Minimization of Emergency Response Time by Incorporating Aerial Transportation

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ABSTRACT

In this thesis, we deal with two different real-life medical emergency service problems. In these problems, we consider a city in which the locations of all the hospitals, medical service centers, and the other emergency care centers are known. In both problems the emergency services are deployed using aerial and ground vehicles 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 the severity accidents which need aerial vehicles and normal accidents which are operated by ground vehicles. According to the average number of the accidents in each location (node) and the severity of the accident, a weight is assigned to each node. In the first problem, we assume that the ground emergency services are optimal and we just deal with assigning a given number of the aerial vehicles to the hospitals or the medical care centers for the severity accidents or emergency medical demands in a way that the total response time by the aerial vehicles is minimized. In another words, this type of the demands for ground and aerial services are different in this type of the problem.

In the second problem, we are dealing with both ground and aerial medical services together and at the same time. As the number of the accidents or the demands for both ground and aerial services are known and separate. In this type of the problem we are aiming to assign a given number of the aerial and ground vehicles to the hospitals or the medical care centers in a way that the total response time by all the aerial and ground vehicles is minimized.

Keywords: Response time, Aerial transportation, Emergency service, Genetic Algorithm.

ÖZ

Bu tezde, iki değişik sıhhi acil servis problemi incelenmiştir. Bu problemlerde bahis konusu şehirdeki tüm hastane, sıhhi servis merkezleri ile diğer acil yardım merkezlerinin bulundukları mahallerin bilindiği varsayılmıştır. Her iki problemlerde de acil servis için telefonla talep alınmasını takiben hava veya kara ambulansının atanması ile başlayan süreç, olay mahallinde verilen ilk yardımı takiben hastanın hastane veya diğer bir sıhhi bakım merkezine naklini içerir. Bu gayeyle, talepler olayın ciddiyetine göre iki guruba ayrılarak, çok acil vakalara hava ambulansı, çok acil olmayan durumlarda ise kara ambulansı ataması yapılır. Şehirde ki her bölgeye (düğüm noktasına) o bölgedeki ortalama olay sıklığı ve çok acil olay sıklığı sayıları ile orantılı kat sayı ataması yapılmıştır.

İlk problem tipinde, kara ambulans sisteminin en iyi şekilde çalıştığı varsayılarak, sadece hava ambulanslarının, hastane (veya sıhhi bakım merkezlerine), çok acil olaylara en kısa toplam zamanda hizmet sağlayacak şekilde atanmasına çalışılmıştır.

İkinci problem tipinde, çok acil ve normal servis taleplerinin sayılarının bilindiği varsayılarak, hem kara hem de hava ambulanslarının aynı zamanda ve birlikte en az toplam talep zamanını sağlayacak şekilde atanmasına çalışılmıştır.

Anahtar kelimeler: Cevap süresi (tepki süresi), Hava taşıması, Acil servis, Genetik algoritma.

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DEDICATION

I would like to dedicate this to my lovely parents, without where early inspiration and coaching none of this would have happened. I hope that this achievement will continue the dream you had for me so many years ago when you chose to give me the best education you could.

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INTRODUCTION

1.1 Preface

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. Technology also boosts health indicators in the community, such as increasing longevity, the eradication of many pandemic diseases and etc. One of the important issues that governments and health managers are involved with is the issue of hardware resources limitations such as ambulances, health centers, medical supplies, and so on. Since in this area it is not possible to consider financial issues because the health of humans is the first priority, therefore it requires management and planning in detail. The operations research technics have a significant role to deal with these issues including allocating resources, planning, scheduling and etc.

On the other hand, in real life there are many events that may have serious effects on human lives. These events can happen due to casual events such as accident; heart attack or other serious diseases, and disasters (such as Tsunami in Indian Ocean (in 2004), Hurricane Katrina (in 2005)) and etc. On the other hand, they can happen deliberately due to fights among people or wars between countries. Each of them causes injuries and deaths. From the engineering point of view, the reason of happening of such events does not matter, but the important thing is to rescue the affected people in shortest times possible based on a schedule.

1.2 Problem statement

Medical service managers in the majority of countries follow two goals generally: Prevention and treatment. Generally, in medical care systems, focus is on providing a level of service, and providing appropriate service levels is one of the most important concerns in this area. One of the major concerns in the field of medical services is the emergency medical service management. 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 center or the hospital. The patient's transportation involves a multi-stage process that starts when the emergency call is received and ends when the patients are delivered to the hospital or suitable treatment centers, in which the transportation of the patients are not the stages of treatment, but they can be one of the key areas in the treatment (Chin et al., 2017). All the discussed issues, including equipment and modeling and placement of ambulances, are designed to be provided at the right time for services.

1.3 Importance of the study

One of the most important services related to healthcare is emergency medical service (EMS). This service has a significant role to save the humans’ lives and also, it is effective in decreasing the deaths and mortality (Aringhieri, Bruni, Khodaparasti, & van Essen, 2017). Therefore in the recent decades, this topic attracted the attentions of the operations research scientists. Having no or the least delays in transporting of patients, or delivery and supplying the first aids to the patient in emergency cases are essential. Generally, the aim of any emergency system is saving lives and reduce fatality inclusive of reaching to the patient in the shortest time, deploying first aids and rescuing tasks, and transporting the patient to the closest and suitable hospital. It is obvious that sometimes it is needed to transport the patient to the nearest special treatment centers such as burn treatment centers.

The design of emergency medical service systems includes several strategies, including the determination of the number and location of ambulance stations, the determination of the number and location of helicopters, and the designation of a system for the dispatch of vehicles. Another aspect of the problem of locating emergency facilities 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 to a hospital or a treatment center, the equipment that the operators have access to, and so on. 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 major part of the response time. Another aspect of the timing of the vehicle itself is the speed of the vehicle, and the traffic congestion of the route which the vehicle is using. Therefore, the traffic flow also plays an important role in the time of the journey and the response time and can have effect on the quality of the provided service. Considering the dependence between traffic flow and the quality of service is very important and makes this issue more compatible with the real world.

1.4 Problem approaches

Emergency facility finding issues or emergency facilities location problems refer to a category of location issues in which the location of the optimal emergency services facility is determined by taking into account certain limitations such as budget constraints, in order to maximize the level of service coverage to applicants. In terms of coverage, location issues can be categorized into two categories, including Set covering location problems (SCLP) and Maximum Coverage Location Problems (MCLP) issues. From the perspective of congestion and demand congestion, emergency location issues are classified into two categories, including emergency facility location issues, with queuing theory and location-based issues of reliability based on emergency facilities. In queuing problems with the queuing theory approach, the problem is considered in the form of a queuing system, and the focus is on determining the number of stations in such a way that the created queue does not exceed the capacity of the system, the servants, and the customers who are waiting for receiving the services. On the other hand, location-based reliability, focuses on the reliability of the system, and maximizes the availability of emergency service at the stations, followed by the service provider's system. To focus on reliability, uncertainty is taken into account at the time of the response and also the availability of vehicles, such that the vehicle's travel time from the relevant station to the service location is determined by the traffic density of the route and the response times are probable in the modeling. Also, by defining the percentage of busy servers, the crowding of demand is considered in modeling the problem. In the context of the investigation, the demand producers and a number of stations are considered as service providers. Each facility, in the event of receiving a request for service from the covered area, dispatches a servant to the customer's location, depending on the type specified for the request, if the vehicle is in the relevant facility. The objective of these problems is to determine the optimal location of the facility, in order to maximize the number of answered emergency calls within time less than the standard time. If the response time for a demand is more than three times the standard time, then request is considered as a lost demand.

There are many different topics related to emergency transportation and medical services in the literature. These topics can be classified as allocation problems (Almehdawe, Jewkes, & He, 2016), redeployment problems (Benabdouallah, Bojji, & El Yaakoubi, 2016), locating EMS problems (Moeini, Jemai, & Sahin, 2015), set covering problems (Stanimirović, Mišković, Trifunović, & Veljović, 2017), ambulance response time problems (McMonagle, Flabouris, Parr, & Sugrue, 2007), dispatching and routing problems (Coppi, Detti, & Raffaelli, 2013) and etc. It is obvious that the real emergency service problems usually include some of these mentioned problem topics, simultaneously.

