ROUTING OF VEHICLES FOR AID DELIVERY IN DISASTER RESPONSE

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Abstract: *Due to limited resources and response times, logistics has played a crucial role in managing events that require humanitarian assistance. One of the major actions in the response stage of relief logistics is distribution of supplies in order to meet the basic subsistence needs of affected people. In this paper, a vehicle routing problem in humanitarian aid distribution in the event of a humanitarian disaster is solved. In the response stage, first-aid resources have to be provided for affected people in large geographical areas. Different service points are selected where users can be served. Each beneficiary has access to at least one service point. A mixed integer linear programming model of team orienteering problem with overlaps is presented to determine efficient vehicle routes, subjected to maximum duration constraints, miximizing the number of beneficiaries served. To solve the problem, a population-based simulated annealing algorithm (PBSA) is developed. This PBSA algorithm is compared with simulated annealing (SA) algorithm. The population-based solution approach outperforms the SA for all instances.*

Keywords*: disaster response, vehicle routing, simulated annealing, first-aid resources.*

1. INTRODUCTION

The term disaster represents an event with the most severe consequences for people, nature, facilities, economy and society. Natural disasters, such as earthquakes, floods, fires etc., are an integral part of human history. In the first two decades of the 21st century humanity was hit by natural disasters of a massive scale (e.g. an earthquake and tsunami in the Indian Ocean (2004), an earthquake in Haiti (2010), a typhoon in the Philippines (2013)).

The numbers of deaths and injuries involved, displaced people or otherwise affected by these natural disasters are mind-numbing. In managing these events logistics has played a crucial role. Limited resources and response times, high degrees of uncertainty and a lack of reliable data, make logistics decisive in carrying out the relief operations. Thus, logistical efforts account for 80% of disaster relief operations (Trunick 2005).

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The disaster stage of relief logistics consists of four phases: mitigation, preparedness, response, and recovery (McLoughlin 1985). Response includes the actions taken directly before, during, and immediately after a disaster in order to save lives, reduce health impacts, ensure public safety and meet the basic subsistence needs of affected people. Limited resources result in difficulties in responding to the needs of the affected population quickly and effectively.

In this paper, routing of vehicles carrying humanitarian aid in the event of a humanitarian disaster is solved. In the response stage, first-aid resources (food, drugs, other supplies) and services have to be provided for affected people in large geographical areas. Different service points are selected where users can be served. Each beneficiary has access to at least one service point. A set of vehicles provides the service points with first-aid resources within a given time period. On days immediately after a disaster, resources such as vehicles are in short supply. The problem is to decide which service point to supply to maximize the number of beneficiaries that have access to service points. This problem is modeled with a mixed integer linear programming model of team orienteering problem with overlaps.

The team orienteering problem (TOP) is a decision-making problem of the class of the vehicle routing problem with profits (Archetti et al. 2014). Given a set of vehicles and a set of customers, each one with an associated profit, the goal of the TOP is to design a set of routes (one for each vehicle) that maximizes the total profit collected by visiting (some of) the customers without exceeding a maximum duration constraint for each route.

There is an analogy between customers and profits in the team orienteering problem and service points and beneficiaries in the problem considered in this paper. In both cases it is necessary to collect as much profit or supply with humanitarian aid as many people as possible after natural disaster. In real-life, some beneficiaries may use more than one service point, which causes overlaps of the service regions. It introduces a new type of orienteering problem known as a team orienteering problem with overlaps (TOPO). The TOPO is inspired by a problem in charge of providing cash collection, counting, and distribution in the group of three banks in Netherlands (Orlis et al. 2020). One of the main challenges is to decide which automated teller machines to replenish by using a set of vehicles, subjected to working hours, to maximize the number of bank account holders that have access to these cash machines. It is assumed that bank account holders (identified by the postal code of residence) have access to cash if there exists a replenished automated teller machine within five kilometers from the residence postal code. Usually, there are users who have access to multiple cash machines, which causes overlaps. The next application of the TOPO is the real-life distribution problem with the decision on which stores to replenish given that beneficiaries can be served from one or several nearby stores.

