



Emergency response time minimization by incorporating ground and aerial transportation

Mazyar Ghadiri Nejad¹✉ • Mahdi Banar²

¹ Production Department, Technology, University of Vaasa, Vaasa, Finland

² Industrial Engineering Department, Engineering Faculty, Eastern Mediterranean University, Famagusta, TRNC, Turkey

✉ mazyar.ghadirinejad@gmail.com

(Received: November 29, 2017 / Accepted: January 14, 2018)

Abstract In real life, many events may have severe effects on human being lives. These events can happen casually such as accident, heart attack or another severe disease, and deliberately like fights among people. From the engineering point of view, it does not matter what the reason of happening such events is, but the important thing is to rescue the affected people as much as possible in a short time and based on a scheduling point of view. In this study, we consider a real-life medical emergency service problem for a city with its known hospitals or medical care center locations. A limited number of ground and aerial vehicles, like ambulance and helicopter, are given to be assigned to these sites in which at most one vehicle from each type can be assigned. The aim is minimizing the total travel distances which are a function of the response time to the patients. To solve the problem, a mathematical formulation is proposed, and a metaheuristic solution method based on the genetic algorithm is developed, since the problem belongs to the NP-hard family of problems.

Keywords Response time; Aerial transportation; Emergency service; Genetic Algorithm.

1. Introduction

In today's modern world, technology is dramatically improving, and the use of technology and tools that are the product of technology has grown more and more. Additionally, technology boosts health indicators in the community such as increasing longevity, the eradication of many pandemic diseases, etc. One of the crucial issues that governments and health managers are involved with is hardware resources limitation such as ambulances, health centers, medical supplies, and so on. In this area, since the

health of humans is the priority, it requires management and planning in details where operations research technics have a significant role to deal with these issues. Generally, in medical care systems, the focus is on providing an appropriate service level. One of the most essential services related to healthcare is emergency medical service (EMS). This service has a significant role to save the humans' lives and decreasing the deaths and mortality [Aringhieri et al. \(2017\)](#). Therefore, in the recent decades, this topic attracted the attention of the operations research scientists. There are many reasons why this issue plays a decisive role in health issues since one of the crucial determinants of medical emergency services is the transportation of the patient at the right time to the treatment centers or hospitals. The patient's transportation involves a multi-stage process that starts when the emergency call is received and ends when the delivery of the patients to the hospital or suitable treatment centers is finished [Chin et al. \(2017\)](#).

The design of emergency medical service systems includes several strategies, including the determination of the number and location of the ground and aerial vehicle stations, and the designation of a method for the dispatch of vehicles. Another aspect of the locating emergency facilities problem is balancing between the costs and the quality of provided services. The quality of offered services includes the response time, the route that the patient is transferred, the equipment that the operators have access to, etc. Therefore, reducing the response time will increase the quality of service delivery. The vehicle's travel time from the service provider's station to the location of demand is a significant part of the response time. Another aspect of the timing of the vehicle itself is the speed of the vehicles and the traffic of the route in which the vehicle is using it to travel. Therefore, the traffic flow also plays a vital role in the time of the journey and the response time and can affect the quality of the provided service. Considering the dependence between traffic flow and the quality of service is paramount and makes this issue more compatible with the real world.

There are many different topics related to emergency transportation and medical services in the literature. These issues can be classified as allocation problems, redeployment problems, locating EMS problems, set covering problems, ambulance response time problems, dispatching and routing problems and etc. It is evident that the real emergency service problems are usually included of some of these mentioned problem topics simultaneously. On the other hand, there are many different approaches to deal with these issues such as developing mathematical models including integer programming models, dynamic programming models and etc. Additionally, proposing heuristic and metaheuristic algorithms such as genetic algorithm, local search algorithm, Tabu-search algorithm, ant colony optimization and etc. to solve such problems is usual since these problems belong to the NP-hard family of the problems.

In this article, an optimization problem aiming to minimize the total response time to the emergency patients is considered. In this problem, a city in which the locations of its hospitals are known is considered. The number of available ambulances and helicopters

to be assigned to the hospitals is given. The mathematical formulations to find the best places to deploy the ambulances and helicopters are represented, and all the necessary assumptions and definitions are discussed in details. Since this problem belongs to the NP-hard family of the problems, a metaheuristic algorithm based on genetic algorithm is represented. The performance of the proposed genetic algorithm by examining various problem instances is highlighted and discussed.