On the other hand, there are many different approaches to deal with these problems such as developing mathematical models including integer programming models (Degel, Wiesche, Rachuba, & Werners, 2015), dynamic programming models (Van Barneveld, Bhulai, & Van der Mei, 2017) and etc. Additionally, proposing heuristic and metaheuristic algorithms, such as genetic algorithm (Fogue et al., 2016), local search algorithm (Talarico, Meisel, & Sörensen, 2015), Tabu-search algorithm (Adenso-Diaz & Rodriguez, 1997), ant colony optimization (Javidenah, Ataee, & Alesheikh, 2010) and etc, to solve such problems is usual since these types of the problems belong to the NP-hard family of the problems.

1.5 The purpose of the thesis

In this thesis, an optimization problem with the aim of minimizing the total response time to the emergency patients is considered. The response time to the patients is defined as the duration time between the time of calling to the emergency service such as hospitals or emergency service centers, and the time that the aerial or ground vehicle reach to their locations after completing their mission. In this problem, a city is considered as a case study. The locations of the hospitals of the city are specified. The number of available aerial and ground vehicles to be assigned to the hospitals is distinguished for emergency medical services. The mathematical formulations to find the best place(s) to deploy the aerial and ground vehicles is represented, and all the necessary assumptions and definitions are discussed in details. Moreover, since this problem belongs to the NP-hard family of the problems, a metaheuristic algorithm based on a genetic algorithm is presented. The performance of the proposed genetic algorithm is examined on various problem instances and discussed.

1.6 The structure of the thesis

This thesis is organized as follows: In chapter 2, we present literature review related to the emergency medical services and aerial and ground service systems in different classifications in details. In chapter 3, the definitions and notations related to the considered problems of this thesis are explained completely. Additionally, in this chapter the mathematical models are presented and explained. Chapter 4 focuses on developing the metaheuristic algorithms for the considered problems in detail. Chapter 5 presents the numerical results of the proposed metaheuristic algorithms. Finally, chapter 6 presents the conclusion and future research proposals on the topic.

Chapter 2

LITERATURE REVIEW

2.1 Preface

There are various problems related to emergency services. In a real-time context, EMS managers are dealing with two main problems such as an allocation problem and a redeployment problem. The allocation problem is related to determining which ambulance from which hospital should be sent after receiving emergency calls, and the redeployment problem is related to sending/relocating an available ambulance to the site in which the emergency calls are received (Gendreau, Laporte, & Semet, 2001). This relocating activity is performed for having a proper coverage in the potential sites.

In the literature, many researches have been performed on the locating EMS problems and a number of studies were done as review articles. Based on the review articles of Brotcorne *et al*. and Rvelle *et al*., EMS locating problems have been classified as deterministic models, probabilistic models, and dynamic models (Brotcorne, Laporte, & Semet, 2003; ReVelle, Bigman, Schilling, Cohon, & Church, 1977) (See Figure 1).

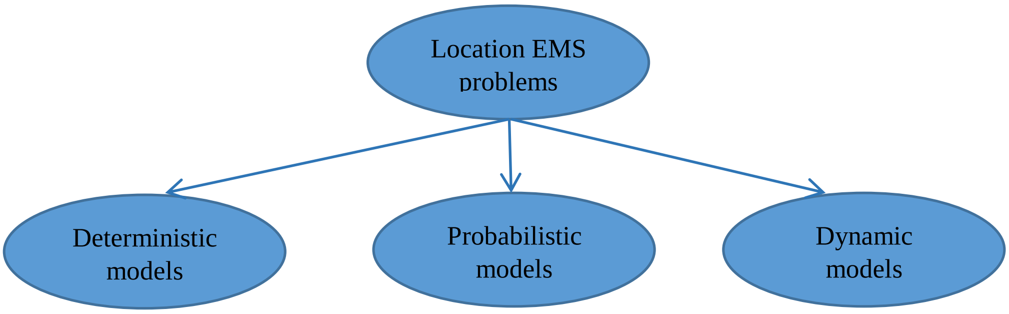

Figure 1. Classification of locating EMS problems

In another review article, all the studied models related to deployment of EMS vehicles have been mentioned (Li, Zhao, Zhu, & Wyatt, 2011). In the last review article, Baser *et al.* taxonomically classified the EMS problems in three groups as: type of problems, modeling problems, and their methodologies (Başar, Çatay, & Ünlüyurt, 2012) (See Figure 2).

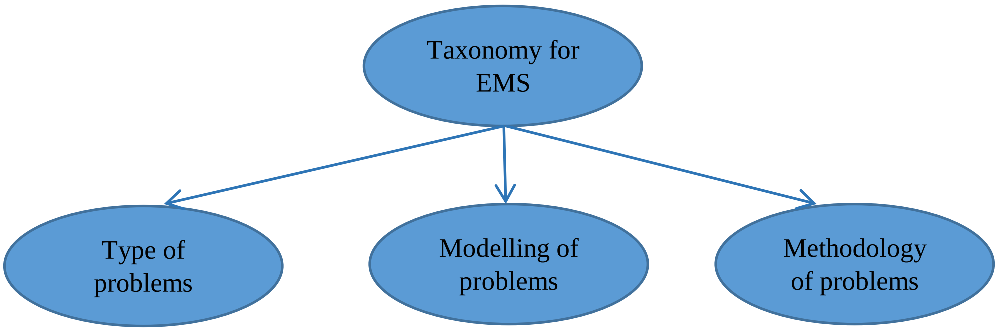

Figure 2. Taxonomic classification of EMS problems

They also continued their classification in details. They divided the type of EMS problems to the structure of the model (deterministic or stochastic), their time variations (static or dynamic), and the number of their objectives. They categorized the modelling of the problems based on divergent in their objective functions, their parameters and the type of their mathematical formulations such as integer, non-linear, etc. and the methodology of the problems classified as exact solution methods, heuristics, metaheuristics, and simulation.

Aringhieri *et al.* (Aringhieri et al., 2017) studied an EMS based on the emergency care pathway (ECP). They mentioned that there are many decision problems from the management of EMS point of view in which getting decision for any of them will affect the other decisions or steps of the ECP. Figure 3 illustrates an ECP that contains five key steps. By receiving an emergency call/request, the ECP begins. Then, the level of urgency should be determined and an ambulance must be transmitted. After the ambulance reaches to the location, the first aids will be performed and the patient will be transported to a hospital and the ECP will be ended at that time. There are some significant problems have been shown in Figure 3. As it mentioned before, the allocation problem is related to determining which ambulance must be sent to the location, after receiving an emergency call and the relocation problem is sending an available ambulance to the site as the coverage. Moreover, the manager of the ambulance fleet must get decision about the dispatching and routing of ambulances. The forth problem is related to the National Health Service (NHS) in which the EMS should be considered as an entry point on NHS that contributes to emergency department overcrowding. Additionally, the workload, emergency demand and transportation times should be forecasted, and the resources such as labors, medical doctors, vehicles, etc. must be hired, trained, managed and organized.

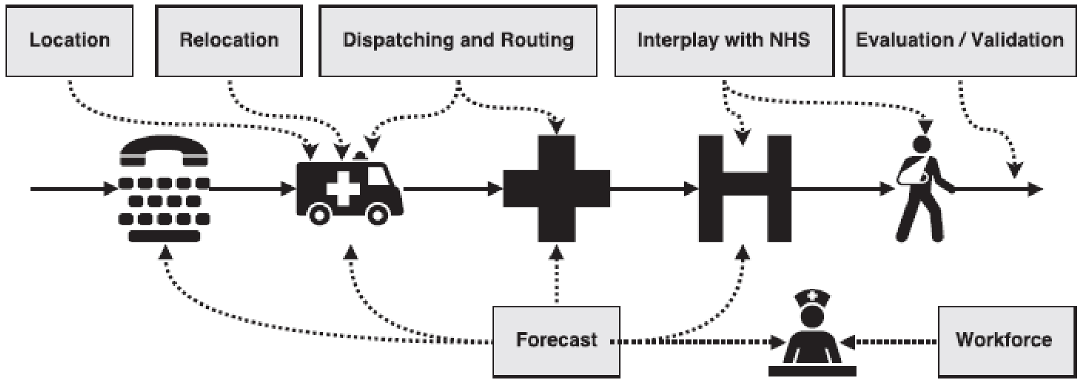

Figure 3. Emergency care pathway and its related problems

Pinto *et al*. (Pinto, Silva, & Young, 2015) constructed a reusable model that explain the working system of the ambulances. They proposed the following figure with mentioning the mile stones of decision making in the ambulance working system (See Figure 4).