Figure 1 shows an example of an instance with 4 service points and 10 beneficiaries and a feasible solution for the instance. Two vehicles are used. The first serves service points 1 and 2, whereas the other serves just point 4. This solution serves nine beneficiaries. Notice that beneficiaries 3 and 4 can access both service points, but they do not count twice in the total number of beneficiaries served.

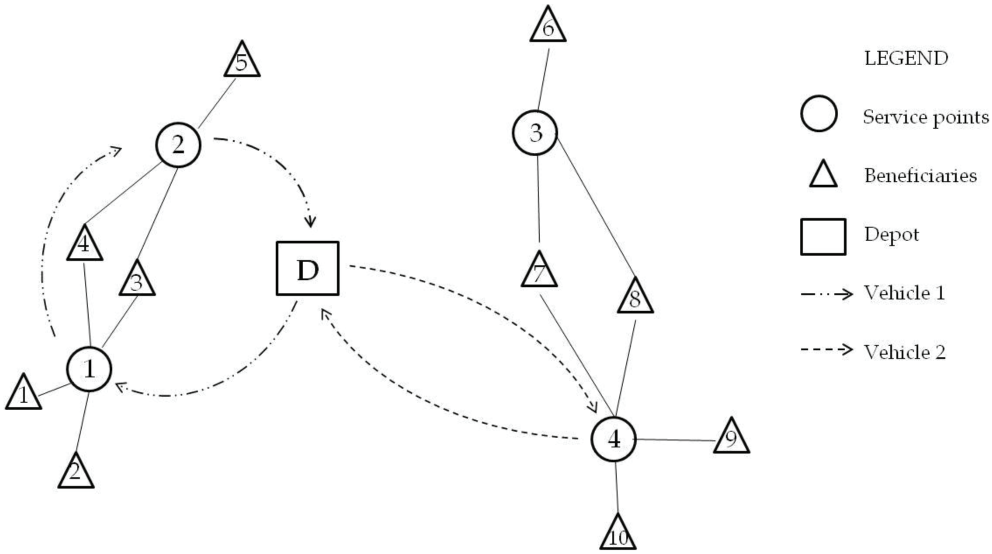

Figure 1. Example of a TOPO instance and a corresponding feasible solution

The main contributions of this paper are the following. A real-life problem of designing routes for vehicles for first-aid delivery in disaster response is modeled as a TOPO and a population-based simulated annealing (PBSA) algorithm that is able to find high-quality solutions of instances with 200 service points and more than 50000 beneficiaries, as well as those with 400 service points and almost 300000 beneficiaries within short computation times is proposed for the problem.

The rest of this paper is organized as follows. In Section 2 the main contributions from the literature on delivery of humanitarian aid are reviewed, while the TOPO is introduced in Section 3. The PBSA algorithm is described in Section 4. The computational results obtained by applying the PBSA and SA algorithms on a set of instances are discussed in Section 5. Finally, conclusions and future research directions are outlined in Section 6.

2. LITERATURE REVIEW

Many studies were conducted using operations research techniques to facilitate the delivery of humanitarian aid. Some of them deal with inventory systems for disaster relief, facility location to site warehouses or routing of vehicles after disaster.

Based on data collected from warehouse operations in Kenya, Beamon and Kotleba (2006) developed a stochastic inventory control model that determines optimal order quantities and reorder points for a long-term emergency relief response. Oh and Haghani (1996) formulate a multicommodity, multi-modal network flow model for a generic disaster relief operation and solve with two heuristics. Ozdamar et al. (2004) developed a dynamic time-dependent transportation problem that needs to be solved repetitively at given time intervals during ongoing aid delivery. New plans are obtained based on new requests for aid materials, new supplies and transportation means and they contain the optimal mixed pick up and delivery vehicle schedules within the considered planning period, as well as the optimal quantities and types of loads picked up and delivered on these routes.