This article is organized as the following: In the next section, the literature review of the emergency medical service in different classifications is presented. In section 3, the definitions, notations, and the proposed mathematical model of the problem are represented. Section 4 discusses developing a metaheuristic algorithm. Section 5 describes the numerical results of the proposed metaheuristic algorithm, and finally, the conclusion and future research are noted in the last part.

2. Literature review

There are various problems related to emergency services. In a real-time context, EMS managers are dealing with two main issues such as allocation and redeployment problems. The allocation problems are related to determining which ambulance from which hospital should be sent after receiving emergency calls, and the redeployment problem is related to shipping/relocating an available ambulance to the site in which the emergency calls are received [Gendreau et al. \(2001\)](#). This relocating activity is performed for having a proper coverage in the potential sites. Based on the review articles of [Brotcorne et al. \(2003\)](#), EMS locating problems have been classified as deterministic models, probabilistic models, and dynamic models.

In another study performed by [Li et al. \(2011\)](#), all the models in the literature related to the deployment of EMS vehicles have been covered. [Başar et al. \(2012\)](#) taxonomically classified the EMS problems into three groups such as the type of problems, modeling problems, and their methodologies. Furthermore, they continued their classification in details. They divided the EMS problems to the structure of the model (deterministic or stochastic), the time variations (static or dynamic), and the number of the objectives. They categorized the modeling of the problems based on divergent in their objective functions, their parameters and the type of the mathematical formulations such as integer, non-linear, etc. and the methodology of the problems classified as exact solution methods, heuristics, metaheuristics, and simulation.

[Pinto et al. \(2015\)](#) constructed a reusable model that explain the working system of the ambulances. They proposed a flowchart with mentioning the milestones of decision making in the ambulance working system and described the concepts of their model that how they simulate the proposed model where the main aim was calculation the response time. They used this model in Belo Horizonte, a city of Brazil, as the real case to show the advantages of the reusability, and applied it to model the UK ambulance system.

Overstreet *et al.* (2011) studied on relief logistics aiming to find the best possible relief services considering available resources. Rahmaniani and Shafia (2013) calculated the performance of EMS based on the time required to response a customer or based on the overall cost of the logistics. McCormack and Coates (2015) presented allocation optimization for vehicle fleet by using the genetic algorithm. They considered two types of vehicles such that ambulance and rapid response cars for transportations and also they defined multiple patient's groups that need different classes of service. Their aim was maximizing the probability of survival of the patients in different classes.

Some of the researchers dealt with the locations of the healthcare facilities. In this type of the problems based on the demands for the healthcare facilities, the number of the constructed facilities or the overall cost of building the facilities is minimized. In another word, in such problems based on the traveling times between the facilities, the number and the locations of the facilities are determined to supply the demands to the healthcare. Schmid and Doerner (2010), proposed a mixed integer programming model for the multi-period set covering problem considering the allowance of maintaining a certain coverage standard. They defined that injured people are covered by a vehicle if they are transported to the hospital from their location within a specified time limit. They also developed a metaheuristic to solve the problem. Ahmadi-Javid *et al.* (2017) studied on the literature of the healthcare facility (HCF) location, and based on the location management, they constructed a framework for different types of the non-emergency and emergency HCFs.

Lam *et al.* (2015) dealt with the response time of the ambulance and considered the risk factors that can make delays at this time. Based on the real data about the incidents in Singapore, they proposed their model and defined the period from the moment that an ambulance is dispatched from its station to the location of the patient, until departing the hospital after delivering the patient to the hospital, as the turnaround of the ambulance. In another study, Knyazkov *et al.* (2015) considered that the transportation time to a hospital has a significant role in the treatment of acute coronary syndrome patients. On the other hand, they mentioned that finding the closest hospital and selecting the best route and delivering the patients from their location to that hospital is a very complicated problem. In this area, they count some uncertain factors as the flow of the traffic, the mobility of the population, and capability of the hospitals of EMS in a city. They studied and analyzed the real data related to Saint-Petersburg in Russia, and they illustrated that the flow of the traffic has a significant influence on selecting the hospital.

In the case of ambulance routing, Javidaneh *et al.* (2010) studied on a vehicle routing problem (VRP) for ambulances transportations. They defined a set of routes for ambulance fleet, considering various depots that are determined by geographically single customers. Additionally, they developed an ant colony optimization (ACO) to solve their discrete optimization problem where there were some limitations for hospitals capacities in their study. Ardekani *et al.* (2014) considered a vehicle routing problem for transportations of patients among the hospitals, by using ambulances in Edmonton and

Calgary, Canada. They proposed heuristic approaches to schedule the transports and to accommodate the emergency transportations in real time.