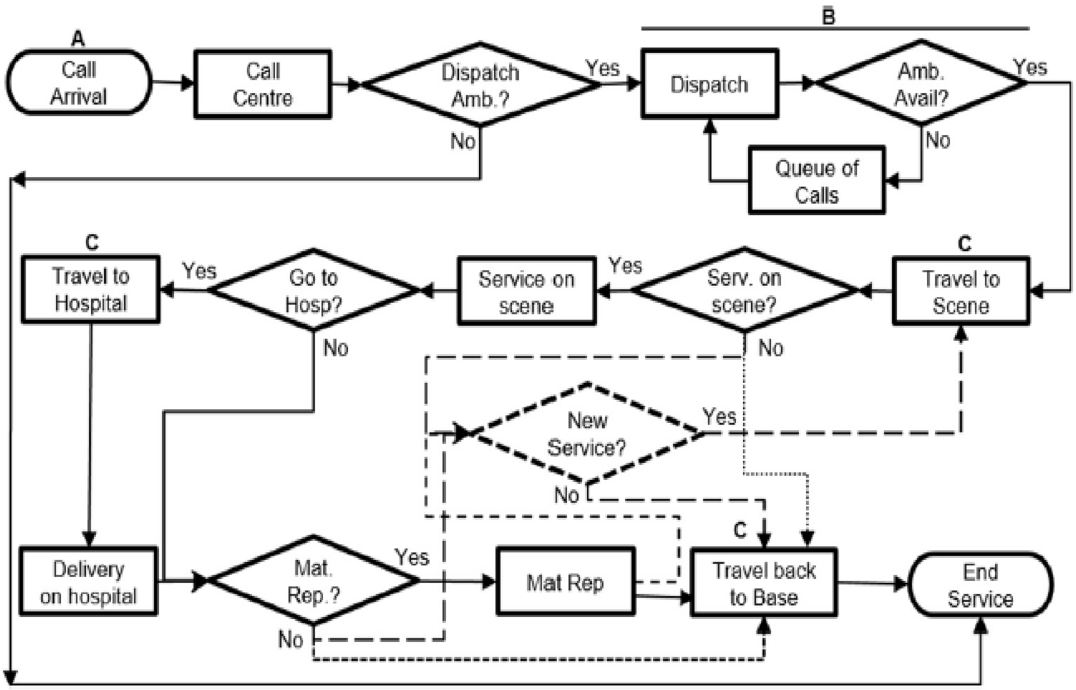

Figure 4. Model of ambulance working system

The solid line show the dispatching of the ambulance and the dashed lines are for the situations that the dispatching of ambulance is not certain. The authors explained the concepts of their model in Figure 5 and illustrated that how they simulate the proposed model where the main aim in that research was calculation the response time. They used this model in Belo Horizonte, a city of Brazil, as real case to show the advantages of the reusability, and also they applied it to model the UK ambulance system.

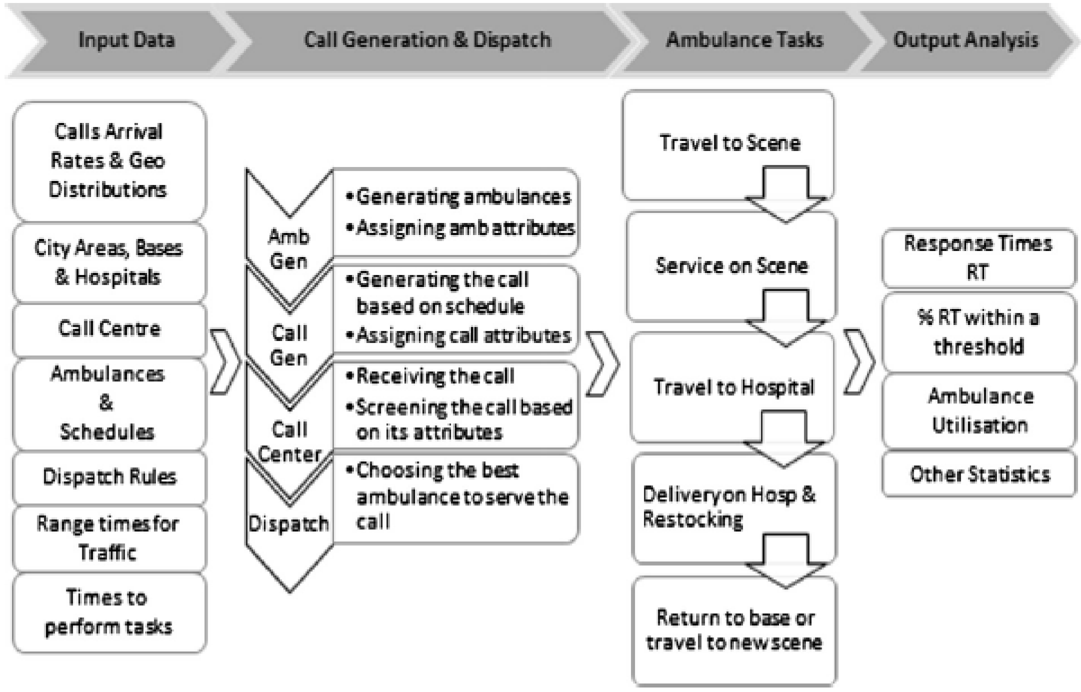

Figure 5. Description of the model structure

2.2 Allocation of ambulances

Relief logistics is related to planning, managing and controlling of relief resources that are utilized for patients and injured people. Its aim is finding the best possible relief services considering available resources (Overstreet, Hall, Hanna, & Kelly Rainer Jr, 2011). Performance of EMS can be calculated based on the time required to respond patient or based on the overall cost of the logistics (Rahmaniani & Shafia, 2013). McCormack and Coates (McCormack & 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 groups that need different classes of service. Their aim was trying to maximize the probability of survival of the patients in different classes. They examined their proposed model on the real case of London ambulance services. They considered the EMS vehicle dispatch and service as it is shown in Figure 6.

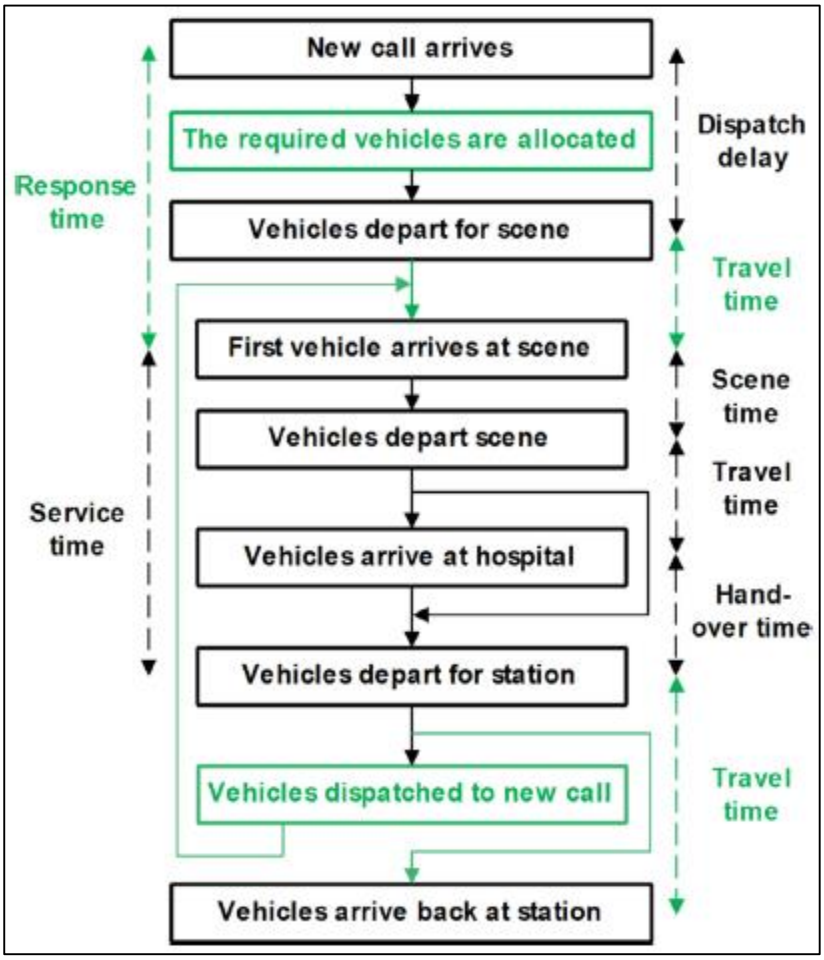

Figure 6. The EMS vehicle dispatch and service process

According to their model, when a new call arrives, a suitable vehicle must be allocated. Then the vehicle moves towards the location. They defined the response time from receiving a call to the vehicle reach to the location. Then, the vehicle comes back from the location to the hospital and after that, it goes to its station. They also define the service time from arriving to the location to the time that the vehicle reaches to its station. From the figure it is obvious that they considered travel times, scene time which is the time from arriving the vehicle to the location and departing the location, and hand over time which is the time from departing from the hospital to the station. Babaei and Shahanaghi developed an algorithm to facilitate decision making in this area (See Figure 7) (Babaei & Shahanaghi, 2017).