Oruc and Kara (2018) propose a post-disaster assessment strategy as part of response operations in which effective and fast relief routing are of utmost importance. In particular, the road segments and the population points to perform assessment activities are selected based on the value they add to the consecutive response operations. A bi-objective mathematical model that provides damage information in the affected region by considering both the importance of population centers and road segments on the transportation network is developed. The first objective aims to maximize the total value added by the assessment of the road segments whereas the second maximizes the total profit generated by assessing points of interests.

Pérez-Rodríguez and Holguín-Veras (2015) developed mathematical models that maximize the benefits derived from the distribution of critical supplies to populations in need after a disaster. An inventory-allocation-routing model for the optimal assignment of critical supplies that minimizes social costs is developed in the paper. Also, heuristic methods are provided along with numerical experiments to assess their performance. The formulations are based on welfare economics and the use of social costs, which are incurred by the segments of society involved in and impacted by the relief distribution strategy.

Eisenhandler and Tzur (2018) dealed with logistic aspect of a food bank that on a daily basis uses vehicles of limited capacity to distribute food collected from suppliers, under an imposed maximal traveling time. The problem is model as a routing resource allocation problem, with the aim of maintaining equitable allocations to the different agencies while delivering overall as much food as possible. An exact solution method, a heuristic approach and numerical experiments on several real-life and randomly generated data sets, are presented.

The routing of vehicles carrying critical supplies can greatly impact the arrival times to those in need. There are articles which discuss both the classic cost-minimizing routing problems and problems with alternative objective functions. Because deliveries should be fast but fair too, Campbell et al. (2008) solve the traveling salesman problem (TSP) and the vehicle routing problem (VRP) with two alternative objective functions: one that minimizes the maximum arrival time and one that minimizes the average arrival time. As a research on alternate objectives for vehicle routing the following papers can be mentioned. França et al. (1995) solved m-TSP where the length of the longest tour is minimized. Averbakh and Berman (1996) consider the two-TSP, where two salesmen must together visit all of the nodes on a tree. The objective is to minimize the length of the longest of the two tours while Applegate et al. (2002) dealed with VRP where the length of the longest of four routes is minimized.

3. MATHEMATICAL MODEL

The TOPO can be formally described as follows (Orlis et al. 2020). A set of beneficiaries B is given. Beneficiaries are served via a set of service points S={1,2,…,n}; in particular, each beneficiary $b \in B$ can be served by a subset of service points $Sc \in S$. Similarly, the subset of beneficiaries that can be served by service point $i \in S$ is indicated by $Bi \subseteq B$. Beneficiariers can be served via the service points by routing a set of homogeneous vehicles K located at a depot, indicated by 0. Each vehicle can perform a route that starts from the depot, visits some service points, and returns to the depot. Each route cannot exceed a maximum route duration denoted by Tmax. The travel time between each pair of depot/service point locations i and j (i, j ∈ V= S ∪ {0}) is indicated by tij. Travel times can be asymmetric and, without loss of generality, are assumed to be strictly positive and to satisfy the triangle inequality (i.e., tij ≤ tik + tkj for each i, j, k ∈ V). The TOPO aims at finding a set of routes, each one not exceeding the maximum route duration, that visit each service point at most once and maximize the number of beneficiariers served.

The TOPO can be defined on a directed graph G(V,A), where the arc set is defined as A={(i,j)|i,j∈V,i≠j}. Let us define the following three sets of variables: xij∈{0,1}, a binary variable equal to 1 if arc (i,j)∈A is traversed by one of the vehicles (0 otherwise); yb∈{0,1}, a binary variable equal to 1 if beneficiary b∈B is served (0 otherwise); and zi∈R+, a continuous variable indicating the arrival time at service point i∈S. Then, the TOPO can be formulated as follows:

$$z^* = \max_{b \in B} y_b \tag{1}$$

$$s.t. \quad \sum_{(0,j) \in A} x_{0j} \leq |K| \tag{2}$$

$$\sum_{(i,j) \in A} x_{ij} \leq 1, \quad i \in S \tag{3}$$

$$\sum_{(i,j) \in A} x_{ij} = \sum_{(j,i) \in A} x_{ji}, \quad i \in S \tag{4}$$

$$z_i + (Tmax + t_{ij})x_{ij} \leq z_j + Tmax, \quad (i,j) \in A: i,j \in S \tag{5}$$

