greedy function evaluates the impact on the objective function value of selecting the candidate. This fitness level is used to associate a probability of selection with each candidate. This process is repeated until all victim has been visited.

3.2 Simulated Annealing

The version of Simulated Annealing used in this work incorporates the feature of reheating [5,6], that is, once the temperature has decreased until a certain point, it is increased or reset. That feature promotes diversification, and with the SA search procedure permits alternating between diversification and intensification along with search. The number of times that is allowed to reheat the solution is provided by the user. On the other hand, each time that the search is reheated the starting temperature is reduced to avoid randomizing completely the search. To do so, the starting temperature is equalized to the provided temperature by the user, divided by the reheating phase where we are located. For example, if the temperature provided by the user is 1000 and we have 3 reheating phases, the starting temperatures would be: 1000, 500 and 333.33.

In Algorithm 1, the pseudocode of the SA approach using reheating (SA-R) is provided. This procedure receives as input an initial solution, s, generated by the GRA. At each iteration, the destroy method is performed, remove p victims of solution s (line 4). The first victim n^* is randomly chosen. After having removed n^*, the closest $p-1$ victims are removed. We proceed with the repair method (line 4), using the GRA. The neighborhood is defined implicitly by a destroy and a repair method. Solution s' is accepted as current solution s (line 6 and 8) with probability given in (4). We allow a temperature reset during the search in order to escape from local optima.

$$P(s', s) = e^{(f(s)-f(s'))/t}, s' \in N(s) \tag{4}$$

Algorithm 1. Pseudocode of Simulated Annealing with reheat strategy (SA-R)

Require: Feasible solution s
1: $s'' = s$
2: **while** *reheat* **do**
3:   **while** $t > t_f$ **do**
4:     $s' = \text{destroy}(s)$
5:     $s' = \text{repair}(s')$
6:     **if** $rand(0,1) < P(s', s)$ **then**
7:       $s = s'$
8:     **end if**
9:     **if** $f(s) < f(s'')$ **then**
10:       $s'' = s$
11:     **end if**
12:     $t = updateTemperature()$
13:   **end while**
14: **end while**
15: return s''

4 Computational Experiments

In this section, the results provided by our metaheuristic approach are presented. The set of 80 instances used in this work were randomly generated considering. Depending on the number of victims and locations each instance is labeled as mxn. Each pair instance-algorithm has been executed 100 times with a maximum computational time adapted to the instance, $5n$ milliseconds. GRA is used in the generation of all initial solutions. The computational experiments were conducted on a computer equipped with Intel Core i7-3632QM CPU @ 2.20 GHz x 8 and 8GB of RAM. With the aim of analyzing the contribution SA-R, the following algorithms are implemented:

1. Variable Neighborhood Search (VNS, [4]) with two environments, *i.e.*, victims swap and victims 2-opt.
2. Simulated Annealing (SA): version described in Sect. 3.2, but without reheat.
3. Large Neighborhood Search (LNS, [11]): it uses the same destroy and repair method as described in Sect. 3.

Parameter configuration is selected based on the Friedman test considering the average objective value. Based on the test, LNS, SA, and SA-R remove 1 percent of victims on every iteration. Otherwise, in SA and SA-R the temperature is progressively decreased from n to 1^{-10}. The cooling schedule follows an exponentially decreasing function.

4.1 SA Computational Results

Table 1 report the minimum (Min.), average (Avg.), and maximum (Max.) objective value obtained during the experiment on large instances: 500, 1000, 1500 and 2000 victims. Since the presented data is grouped by instance identifier $m \times n$, the values correspond to the average. Also, the computational time limit does not depend on the metaheuristic but on the size of the problem instances ($5 \cdot n$ milliseconds), the average computational time thus is not reported.

First, in the results reported in Table 1, it can be seen that VNS for no instance performs better than the other approaches, although it obtains competitive results.

Moreover, it should be noted that LNS and SA approaches implemented are only differentiated by the probability of making the transition from the current state s to a candidate new state s'. Therefore, both approaches exhibit similar performance in terms of solution quality. Furthermore, the average quality of the solutions is better when SA incorporates the reheat strategy than without it. Since all approaches were executed under the same time limit, it can be concluded that SA-R is the most appropriate method for tackling this problem.