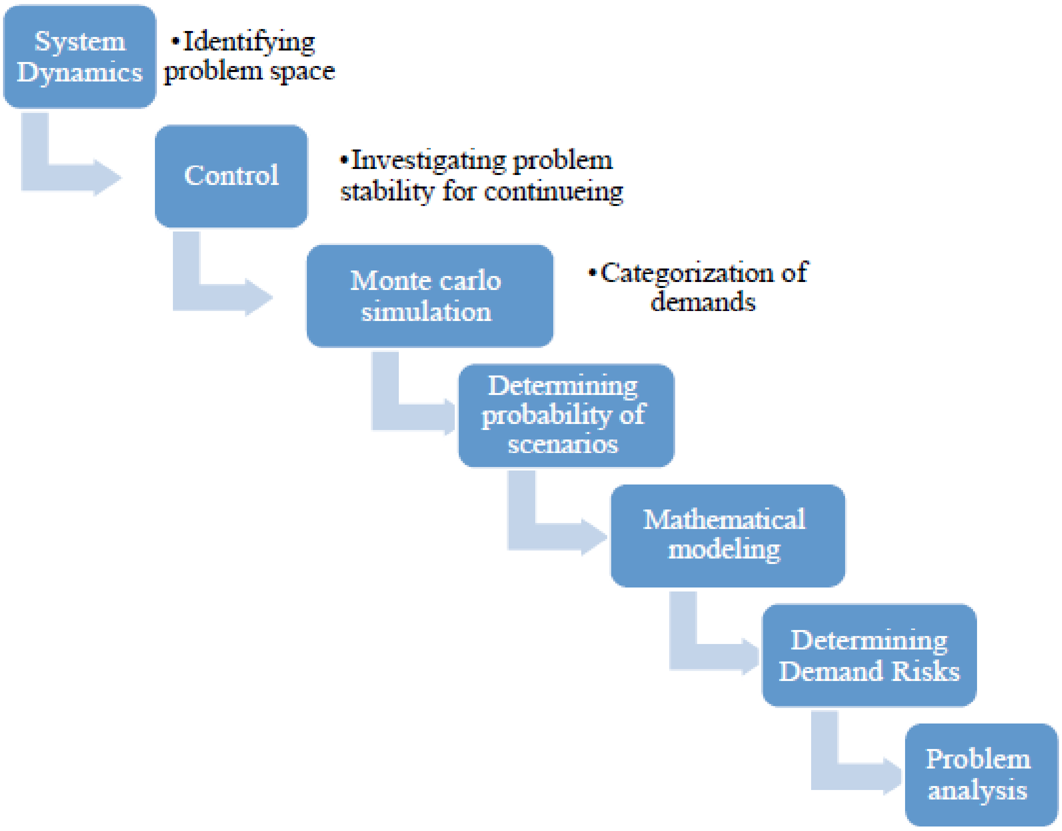

Figure 7. Relief logistics decision making algorithm

2.3 Set covering location problems

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 constructing the facilities is minimized. In another words, 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 (Schmid & 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.* (Ahmadi-Javid, Seyedi, & Syam, 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 (See Figure 8).

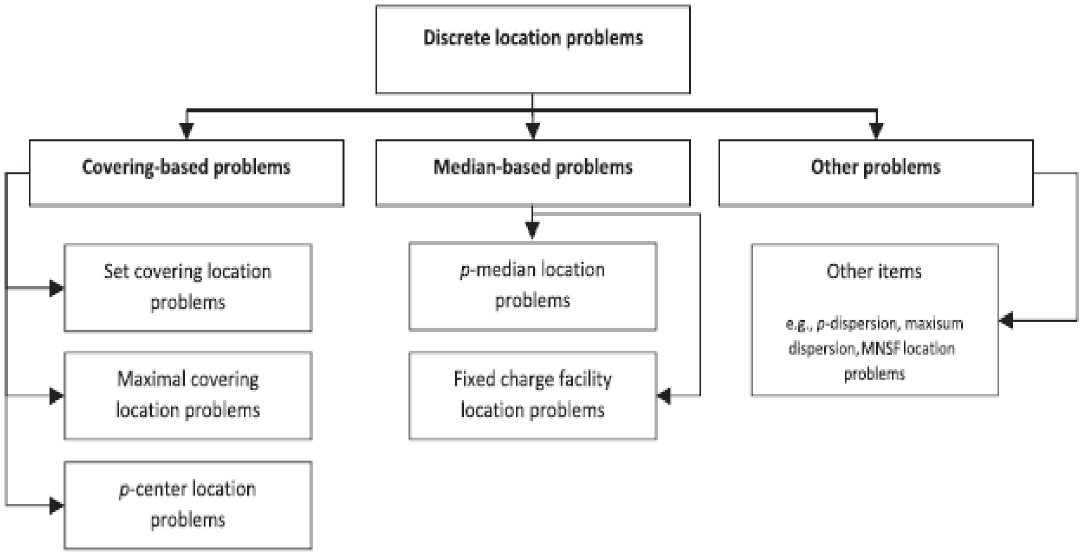

Figure 8. A classification of discrete location problems

2.4 Ambulance response time

Lam et al. (Lam et al., 2015) dealt with the response time of the ambulance and considered the risk factors that can make delays on this time. Based on the real data about the incidents in Singapore, they proposed their model as follows (See Figure 9). According to the model, they defined the time 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.

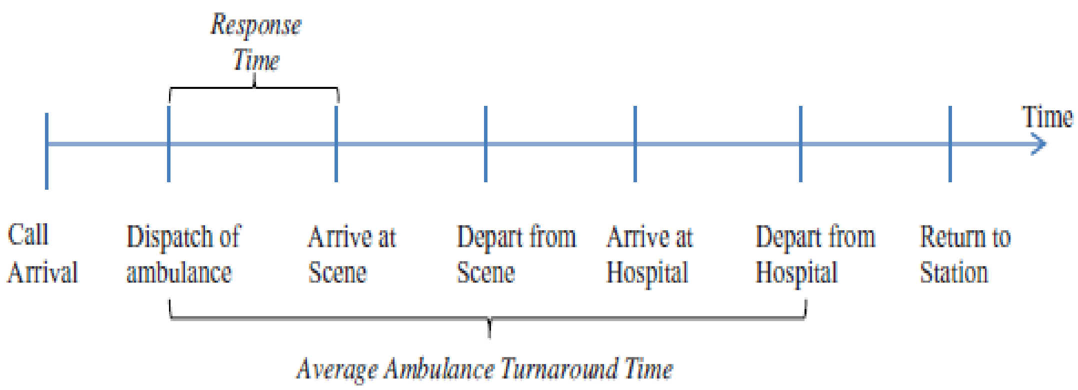

Figure 9. Time delays in EMS response

In another study, Knyazkov et al. (Knyazkov, Derevitsky, Mednikov, & Yakovlev, 2015) considered that the transportation time to a hospital has a very important role in 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 flow of the traffic, 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. Figure 10 shows their considered model.