$$t_{0i} \sum_{(i,j) \in A} x_{ij} \leq z_i \leq (Tmax - t_{i0}) \sum_{(i,j) \in A} x_{ij}, \quad i \in S \tag{6}$$

$$\sum_{(i,j) \in A: i \in S_b} x_{ij} \geq y_b, \quad b \in B \tag{7}$$

$$x_{ij} \in \{0,1\} \quad (i,j) \in A \quad y_b \in \{0,1\} \quad b \in B \quad z_i \in R^+, \ i \in S \tag{8}$$

The objective function (1) asks for maximizing the number of beneficiaries served. Constraint (2) ensures that no more than *|K|* routes are designed. Constraints (3) guarantee that each service point is visited at most once. Constraints (4) are flow conservation constraints for the service points. Constraints (5) link *x* and *z* variables to set the arrival time at each service point based on the traversed arcs and also prevent subtours in the designed routes. Constraints (6) guarantee that if service point $i \in S$ is visited, the arrival time of the vehicle visiting it is not less than the travel time from the depot to *i* and not greater than T_{max} - t_{i0}. Constraints (7) ensure that each beneficiary $b \in B$ is served only if at least one of the service points of the set S_b is visited. Constraints (8) define the range of the decision variables.

4. SOLUTION METHODS

Simulated annealing (SA) is a discrete optimization technique of combining the principle of deterministic descends strategy with Monte Carlo approach. Kirkpatrick et al. (1983) and Cherny (1985) independently pointed out the analogy between the activities of the thermodynamic system and the search for the global minimum in the problems of discrete optimization. In searching for the optimal solution, the SA utilizes a stochastic approach. Local optima are avoided through accepting non-improving solutions with a certain probability in each temperature. Different applications of the SA can be found in the literature for solving many non-polynomial hard optimization and operation research problems.

In this paper, a population-based simulated annealing (PBSA) is applied which has a similar structure to SA though had been developed by varying in number of initial solutions in order to achieve more accurate solutions by diversification. Some of the applications of the PBSA can be found in papers of Jolai et al. (2012), Shaabani and Kamalabadi (2016).

A solution is encoded as a permutation of integers which represent service points to be visited. Based on an example of an area with 10 service points (Figure 2) each vehicle in the solution is assigned a sequence of service points to be visited during the planning period (minimum route duration).

7	2	3	10	1	5	6	9	4	8
Vehicle 1			Vehicle 2			Vehicle 3		unassigned	

Figure 2. An example of solution representation

In the example solution (Figure 2), there are three vehicles. Vehicle 1 and 2 are assigned three service points each, while the thirth vehicle visits two service points. In this solution, service points 4 and 8 are not assigned.

The fitness function of the solution corresponds to the negative equivalent of objective function (2) which represents the total number of beneficiaries “collected” from all service points in the order of the visits given by the solution.

The SA (also the PBSA) is basically a simulation of the recrystallisation of atoms in metal during its annealing. It begins with a starting temperature denoted by τ_0 which decreases until it reaches its final number of iterations (It) using an annealing schedule to define how the temperature has changed during the annealing process. In this paper the geometric cooling approach is adopted and the temperature is decreased according to the scheme $\tau_{i+1} = \alpha\tau_i$, where α represents a positive constant number less than one named cooling factor, after L moves of stage length.

Algorithm proceeds by creating feasible initial solution x_0 wich is repeated n_{pop} times to form a primary population (of size n_{pop}).

The feasible initial solution x_0 is obtained in a few steps. First, the service points are sorted in decreasing order of number of beneficiaries associated with them. The service points are assigned to the vehicle until constraint related to the maximum route duration of the vehicle is not violated. On that way, algorithm obtains subsets of service points assigned to the vehicles, as well as subset of service points which will not be visited.

According to the fitness of the problem, the cost of each candidate is calculated in order to determine the best solution at each temperature. These best solutions are used to generate the next candidates using an approach such as neighbourhood generation.