In recent decades, the medical emergency service by using helicopters is a public policy to deliver the patients to hospitals as fast as it is possible. This method has improved the rescue time, and also it increased the areas under cover [Andruszkow *et al.* \(2016\)](#). [Sullivent *et al.* \(2011\)](#) studied different transportations of the injured people such as ground transportation by ambulances and air transportations by helicopter. They compared the effectiveness these two types of transports on mortality of the patients. They controlled age, gender, and severity of injuries and found that deaths are 39% lower in transit by helicopter than the ground transportations. Thomas studied in the literature and published a review article about the helicopter medical service for the publications from 2004 to 2006 [Thomas \(2007\)](#), and [Browns *et al.* \(2012\)](#) published another review article about this topic for all the publications from 2007 to 2011. [Wisborg and Bjerkan \(2014\)](#) studied on the National Air Ambulance Service in Norway where the areas of their services are very far from hospitals. Therefore they are ready for service or not. The authors studied on the six-year transportations by this air ambulance service which was about 217 flights, 3 per month on average.

[Diaz *et al.* \(2005\)](#) performed one of the pioneer studies to comparing the ground and air transportations of patients by ambulance and helicopter, respectively. They considered 7854 ground ambulances transportations and 1075 air transportations. They conclude that response time for the air transportations of patients by helicopters is significantly shorter than the ground transportations of patients by ambulances when the distance between the locations of patients to hospitals destinations are more than ten miles. [Galvagno \(2013\)](#) studied on comparisons between the ground and air transportation of trauma patients by using the technique of multivariable regression. He proposed for essential parameters for survival by using helicopter transportations. His mentioned parameters are a crew of the flights, the severity of the trauma, speed of the helicopter and other service activities and accessibility to hospitals or trauma centers. Similarly, [Abe *et al.* \(2014\)](#) researched on 2090 and 22203 patients who transported by helicopter and ambulance to hospitals in Japan, respectively. According to their reports, 546 patients (26.1%) died when they wanted to be carried by helicopter, and 5765 patients died by using ambulance 26.0%. They concluded that considering time, costs, limited recourses, etc. transportation of trauma patients by helicopter is more efficient than the ground transportations. This study is based on [McCormack and Coates \(2015\)](#) and contributing helicopters in serving the patients in the severe cases which in the next section, it is explained in details.

3. Problem definition and formulation

In this article, a real-life medical emergency service problem is considered. In this issue, we consider a city in which the locations of all the hospitals, medical service centers, and

the other emergency care centers are known. Additionally, the emergency services are deployed using ambulances and helicopters for moving towards patients in their locations after receiving a call, performing the initial emergency medical care, and transporting the patients to the hospitals or other medical care facilities. For this reason, the accidents or demands are classified into two types of the severe accidents which need helicopter operations and common accidents which are operated by ambulances. According to the average number of the accidents in each location/node and the severity of the accident, weight is assigned to each node. In this problem, the objective is assigning a given number of the ambulances and the helicopters to the hospitals or the medical care centers in a way that the travel distances passed by all the ambulances and the helicopters become minimized entirely.

It is assumed that the speed of the vehicles are fixed. Therefore, considering minimization the total distance traveled by the vehicles and the fact that the time of transportations between origins/sources and destinations/sinks are known as a function of the distance between them, with these assignments, the total average response time to the patients is minimized. It should be mentioned that the conditions of assigning the nodes of the accidents or demands to the hospitals in the case of severe injuries, should be within an acceptable time period. Likewise, some of the existing locations should be equipped with ambulances or helicopters. The frequency of accidents and the severity of them can be obtained by the study of accident records in related organizations. The helicopters and ambulances use Euclidean distances. As a result, to measure the time between dispatching unit and the scene, we can use the distance between these two locations. The decision variables and parameters to formulate the problem are the following:

Decision variables and parameters:

- j, j' index of hospital
- i index of nodes
- H_j $\begin{cases} 1 & \text{if a helicopter is assigned to hospital } j \\ 0 & \text{otherwise} \end{cases}$
- A_j $\begin{cases} 1 & \text{if ambulance is assigned to hospital } j \\ 0 & \text{otherwise} \end{cases}$
- h_{ij} $\begin{cases} 1 & \text{if node } i \text{ is assigned to a helicopter in hospital } j \\ 0 & \text{otherwise} \end{cases}$
- a_{ij} $\begin{cases} 1 & \text{if node } i \text{ is assigned to a ambulance in hospital } j \\ 0 & \text{otherwise} \end{cases}$
- d_{ij} distance between node i and hospital j
- w_i average number of serious accidents in node i (demand for helicopter)
- w'_i average number of normal accidents in node i (demand for ambulance)
- M A large positive number
- n total number of locations to be equipped with helicopter

m total number of locations to be equipped with ambulance

Considering the defined variables and parameters, the model is written as follows:

$$\text{Min } \sum_i \sum_j w_i d_{ij} x_{ij} + w'_i d_{ij} x'_{ij} \quad (1)$$

subject to

$$\sum_j H_j = n \quad (2)$$

$$\sum_j A_j = m \quad (3)$$

$$d_{ij'} x_{ij'} H_{j'} \leq d_{ij} H_j + (1 - H_j) M \quad \forall j, \forall j', \forall i \quad (4)$$

$$d_{ij'} x_{ij'} A_{j'} \leq d_{ij} A_j + (1 - A_j) M \quad \forall j, \forall j', \forall i \quad (5)$$

$$h_{ij} \leq H_j \quad \forall j, \forall i \quad (6)$$

$$a_{ij} \leq A_j \quad \forall j, \forall i \quad (7)$$

$$\sum_j h_{ij} = 1 \quad \forall i \quad (8)$$

$$\sum_j a_{ij} = 1 \quad \forall i \quad (9)$$

$$h_{ij}, a_{ij}, H_j, A_j \in \{0,1\} \quad \forall j, \forall i \quad (10)$$

The objective function minimizes the total distance traveled by helicopters and ambulances. The weights of the nodes in this function help to consider the shorter distances for those nodes that have a larger average number of the accidents and more severe accident. Constraint (2) shows that the total number of the available helicopters is limited to n . Constraint (3) indicates that the total number of the available ambulances is limited to m . Constraints (4) -(5) guarantee that the demand on each node receive its services from the closest facility. Constraints (6) -(7) guarantee that the demand is assigned to a facility with required resources. Constraints (8) -(9) guarantee that each demand is assigned to only one hospital, and finally, constraint (10) indicates the binary variables used in the proposed mathematical formulation.

4. Solution method

To solve the problem by using the proposed mathematical models, it is obvious that since the problem belongs to the non-polynomial hard (NP-hard) family of the problems, the solution time rises exponentially [Mosallaeipour et al. \(2018\)](#), [Ghadiri Nejad et al. \(2017\)](#) a. In other words, in these problems when the number of nodes, ambulances, and helicopters rises, it causes rapid enhancement in the number of the decision variables and constraints in modeling the problem and the computation time highly increases. Therefore, according to the characteristics of the NP-hard problems, the exact solution methods fail to solve the problems when the problems become larger.

Genetic algorithm (GA) which is proposed by John Holland in the 1970s is one of the well-known approaches to deal with NP-hard problems [Holland \(1973\)](#). In the recent decade, GA has been used to solve a broad range of optimization problems. This method has been used for solving different problems such as humanitarian relief [Golabi et al. \(2017\)](#), facility location [Shavarani et al. \(2017\)](#), and production scheduling [Ghadiri Nejad et al. \(2017\) c](#). The GA has a high solution performance to find a good and feasible result in a short time.

Generally, GA starts by generating some random initial solutions. These initial solutions are called the population of the solution. Then, GA produces a number of new solutions by utilizing specific operators in each step. To converge to the optimal solution, the objective function value of the generated solutions are found in each step and compared by the objective function value of the current solution. If the new objective function value is better than the current (existing) objective value, the new solution is considered as the current solution to be used in the next iteration. The search continues until reaching the considered stopping criteria. The details of the proposed genetic algorithm are given in the following:

4.1. Representation

Representation or encoding is the most important part of developing solutions [Ghadiri Nejad et al. \(2017\) b](#). In the proposed algorithm, each solution is represented by an array having $n+m$ elements where n and m are the number of locations that should be equipped with helicopters and ambulances, respectively. Each cell of the array indicates the index of a hospital to which a helicopter or/and ambulance is assigned. In this type of solution representation, since a hospital may receive both of the ambulance and helicopter, some indexes may be repeated from the first n cells into the last m cells. On the other hand, since each hospital may at most receive only one from each vehicle type, thus there cannot be repeated indices within the first n cell or within the last m cells. Figure 1 represents an instance of the solution encoding.