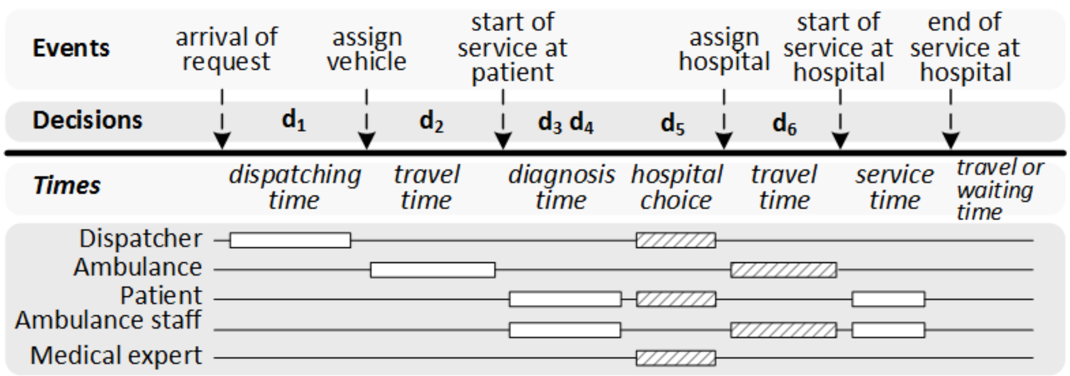

Figure 10. Scheme of EMS operation

2.5 Dispatching and routing policies

In the case of ambulance routing, Javidaneh *et al*. (Javidenah 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*. (Ardekani, Haight, Ingolfsson, Salama, & Stanton, 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 transportations, and to accommodate the emergency transportations in real time. After that, Talarico *et al*. (Talarico et al., 2015) considered a disaster scenario and model it as the process of disaster response which is shown in Figure 11. In their study, they focused on servicing and transporting a huge number of injured people to hospitals. In that study, the patients have been classified into two different groups. The group of patients with slight injuries that can be helped in their locations and the other group of patients that is necessary to carried out to hospital. They developed two mathematical formulations to minimize the latest service completion time and also proposed a metaheuristic algorithm based on the neighborhood search method.

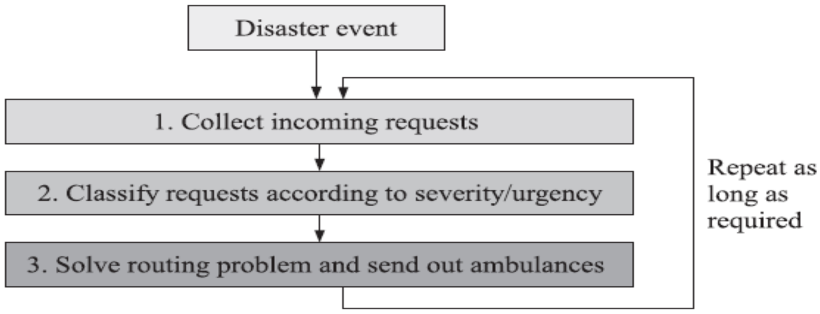

Figure 11. Disaster response process

2.6 Helicopter emergency medical service (HEMS)

In recent decades, the medical emergency service by using helicopters is a well-known 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*. (Sullivent, Faul, & Wald, 2011) studied different transportations of the injured people such as ground transportation by ambulances and air transportations by helicopter. They compared the effectiveness of these two types of transportations on mortality of the patients. They controlled age, gender and severity of injuries and found that deaths are 39% lower in transportation 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* published another review article about this topic for all the publications from 2007 to 2011 (Brown et al., 2012). Wisborg and Bjerkan (Wisborg & Bjerkan, 2014) studied the National Air Ambulance Service in Norway where their service areas are very far from hospitals, The authors studied the six-year transportation data by this air ambulance service which was about 217 flights, 3 per month in average. Fattah *et al*. (Fattah et al., 2016) by using a Delphi study, prepared a specific template for major incidents of HEMS which is available at "www.majorincidentreporting.net" website, presently.

Diaz *et al*. (Diaz, Hendey, & Bivins, 2005) performed one of the pioneer studies to compare 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 (Galvagno, 2013) performed comparison study between the ground and air transportation of trauma patients by using the technique of multivariable regression. He proposed important parameters for survival by using helicopter transportations. His proposed parameters are crew of the flights, severity of the trauma, speed of the helicopter and other service activities and accessibility to hospitals or trauma centers as they are shown in Figure 12. In this figure, HRQoL stands for Health Related Quality of Life.

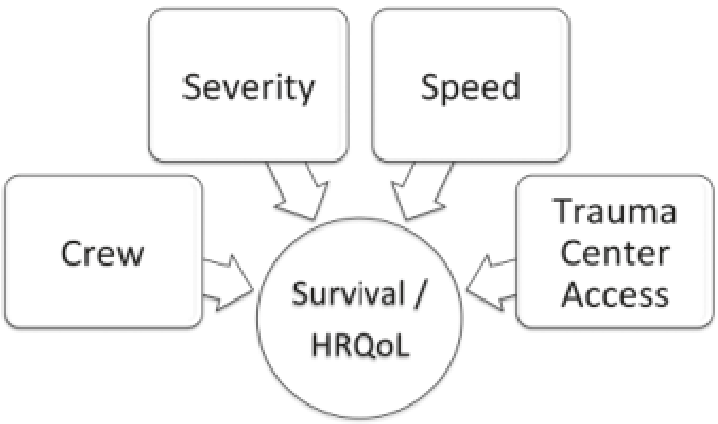

Figure 12. Effective parameters on survival by HEMS

Similar to the previous study, Abe *et al*. (Abe, Takahashi, Saitoh, & Tokuda, 2014) researched on 2090 and 22203 patients who were transported by helicopter and ambulance to hospitals in Japan, respectively. According to their reports, 546 patients (26.1%) died when they wanted to be transport by helicopter and 5765 patients died by using ambulance 26.0%. They concluded that considering time, costs, limited recourses and etc. transportation of trauma patients by helicopter is more effective than the ground transportations.

Chapter 3

PROBLEM DEFINITION AND FORMULATION

3.1 Preface

In this chapter, we deal with two different real-life medical emergency service problems. In these problems we consider a city in which the locations of all the hospitals, medical service centers, and the other emergency care centers are known. In both problems the emergency services are deployed using aerial and ground vehicles for going to the location of patients after receiving a call, performing the initial emergency medical care, and transporting the patients to the hospitals or other medical care facilities. For this purpose, the accidents or demands are classified into two types based on severity and for sever accidents aerial vehicles used and others several by ground vehicles. According to the average number of the accidents in each location (node) and the severity of the accident, a weight is assigned to each node.

In the first problem, we assume that the ground emergency services is optimal and we just deal with assigning a given number of the aerial vehicles to the hospitals or the medical care centers for the sever accidents or emergency medical demands in a way that the total response time by the aerial vehicles become minimized. In another words, this type of the demands for ground and aerial services are different in this type of the problem.

In the second problem, both the ground and the aerial medical services are considered together and at the same time. The number of the accidents or the demands for both ground and aerial services are known and separate. In this type of the problem the aim is to assign a given number of the aerial and ground vehicles to the hospitals or the medical care centers in a way that the total response time by all the aerial and ground vehicles minimized as a whole.

It is assumed that the speed of the helicopters and ambulances are fixed. Additionally, the time of transportations between origins/sources and destinations/sinks are considered as a function of the distance between them. Therefore, the aim is minimizing the total response time to the patients. It should be mentioned that the conditions of assigning the nodes of the accidents or demands to the hospitals in the case of serious injuries, should be within an acceptable time period. Likewise, some of the existing locations should be equipped by aerial and ground vehicles. The frequency of accidents and the severity of them can be obtained by the study of accident records in related organizations. Euclidean distances are used for the aerial vehicles.

3.2 The first problem: optimizing aerial traveled distance

As it is mentioned in section 3.1, in the first problem of this thesis, the ground emergency services are not considered. Therefore, the assignment of only aerial vehicles to the hospitals is determined to minimize the total traveling distance by the aerial vehicles. The decision variables and parameters to formulate this problem are the following:

j, j': $index\ of\ hospital$

$i: index\ of\ nodes$

$$H_j = \begin{cases} 1\ if\ an\ aerial\ vehicle\ is\ assigned\ to\ hospital\ j \\ 0\ otherwise \end{cases}$$

$$x_{ij} = \begin{cases} 1\ if\ node\ i\ is\ assigned\ to\ hospital\ j \\ 0\ otherwise \end{cases}$$

$d_{ij} = distance\ between\ node\ i\ and\ hospital\ j$

$w_i = weight\ of\ node\ i$

$M: A\ large\ positive\ number$

$n: available\ number\ of\ aerial\ vehicles$

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

$$Min \sum_i \sum_j w_i d_{ij} x_{ij} \tag{1}$$

$subject\ to$:

$$\sum_j H_j = n \tag{2}$$

$$d_{ij'} x_{ij'} H_{j'} \leq d_{ij} H_j + (1 - H_j) M \qquad \forall j, \forall j', \forall i \tag{3}$$

$$x_{ij} \leq Hj \qquad \forall j, \forall i \tag{4}$$

$$\sum_{j} x_{ij} = 1 \qquad \forall\, i \qquad (5)$$

$$x_{ij}, H_j \in \{0,1\} \qquad \forall j, \forall i \qquad (6)$$

The objective function minimizes the total distance travelled by aerial vehicles. The weights of the nodes in this function helps to consider the shorter distances for those nodes that have larger average number of the accidents and/or more severe accident. Constraint (2) shows that the total number of the available aerial vehicles are limited to n. Constraints (3) assigns each node to its nearest hospital with an aerial vehicle. Constraint (4) ensures that each node is only assigned to a hospital with an aerial vehicle. By constraint (5) only one hospital is assigned to each node. Finally, the last constraint is related to the decision variables that are binary and cannot get any other value except zero or one.