For the neighbourhood procedure three cases are applied: swap, reversion and insertion. The *swap* rule implies the replacement of two randomly selected service points from the current solution. *Reversion* rule means alter of the order of all service points between two arbitrarily selected service points, including them as well, so that the first becomes the last one, etc. *Insert* rule interpolates the arbitrary service point in a randomly selected position, omitting the service point on its previous position. The neighborhood relation is defined as the movement of a service point to a new position in the sequence. The movement of an assigned service point to the subset of unassigned service points is forbidden.

The algorithm accepts candidates if there is improvement in the fitness but, to avoid local optimum solutions, the algorithm also allows others to be kept with a probability obtained from Boltzman distribution which equals $e^{\frac{-\Delta f}{k\tau}}$ where Δf is the difference in fitness between the old and new states and τ denotes the temperature of the process and k is a constant parameter of the process.

The current temperature τ is decreased after running L iterations (maximum iteration per temperature) according to a cooling schedule.

In the PBSA, if each member of the current population (of size n_{pop}) generates n_{move} neighbors at each iteration, $n_{pop} \cdot n_{move}$ new solutions will be created. All the generated neighbors are placed in a set. Members of this set will be compared with each other, and n_{pop} number of best members will be selected. This procedure guarantees that each member of the population will interact with all generated neighbors, rather than just its own neighbors. In accordance with the previous procedure, again n_{move} neighbors should be generated for each of n_{pop} best selected members, and the entire process repeated until the termination condition is fulfilled.

5. NUMERICAL EXPERIMENTS

The computational results obtained by applying the proposed PBSA and SA algorithms on the set of problem instances are presented in this section.

The possibilities of the developed metaheuristics are presented on a set of 18 numerical examples which are created in the following way. First, two networks were simulated, with 200 and 400 nodes representing service points, respectively. For the first network (n=200 nodes and the depot), coordinates (x, y) of service points are simulated according to the uniform distribution U[0, 45], while the number of beneficiaries (profit in service point) is simulated by the uniform distribution U[100, 900]. The set of the maximum route duration values is {90, 100, 110}, while the set of the numbers of vehicles is {14, 15, 16}, which makes 9 examples in total. For the other network (n=400 nodes and the depot) coordinates (x, y) are simulated according to the uniform distribution U[0, 150], while the number of beneficiaries is simulated according to the uniform distribution U[100, 4000]. The set of the maximum route duration values is {250, 260, 270}, while the set of the numbers of vehicles is {55, 56, 57}, which makes 9 examples, 18 in total. It is assumed that the coordinates of the nodes and the route duration are of the same dimensions. The total number of beneficiaries are 50825 and 291838 for the first and the second network, respectively.

Than, similar to the procedure presented in Orlis et al. (2020), a service radius ρ defining the maximum distance between a service point and the beneficiaries it can serve is computed as $\rho = 0.5 \cdot min\{t_{ij} \mid i,j \in S, i \neq j\}$. The service radius ρ subsequently is used to define nonoverlapping circular service regions centered around each service point. Then, for every service point, within its service region, as many beneficiaries as the profit of the associated service point are allocated. In the end, the smallest value of ρ such that $\sum_{i \in S}|C_i| \geq (1+\gamma) \cdot |C|$ is computed, where γ is degree of overlap.

The value of the parameters τ_0, L and α are determined according to the suggestion proposed in Johnson et al. (1989). The parameter L is given to be 3 times the number of the vehicles, τ_0=25, α=0.95, probability distribution p=[0.3, 0.4 0.3], the number of iterations It=2000. Specially, for the PBSA, the population size is 5, while the number of moves is 3. Degree of overlap γ equals 10%.

The developed PBSA and SA algorithms were implemented in MATLAB 7.6.0. on a 3.20 GHz Intel Core i5-3470 64-bit computer with 8 GB of RAM.