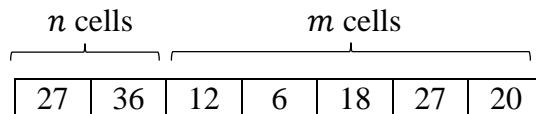


Figure 1. Representation a solution.

In Figure 1, there are two and five numbers of helicopters and ambulances available to be assigned to the hospitals, respectively. Each of the hospitals indicated by the location number of 27, 36 must be enriched by a helicopter and the hospitals shown by the numbers of 12, 6, 18, 27, and 20 must be enriched by an ambulance. Additionally, this figure depicts that the hospital number 27 must receive a helicopter and an ambulance at the same time.

4.2. Initial solution

The initial solutions are a set of randomly generated solutions consists of non-repetitive indices of hospitals and ambulances, which are called the population of the algorithm. In this study, 100 solutions are generated initially for the considered problem.

4.3. Fitness function evaluation

The value of the fitness function for each solution is calculated considering the described formulations and given parameters. Since all of the generated solutions in this research are feasible, there is no need to consider any penalty function to escape from evaluating the infeasible solutions.

4.4. Neighborhood generating operators

The crossover operator in this article is a kind of two-point-crossover operator in a way that one point is randomly decomposed the first n chromosomes of both initial solutions into two segments, and the other point is randomly decomposed the other m chromosomes of both initial solutions into two segments. Therefore, the crossovers are applied independently for each part of the n and m chromosomes, separately. Then, by keeping one segment from each solution and merging it with the other part of the other solution, two different solutions are generated. The graphical representation of the crossover operation is shown in Figure 2.

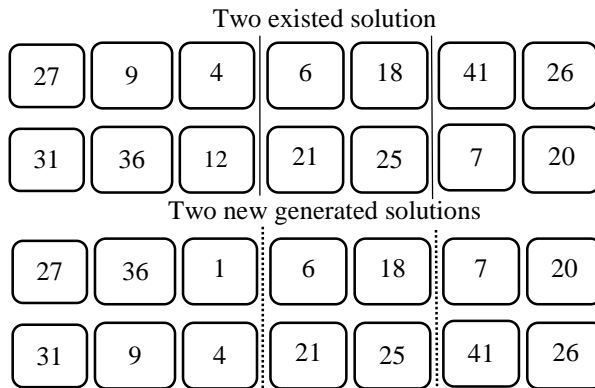


Figure 2. An example of the crossover operation.

After using the crossover operation, it is possible that the generated solutions are infeasible since some of their indices are repetitive. Therefore, these repetitive indices are removed from the solutions. Then, other indices are added from two parents to replace the deleted ones. To perform mutation operator, some indices are selected randomly, and they are substituted with other indices that are absent in the solution. If there are repetitive numbers for each vehicle type, by randomly selecting one of the repeated numbers, and a random generation of a new ambulance or hospital number, the mutation operator is completed.

4.5. Selection and stopping criteria

After generating the new offsprings by the crossover and mutation operators and adding them to the population, the found solutions are sorted based on their fitness function values, and the best solutions are selected for starting the next iteration. The algorithm continues for a pre-determined number of iterations. To stop the GA, different criteria such as a maximum number of iteration, maximum solution time, etc. can be used. In this article, a pre-determined number of iterations is considered as the stopping criteria in which after performing the iterations, the best solution with its fitness function value is reported. Figure 3, represents the pseudo code of the proposed GA for the problem.

```

1: Initialize the GA parameter ( $n$ ,  $m$ ,  $Pop$ ,  $Iter_{max}$ ,  $P_c$ , and  $P_m$ )
2: Generate initial solutions with genes size of  $n$  and  $m$ , and population size of  $Pop$ 
3: Check their feasibility and correct them if needed
4: Compute the fitness function value for the initial solutions
5: Iteration_no  $\leftarrow$  0
6: while (Iteration_no <  $Iter_{max}$ ) do
7:   for  $i = 1: (P_c * Pop)/2$ 
8:     Select two parents from the population randomly
9:     Find a crossover point randomly
10:    Generate two new solutions
11:    Check their feasibility and correct them if needed
12:    Compute their fitness function value
13:    Add them to the population
14:   End
15:   for  $j = 1: P_m * Pop$ 
16:     Select one solution from the population randomly
17:     Perform the mutation
18:     Check their feasibility and correct them if needed
19:     Compute its fitness function value
20:     Add it to the population
21:   End
22:   Sort the solutions based on their fitness function values, increasingly
23:   Select the first  $Pop$  size solutions
24:   Update the population
25:   Iteration_no  $\leftarrow$  Iteration_no + 1
26: end while
27: Return the best solution;

```

Figure 3. The pseudo code of the proposed GA.