3.3 The second problem: optimizing total ground and aerial traveled distance

As it mentioned in section 3.1, in this problem the both ground and aerial emergency services are considered together. It means a limited number of aerial and ground vehicles are assigned to the locations of hospitals for the both normal and sever emergency medical demands respectively, aiming to minimize the total of aggregate response time. The total number of the aerial and ground vehicles is less than the number of the hospitals, and the number of the aerial vehicles is significantly less than the number of the ground vehicles. In this case, there are a set of nodes that each of them has a probability of accident. The time to respond an accident should be less than the time limit of T. The aerial vehicles do not serve a node if the distance between the node and the corresponding hospital is less than the distance limit of L. The decision variables and parameters to formulate this problem are the following:

$j, j': index\ of\ hospital$

$i: index\ of\ nodes$

$$x_{ij} = \begin{cases} 1\ if\ the\ demand\ on\ node\ i\ is\ assigned\ to\ the\ aerial\ vehicles\ in\ hospital\ j \\ 0\ otherwise \end{cases}$$

$$y_{ij} = \begin{cases} 1\ if\ the\ demand\ on\ node\ i\ is\ assigned\ to\ the\ ground\ vehicles\ in\ hospital\ j \\ 0\ otherwise \end{cases}$$

$$h_j = \begin{cases} 1\ if\ an\ aerial\ vehicle\ is\ assigned\ to\ hospital\ j \\ 0\ otherwise \end{cases}$$

$$a_j = \begin{cases} 1\ if\ at\ most\ one\ ground\ vehicle\ is\ assigned\ to\ hospital\ j \\ 0\ otherwise \end{cases}$$

$p_i: the\ probability\ of\ accidents\ in\ node\ i$

$L: distance\ limit$

$T: time\ limit$

$n: number\ of\ hospitals\ to\ be\ equipped\ with\ aerial\ vehicles$

$m: The\ maximum\ number\ of\ hospitals\ to\ be\ equipped\ with\ ground\ vehicles$

$t_{ij} = time\ between\ node\ i\ and\ hospital\ j$

$e_{ij} = time\ to\ pass\ the\ euclidean\ distance\ between\ node\ i\ and\ hospital\ j$

$d_{ij} = time\ to\ pass\ the\ ground\ distance\ between\ \ node\ i\ and\ hospital\ j$

M: $A\ large\ positive\ number$

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

$$Min \sum_i \sum_j \left(p_i t_{ij}\right) \tag{7}$$

$subject\ to$:

$$\sum_j h_j \leq n \tag{8}$$

$$\sum_j a_j \leq m \tag{9}$$

$$t_{ij} \geq a_j y_{ij} d_{ij} + \ h_j x_{ij} e_{ij} \qquad \forall i, \forall j \tag{10}$$

$$\sum_{j'} x_{ij'}\, e_{ij'} \leq e_{ij} + \left(1 - h_j\right)M \qquad \forall j, \forall j', \forall i \tag{11}$$

$$\sum_{j'} y_{ij'}\, d_{ij'} \leq d_{ij} + \left(1 - a_j\right)M \qquad \forall j, \forall j', \forall i \tag{12}$$

$$x_{ij} \leq h_j \qquad \forall j, \forall i \tag{13}$$

$$y_{ij} \leq a_j \qquad \forall j, \forall i \qquad (14)$$

$$t_{ij} < T \qquad \forall\, i, j \qquad (15)$$

$$\sum_j (x_{ij} + y_{ij}) = 1 \qquad \forall\, i \qquad (16)$$

$$x_{ij} = 0 \qquad \forall\, i, j | e_{ij} < L \qquad (17)$$

$$h_{ij}, a_{ij}, x_{ij}, y_{ij} \in \{0,1\} \qquad \forall j, \forall i \qquad (18)$$

The objective function minimizes the total time travelled by aerial and ground vehicles. Constraint (8) shows that the total number of the available aerial vehicles is limited to n. Constraint (9) indicates that the total number of the available ground vehicles is limited to m. Constraints (10) defines distance that should be travelled to service node i from hospital j. Constraint (11)-(12) guarantee that the demand on each node receives its services from the nearest facility. Constraints (13)-(14) guarantee that the demand is assigned to a facility with required resources. Constraint (15) guarantees that the response time must be less than the predetermined duration T. Constraints (16) guarantee that each demand is assigned to only one hospital. Constraint (17) guarantees that the aerial vehicles do not serve a node if the distance between the node and the corresponding hospital is less than the distance limit. Finally, Constraint (18) indicates the binary variables used in the proposed mathematical formulation.

3.4 The genetic algorithm

To solve the considered problems by using the proposed mathematical models, it is obvius that since the problems belong to the non-polynomial hard (NP-hard) family of the problems, the solution time rises exponentially (Mosallaeipour et al., 2018, Ghadiri Nejad et al. 2017a). In other words, in these problems when the number of nodes and vehicles 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 becomes larger.

In the recent decades, genetic algorithm (GA) has been used to solve a broad range of optimization problems. The GA has a high solution performance to find a good and feasible result in a short time. This method has been used for solving different problems such as humanitarian relief (Golabi et al., 2017), facility location (Shavarani, et al., 2017), production scheduling (Ghadiri Nejad et al., 2017c) and transportation (Michalewicz, Vignaux, & Hobbs, 1991). To solve the large-size problems in the considered problems in this thesis, the GA is utilized.

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). GA generally starts by generating a number of random initial solutions. These initial solutions are called the population of the solution. Thereafter, 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 to the considered stopping criteria. For each type of the problems in this thesis, a genetic algorithm is proposed. The details of the proposed genetic algorithms are given in the following:

3.4.1 Representation

Representation or encoding is the most important part of developing solutions (Ghadiri Nejad et al., 2017b). For each of the considered problems in this thesis, an especial representation is proposed which are is the follows:

3.4.1.1 The representation for the first problem

For the first problem considered in this thesis, each solution is represented by an array having n elements, where n is the number of available aerial vehicles. Each cell of the array indicates the index of a hospital to which an aerial vehicle is assigned. Figure 13 shows an instance of the solution encoding.

27	36	12	6	18	7	20

Figure 13. Representation a solution

Figure 13 shows that there are seven aerial vehicles available to be assigned to the hospitals, and each of the hospitals indicated by the location numbers 27, 36, 12, 6, 18, 7, and 20 must be enriched by an aerial vehicle.

3.4.1.2 The representation for the second problem

In this thesis, for the representation of the second problem, 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 aerial and ground vehicles, respectively. Each cell of the array indicates the index of a hospital to which an aerial vehicle or/and a ground vehicle is assigned. Figure 14 shows an instance of the solution encoding. A hospital may receive at most one aerial vehicle. Some indecies may be repeated from the first n cells into the last m cells, and vice versa but, there cannot be a repeated indices within the first n cell or within the last m cells.

n cells		m cells				
27	36	12	6	18	27	20

Figure 14. Representation a solution

Figure 14 shows that there are two and five number of aerial and ground vehicles available to be assigned to the hospitals, respectively, and each of the hospitals indicated by the location number of 27, 36 must be enriched by aerial vehicle each, and the hospitals which shown by the numbers of 12, 6, 18, 27, and 20 must be enriched by an ground vehicle each. Additionally, this figure depicts that the hospital depicted by number of 27 must be enriched by an aerial and a ground vehicle at the same time.

3.4.2 Initial solution

The initial solutions are a set of randomly generated solutions consist of non-repetitive indices of hospitals which are called the population of the algorithm. In this study, *100* solutions are generated initially for the both first and second considered problems.