Table 1 summarizes the computational results of the PBSA and the SA algorithms applied on 18 created instances. Columns report the following information: the ordinal number of instances along with the number of the service points n and the number of beneficiaries |B|, the maximum route duration (Tmax), the number of vehicles (|K|), the number of served beneficiaries obtain by the PBSA and the SA algorithm (BPBSA and BSA, respectively), running time of the algorithms (tPBSA and tSA), relative difference between the number of served beneficiaries obtain by the PBSA and the SA algorithm (BPBSA - BSA)/ BPBSA).

Table 1 indicates that the SA algorithm based on population (PBSA) has a better performance than the classical SA algorithm. Columns 4 and 6 show that the values of the number of beneficiaries served obtained by the PBSA is greater than those obtained by the SA for all instances. The superiority is shown in column 8, too, where the relative differences between the total beneficiaries served obtained by the PBSA and the SA are given. For the first set of 9 instances (n=200) the average value of relative differences between the total beneficiaries served is 1.47%, while for the second set of 9 instances (n=400) it is 2.25%.

In addition to the values of relative differences, run times of the algorithms are presented in Table 1. It can be seen that the average run times of both algorithms are very reasonable. For the set of 9 instances and 200 service points run times are in average 515.17 sec. and 282.85 sec. for the PBSA and the SA, respectively, while for the set of 9 instances and 400 service points the average execution times equals 1512.56 sec and 864.48 sec., respectively. It takes longer to solve the instances by the PBSA, but not significantly. Both algorithms are appropriate for application in real time.

It can be observed that for all maximum route duration, the greater the number of vehicles the greater the number of beneficiaries served on all instances.

Generally, the proposed PBSA algorithm has respectable potentials for a practical application.

Table 1. Comparison of the results obtained by the PBSA and the SA

n=200 |B|=50825	T_{max}	|K|	B_{PBSA}	t_{PBSA}	B_{SA}	t_{SA}	$(B_{PBSA} - B_{SA})/B_{PBSA}$ (%)
1	90	14	43888	462.95	43261	213.47	1.43
2		15	45732	484.45	45138	219.89	1.3
3		16	47011	494.24	46474	268.90	1.14
4	100	14	47161	500.46	46242	263.02	1.81
5		15	47352	524.80	46497	301.29	1.94
6		16	48241	554.59	47586	338.76	1.36
7	110	14	49672	547.28	49048	274.21	1.26
8		15	50262	503.79	49585	303.56	1.35
9		16	50825	563.98	50002	362.57	1.62
n=400 |B|=291838	**average**	**15**	**47793.78**	**515.17**	**47092.56**	**282.85**	**1.47**
10	250	55	272843	1277.83	266506	758.96	2.32
11		56	275784	1367.61	267888	797.26	2.86
12		57	278042	1556.14	271119	796.03	2.49
13	260	55	281399	1399.80	274077	802.35	2.6
14		56	283841	1558.39	280072	844.63	2.34
15		57	287848	1634.70	281105	937.42	1.33
16	270	55	290987	1486.89	284865	924.84	2.11
17		56	291350	1567.50	285241	984.16	2.09
18		57	291838	1764.22	285675	934.63	2.12
	average	**56**	**283777.22**	**1512.56**	**277394.22**	**864.48**	**2.25**

6. CONCLUSION

The delivery of first-aid resources is one of the main components of an operational emergency logistics system after a disaster. This paper deals with a problem of routing of vehicles for first-aid distribution in the event of a humanitarian disaster.

The problem considered here is to determine vehicle routes, subjected to maximum duration constraints, which maximize the number of served beneficiaries who has access to at least one service point. This optimization problem is modeled as a mixed integer linear programming model of the team orienteering problem with overlaps.

To solve the problem, the PBSA and the SA algorithms are developed and tested on a set of numerical examples.

The efficiency and superiority of the PBSA is proven by the number of beneficiaries served for a given set of vehicles subjected to maximum duration constraints. Computing time of both algorithms is reasonable and each of them is acceptable for solving the problem in real time.

Another research direction is a comparison between the algorithms according to parameters different than those considered in this paper, such as the impact of different values of degree of overlaps among service regions. Additional research opportunity is the usage of real data set with larger number of instances.

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