Table 1. Overall performance in terms of objective function value of VNS, LNS, SA, and SA-R. Best values among VNS, LNS, SA, and SA-R are shown in boldface type

Instance	GRA	VNS			LNS			SA			SA-R		
$m \times n$	Avg	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max
10×500	2855978.85	2739808.87	2781444.43	2841265.52	2707022.85	2723102.46	2745797.18	2707206.83	**2722701.38**	**2744166.39**	**2704206.99**	2723037.09	2744438.22
20×500	2864564.65	2753129.76	2788354.97	2861673.13	2712009.17	2731087.25	**2751207.88**	2713068.20	**2730964.35**	2752756.14	**2711704.95**	2731043.62	2752659.70
50×500	2882140.63	2765855.09	2807526.48	2875829.35	2731627.67	2750625.01	**2770153.52**	2730625.44	2750651.34	2771939.85	**2727105.11**	**2750048.45**	2770521.39
100×500	2798816.32	2692578.72	2727887.45	2804925.29	**2651462.03**	2671447.45	**2691583.32**	2652759.67	2671320.18	2692830.92	2652051.36	**2671159.08**	2692430.97
10×1000	10505697.18	10233144.59	10346240.16	10506536.25	10140918.85	10196574.30	10263076.13	**10140339.67**	10197001.97	**10257744.35**	10141749.81	**10194218.98**	10264027.73
20×1000	10377501.85	10094603.69	10217089.93	10376578.63	10010907.69	10068280.68	10132804.58	10012296.08	10067000.43	**10125970.73**	**10007005.45**	**10065758.02**	10130255.92
50×1000	10391317.14	10114226.37	10236307.84	10406970.15	10023461.25	10079612.18	**10143831.77**	**10021368.80**	10078650.15	10152204.01	10025038.18	**10078561.42**	10148575.62
100×1000	10456359.25	10175806.31	10296481.39	10435176.28	10086242.99	10145034.57	**10198344.98**	10092143.93	10145506.33	10204109.29	**10082229.94**	**10143755.35**	10202245.91
10×1500	22820733.10	22398006.72	22579160.10	22820131.88	22325727.08	22431120.57	22552949.77	**22319402.30**	22426462.75	**22544822.84**	22328878.49	**22422927.51**	22545218.39
20×1500	22614206.38	22185849.43	22375997.17	22626109.73	**22075372.03**	**22214896.93**	22328187.48	22107606.70	22219189.97	**22324162.70**	22089342.39	22218759.65	22344936.47
50×1500	22866662.92	22462764.79	22631322.35	22882694.78	22361988.31	22466634.12	22563924.45	22362717.62	22465930.57	22572107.44	**22359952.41**	**22462527.24**	**22562735.93**
100×1500	22602553.61	22183481.20	22369850.65	22595984.48	**22065031.24**	22212778.73	22340233.02	22103852.24	22215048.17	**22329287.22**	22066643.56	**22209689.95**	22337659.52
10×2000	39187681.46	38655408.13	38901996.83	39216127.75	38600621.58	38817471.48	38989732.37	38651009.77	38816435.76	38992861.37	**38590113.90**	**38803994.22**	**38968166.53**
20×2000	39493200.69	38978894.51	39206610.39	39521499.76	38965045.25	39123462.51	**39268156.48**	38953846.25	39122245.66	39269202.32	**38948261.91**	**39117832.92**	39285008.03
50×2000	39734952.79	39211799.22	39460001.33	39777703.95	39220235.22	39368492.42	39538841.70	39206533.40	39374459.53	39546133.30	**39204801.14**	**39365165.76**	**39534960.54**
100×2000	39215610.63	38688501.09	38933269.23	39259760.15	**38595547.51**	38842455.43	39017656.06	38703941.23	38844426.93	**39012417.74**	38625491.71	**38834700.88**	39026576.39
Average	18854248.59	18520866.16	18666221.29	18863060.44	18454576.29	18552692.26	18643530.04	18467419.88	18552999.72	**18643294.79**	**18454036.08**	**18549573.76**	18644401.08

5 Conclusions

In this work, we have addressed the Emergency k-Location Routing Problem by means of a Simulated Annealing-based approach that incorporates temperature resets (i.e., SA-R) during the search. To contextualize this approach, it was compared with other trajectory-based approaches (i.e., GRA, SA, LNS, and VNS). The computational results show that SA-R performs better in terms of objective function value under the same computational time limitations than the other considered approaches. Furthermore, when assessing the contribution of the reheating strategy, it can be seen that it leads to better solution quality than without using it in the majority of cases. This work thus contributes to the SA state-of-the-art with another example of its benefit for addressing hard combinatorial problems.

As future work, we plan to investigate different reheating schemes for SA in this and other optimization problems.

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