3.4.3 Fitness function evaluation

The value of the fitness function for each solution is calculated considering the described formulations and given parameters. For each emergancy node, first the nearest ground vehicle is determined. If the response time is less than the determined time limit the ground vehicle would be assigned to that node, otherwise the nearest aerial vehicle is determined which should satisfy both time and distance limits. If the constraints are satisfied the aerial vehicle is assigned, if not a penalty function is applied, making the solution infeasible.

3.4.4 Neighborhood generating operators

Crossover and mutation are two of the well-known operators that are used to generate neighborhood solutions in the GAs. In this thesis two different crossover have been considered for the mentioned problems as the followings.

3.4.4.1 Crossover operator for the first problem

The crossover operator for the first considered problem in this thesis is a one-point-crossover operator which randomly decomposes the both initial solutions into two segments. Then, by keeping one segment from each solution, let say the left part, and merging it with the other part of the other solution, the right part, two different solutions are generated. A graphical representation of the crossover operation is shown in Figure 15.

Two existed solution

27	36	12	6	18	7	20
31	9	4	21	25	41	26

Two new generated solutions

27	36	12	21	25	41	26
31	9	4	6	18	7	20

Figure 15. A crossover example for the first problem

3.4.4.2 Crossover operator for the second problem

The crossover operator for the second considered problem in this thesis is a kind of two-point-crossover operator in a way that one point is randomly decompose the first *n* chromosomes of the both initial solutions into two segments, and the other point is randomly decompose the other *m* chromosomes of the both initial solutions into two segments. Then, the ceossovers are applied independently for each parts of the n and m cromosomes, separately. The changing of the chromosomes between two parents are similar to what was mentioned for the crossover of the first problem in the previous subsection. The graphical representation of the crossover operation for the second problem is shown in Figure 16.

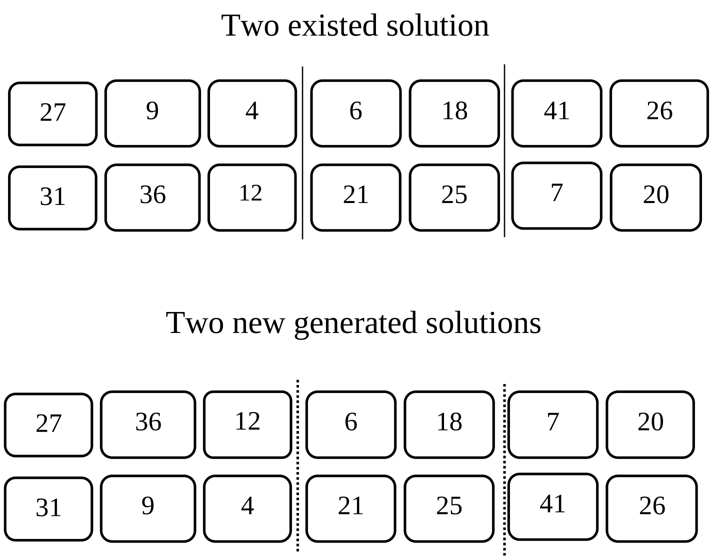

Figure 16. An example of the crossover operation

3.4.4.3 Mutation operator for the both problems

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 is absent in the solution. Figure 17 shows a mutation operator to generate of neighboring solutions for the first problem considered in this thesis. As it shown in this figure, there are two times assigning an aerial vehicle to the hospital depicted by number of 18. To solve this repetition, one of the genes including the hospital number of 18 must be changed. Therefore, by randomly selecting one of them, and a random generation of a new hospital number, like 11, the mutation operator is completed.

27	36	12	6	18	7	18	20	Parent Solution

27	36	12	6	11	7	18	20	Child Solution

Figure 17. Generation of neighboring solutions by mutation operator

It should be mentioned that the mutation operator for the second problem is operated similarly and by considering the repetition of the hospital numbers just in each of n or m genes of the chromosomes together.

3.4.5 Selection and stopping criteria

For the both first and second problems discussed in this thesis, after generating the offsprings by the crossover and mutation operators, and adding them to the population, the found solutions are sorted based on their fitness function values. 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 maximum number of iteration, maximum solution time and etc. can be used. In this thesis 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. Figures 18, represents the pseudo code of the proposed GA for the first problem mentioned in this thesis.

```
Initialize the GA parameter (n, Pop, Iter_max, P_c and P_m)
Generate initial solutions with genes size of n and population size of Pop
Check their feasibility and correct them if needed
Compute the fitness function value for the initial solutions
Iteration_no ← 0
while (Iteration_no < Iter_max) do
    for i = 1: (P_c * Pop)/2
        Select two parents from the population randomly
        Find a crossover point, randomly
        Generate two new solutions
        Check their feasibility and correct them if needed
        Compute their fitness function value
        Add them to the population
    End
    for j = 1: P_m * Pop
        Select one of the solutions, randomly from the population
        Perform the mutation
        Check their feasibility and correct them if needed
        Compute its fitness function value
        Add it to the population
    End
    Sort the solutions based on their fitness function values, increasingly
    Select the first Pop size solutions
    Update the population
    Iteration_no ← Iteration_no + 1
end while
Return the best solution;
```

Figure 18. The pseudo code of the proposed GA for the first problem

Similar to Figures 18, Figure 19 represents the pseudo code of the proposed GA for the second problem mentioned in this thesis.

```
Initialize the GA parameter (n, m, Pop, Iter_max, P_c and P_m)
Generate initial solutions with genes size of n and m, and population size of Pop
Check their feasibility and correct them if needed
Compute the fitness function value for the initial solutions
Iteration_no ← 0
while (Iteration_no < Iter_max) do
    for i = 1: (P_c* Pop)/2
        Select two parents from the population randomly
        Find a crossover point, randomly
        Generate two new solutions
        Check their feasibility and correct them if needed
        Compute their fitness function value
        Add them to the population
    End
    for j = 1: P_m* Pop
        Select one of the solutions, randomly from the population
        Perform the mutation
        Check their feasibility and correct them if needed
        Compute its fitness function value
        Add it to the population
    End
    Sort the solutions based on their fitness function values, ascending order
    Select the first Pop size solutions
    Update the population
    Iteration_no ← Iteration_no + 1
end while
Return the best solution;
```

Figure 19. The pseudo code of the proposed GA for the second problem

Chapter 4

COMPUTATIONAL RESULTS

4.1 Preface

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

4.2 The case study

For the case study of this thesis, a network of 1000 nodes showing the location of the accidents or medical care demands, and 50 hospitals is generated using MATLAB software. In the generated network, the nodes of accidents are illustrated with blue and candidate hospital locations are depicted by red asterisks. The number of available aerial vehicles to be assigned to the hospitals or medical care centers is equal to 20 solely for the first problem, and the same number of the aerial vehicles and also 30 number of ground vehicles are considered for the case that is solved by the second problem. The network is displayed in Figure 20, is used for the both first and second problem. 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.

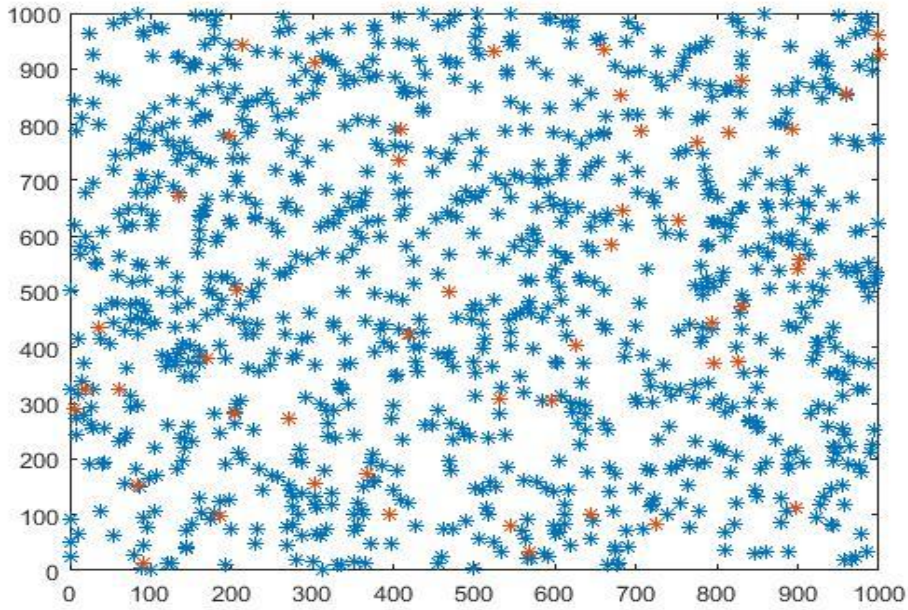

Figure 20. The generated network by MATLAB

In the following, Table 1 shows the candidate locations for the hospitals where the first column is related to the location number and x and y show the coordinated of the locations.