5. Computational results

In this section, at first, a case study to be solved by the proposed solution methods is explained in details. Then the results of solving the problem are presented and discussed.

5.1. The case study

For the case study, a network of 1000 nodes showing the location of the accidents or medical care demand, and 50 locations depicting the hospitals is generated using MATLAB. In the generated network, the nodes are illustrated with blue, and red asterisks depict candidate locations (see Figure 4). The number of available helicopters and ambulances to be assigned to the hospitals is equal to 20 and 30, respectively. The weights of the nodes are also generated randomly. These data are used to perform the case study, and the results are discussed in the last section.

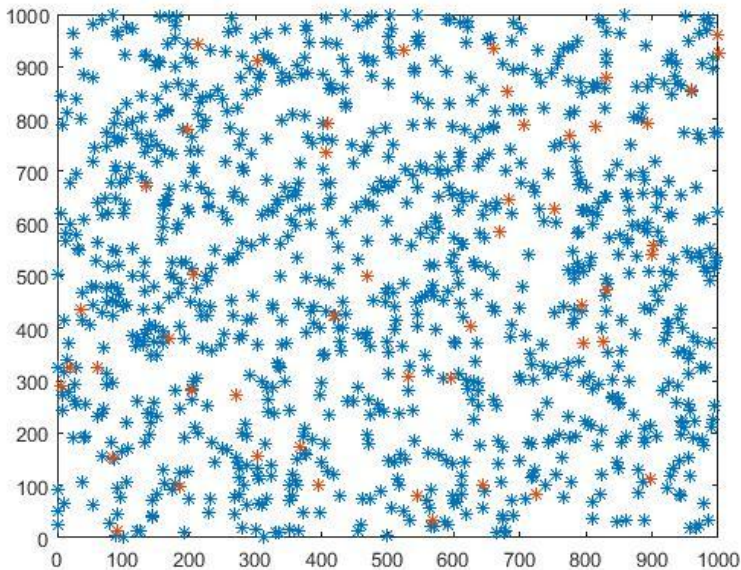


Figure 4. The network consisting of 1000 nodes and 50 candidate locations

5.2. Results

To solve the considered problem in this article, the GA was run with the population size of 100 and iteration number of 100. The results indicate that the optimal total travel distance is equal to 82180.55 distance unit, including 44925.34 for the helicopters and the rest which is 37255.21 for the ambulances. The runtime for this problem was equal to 13.39 seconds. Red and blue asterisks have displayed the position of the selected hospitals to assign the helicopters and ambulances in Figure 5, respectively.

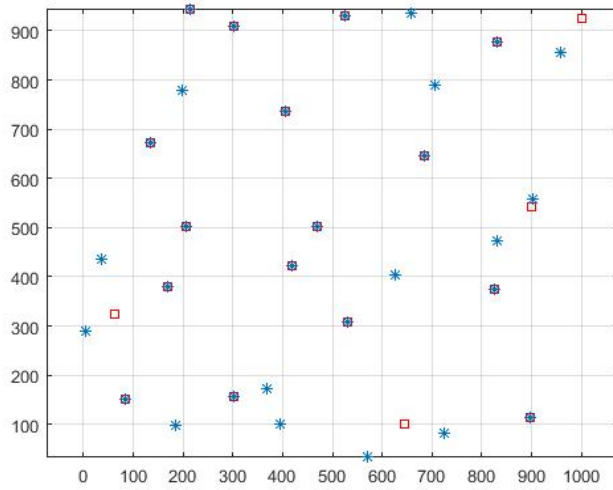


Figure 5. The assignment of the ambulances and helicopters to the hospitals

The chart of the best cost function values acquired in each iteration is illustrated in Figure 6.

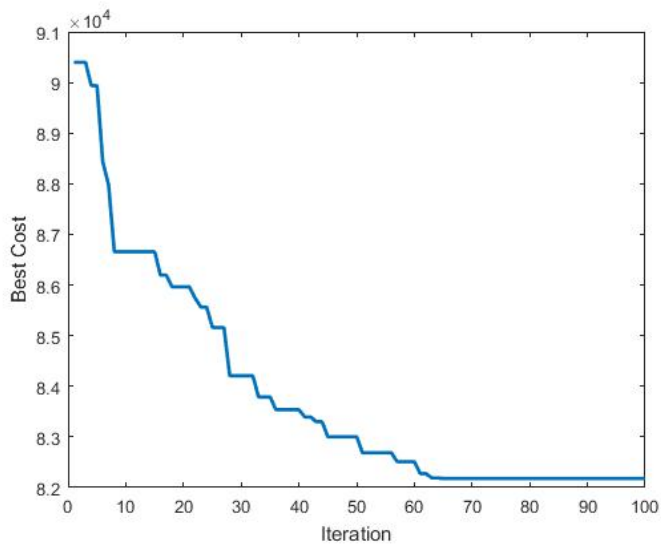


Figure 6. The best cost function values found in each iteration

6. Conclusion

In this study, we dealt with a real-life medical emergency service problem where a city with its known hospitals or medical care center locations was considered. The aim was

assigning a given number of ambulances and helicopters to some of the hospitals or medical service centers in a way that the total travel distances which are a function of the response time to the patients were minimized. To solve the problem, a mathematical formulation was proposed for the problem. Since the problem belonged to the NP-hard family of problems, a metaheuristic algorithm based on the genetic algorithm was proposed. A case study including 1000 medical service demands, such as accidents or emergency cases with 50 hospitals or medical care centers were considered and plotted according to their locations. 20 and 30 number of helicopters and ambulances were considered for this assignment problem.

For the future studies, except considering real case problems and applying the proposed solution methods, different types of vehicles, helicopters, and drones may be regarded as the problem modifications. Different solution methods such as heuristic and metaheuristic algorithms can also be considered for developing the problem. Furthermore, the problem can be modified as a multi-objective problem by adding a different and opposite objective function in relation to the minimization of the response time or the minimization of the total traveled distances.

References

1. Abe, T., Takahashi, O., Saitoh, D., & Tokuda, Y. (2014). Association between helicopter with physician versus ground emergency medical services and survival of adults with major trauma in Japan. *Critical care*, 18(4), R146.
2. Adenso-Diaz, B., & Rodriguez, F. (1997). A simple search heuristic for the MCLP: Application to the location of ambulance bases in a rural region. *Omega*, 25(2), 181-187.
3. Ahmadi-Javid, A., Seyedi, P., & Syam, S. S. (2017). A survey of healthcare facility location. *Computers & Operations Research*, 79, 223-263.
4. Andruszkow, H., Schweigkofler, U., Lefering, R., Frey, M., Horst, K., Pfeifer, R., ... & Hildebrand, F. (2016). Impact of helicopter emergency medical service in traumatized patients: which patient benefits most? *PLoS one*, 11(1), e0146897.
5. Ardekani, L. H., Haight, D., Ingolfsson, A., Salama, M., & Stanton, M. (2014). *Scheduling and routing ambulances that provide inter-facility patient transfers*. working paper.
6. Aringhieri, R., Bruni, M. E., Khodaparasti, S., & van Essen, J. T. (2017). Emergency medical services and beyond: Addressing new challenges through a wide literature review. *Computers & Operations Research*, 78, 349-368.
7. Başar, A., Çatay, B., & Ünlüyurt, T. (2012). A taxonomy for emergency service station location problem. *Optimization letters*, 6(6), 1147-1160.
8. Brotcorne, L., Laporte, G., & Semet, F. (2003). Ambulance location and relocation models. *European journal of operational research*, 147(3), 451-463.

9. Brown, B. S., Pogue, K. A., Williams, E., Hatfield, J., Thomas, M., Arthur, A., & Thomas, S. H. (2012). Helicopter EMS transport outcomes literature: annotated review of articles published 2007–2011. *Emergency medicine international*, 2012.
10. Chin, S. N., Cheah, P. K., Arifin, M. Y., Wong, B. L., Omar, Z., Yassin, F. M., & Gabda, D. (2017, April). Determinants of ambulance response time: A study in Sabah, Malaysia. In *AIP Conference Proceedings* (Vol. 1830, No. 1, p. 080003). AIP Publishing.
11. Diaz, M. A., Hendey, G. W., & Bivins, H. G. (2005). When is the helicopter faster? A comparison of helicopter and ground ambulance transport times. *Journal of Trauma and Acute Care Surgery*, 58(1), 148-153.
12. Galvagno, S. M. (2013). Comparative effectiveness of helicopter emergency medical services compared to ground emergency medical services. *Critical Care*, 17(4), 169.
13. Gendreau, M., Laporte, G., & Semet, F. (2001). A dynamic model and parallel tabu search heuristic for real-time ambulance relocation. *Parallel computing*, 27(12), 1641-1653.
14. Ghadiri Nejad, M., Güden, H., Vizvári, B., & Vatankhah Barenji, R. (2017). A Mathematical Model and Simulated Annealing Algorithm for Solving the Cyclic Scheduling Problem of a Flexible Robotic Cell. *Advances in Mechanical Engineering*. In press.
15. Ghadiri Nejad M, Kovács G, Vizvári B, Barenji RV. (2017). An optimization model for cyclic scheduling problem in flexible robotic cells. *International Journal of Advanced Manufacturing Technology*.
16. Ghadiri Nejad, M., Shavarani, S. M., Vizvári, B., & Vatankhah Barenji, R. (2017). Trade-off between process scheduling and production cost in cyclic flexible robotic cell. *International Journal of Advanced Manufacturing Technology*. In press.
17. Golabi, M., Shavarani, S. M., & Izbirak, G. (2017). An edge-based stochastic facility location problem in UAV-supported humanitarian relief logistics: a case study of Tehran earthquake. *Natural Hazards*, 87(3), 1545-1565.
18. Holland, J. H. (1973). Genetic algorithms and the optimal allocation of trials. *SIAM Journal on Computing*, 2(2), 88-105.
19. Knyazkov, K., Derevitsky, I., Mednikov, L., & Yakovlev, A. (2015). Evaluation of Dynamic Ambulance Routing for the Transportation of Patients with Acute Coronary Syndrome in Saint-petersburg. *Procedia Computer Science*, 66, 419-428.
20. Lam, S. S. W., Nguyen, F. N. H. L., Ng, Y. Y., Lee, V. P. X., Wong, T. H., Fook-Chong, S. M. C., & Ong, M. E. H. (2015). Factors affecting the ambulance response times of trauma incidents in Singapore. *Accident Analysis & Prevention*, 82, 27-35.
21. Li, X., Zhao, Z., Zhu, X., & Wyatt, T. (2011). Covering models and optimization techniques for emergency response facility location and planning: a review. *Mathematical Methods of Operations Research*, 74(3), 281-310.

22. McCormack, R., & Coates, G. (2015). A simulation model to enable the optimization of ambulance fleet allocation and base station location for increased patient survival. *European Journal of Operational Research*, 247(1), 294-309.
23. Mosallaeipour, S., Nejad, M. G., Shavarani, S. M., & Nazerian, R. (2017). Mobile robot scheduling for cycle time optimization in flow-shop cells, a case study. *Production Engineering*, 1-12.
24. Overstreet, R. E., Hall, D., Hanna, J. B., & Kelly Rainer Jr, R. (2011). Research in humanitarian logistics. *Journal of Humanitarian Logistics and Supply Chain Management*, 1(2), 114-131.
25. Pinto, L. R., Silva, P. M. S., & Young, T. P. (2015). A generic method to develop simulation models for ambulance systems. *Simulation Modelling Practice and Theory*, 51, 170-183.
26. Rahmaniani, R., & Shafia, M. A. (2013). A study on maximum covering transportation network design with facility location under uncertainty. *Journal of Industrial and Production Engineering*, 30(2), 78-93.
27. Schmid, V., & Doerner, K. F. (2010). Ambulance location and relocation problems with time-dependent travel times. *European journal of operational research*, 207(3), 1293-1303.
28. Shavarani, S. M., Ghadiri Nejad, M., Rismanchian, F., & Izbirak, G. (2017). Application of hierarchical facility location problem for optimization of a drone delivery system: a case study of Amazon prime air in the city of San Francisco. *The International Journal of Advanced Manufacturing Technology*, 1-13.
29. Sullivent, E. E., Faul, M., & Wald, M. M. (2011). Reduced mortality in injured adults transported by helicopter emergency medical services. *Prehospital Emergency Care*, 15(3), 295-302.
30. Thomas, S. H. (2007). Helicopter EMS transport outcomes literature: annotated review of articles published 2004-2006. *Prehospital Emergency Care*, 11(4), 477-488.
31. Wisborg, T., & Bjerkan, B. (2014). Air ambulance nurses as expert supplement to local emergency services. *Air medical journal*, 33(1), 40-43.