Table 1. The locations of the hospitals

Number	x	y	Number	x	y	Number	x	y
1	826	375	18	669	585	35	625	405
2	91	12	19	135	673	36	5	290
3	207	502	20	894	793	37	776	769
4	794	444	21	170	381	38	213	944
5	682	853	22	545	80	39	204	280
6	470	501	23	35	435	40	795	372
7	898	113	24	815	786	41	270	274
8	409	792	25	596	305	42	831	474
9	659	935	26	406	735	43	998	961
10	959	856	27	645	101	44	396	102
11	302	156	28	367	173	45	900	541
12	725	82	29	1000	926	46	531	308
13	752	629	30	707	789	47	83	152
14	186	97	31	197	779	48	419	423
15	569	34	32	830	878	49	19	325
16	62	324	33	303	910	50	902	557
17	684	646	34	524	931			

4.3 The results of solving the first problem

To solve the first considered problem in this thesis, the algorithm was run with the population size of 100, iteration number of 100, and 20 number of the aerial vehicles. The results indicate that the optimal total response time is equal to 65574.2374 time unit, where the runtime is equal to 7.30915 seconds. The position of the selected hospitals is displayed in Figure 21.

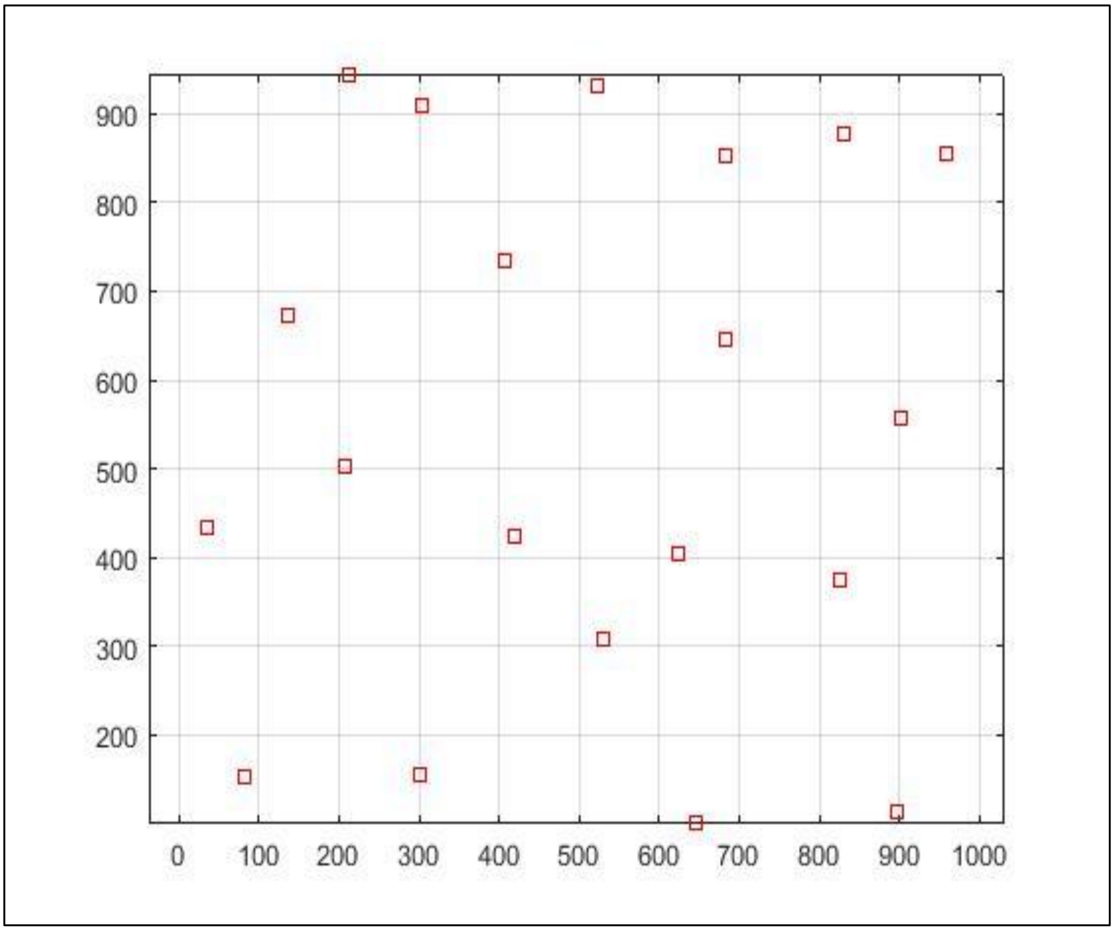

Figure 21. Position of the hospitals to assign the aerial vehicles in the first problem

4.4 The results of solving the second problem

To solve the second considered problem in this thesis, the algorithm was run with the population size of 100, iteration number of 100, 20 number of the aerial vehicles, and 30 number of the ground vehicles. The results indicate that the optimal total response time is equal to 46790.8459 time unit, including 9075.4739 for the aerial vehicles and the rest which is 37715.3719 for the ground vehicles. The runtime for this problem is equal to 13.3985 seconds which is about %50 more than the runtime of the first problem. The position of the selected hospitals to assign the aerial vehicles and the position of the selected hospitals to assign the ground vehicles for the second problem are displayed by red and blue asterisks in Figure 22, respectively.

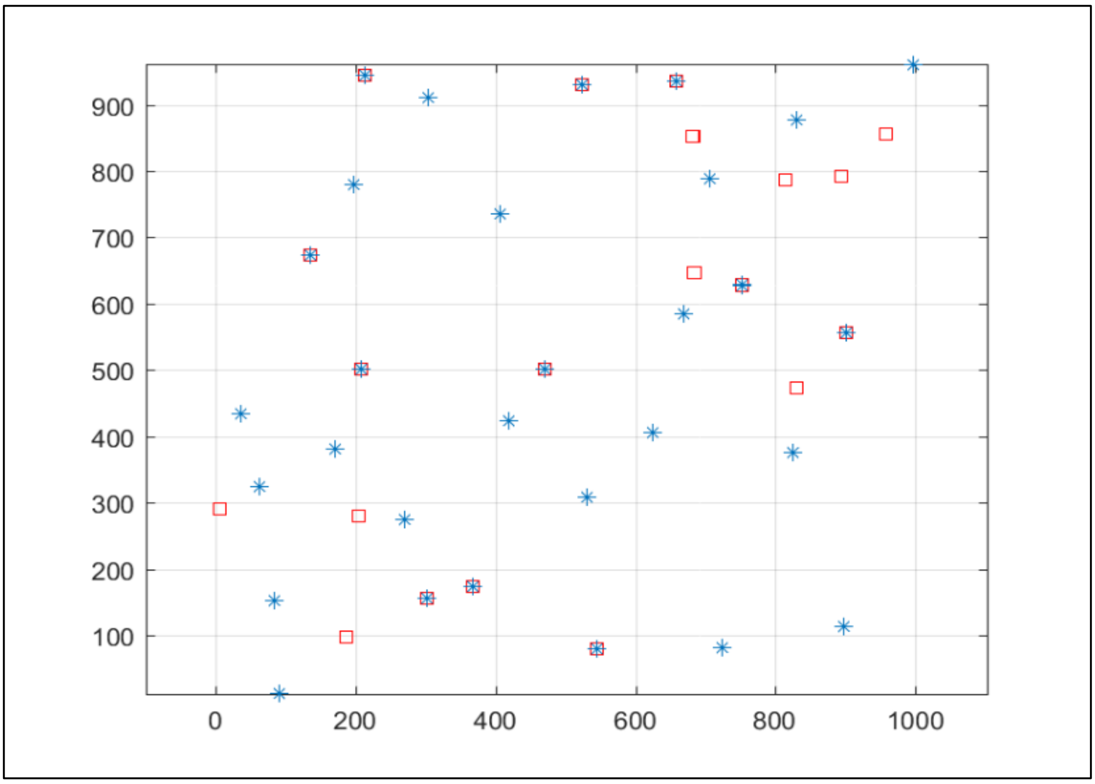

Figure 22. The assignment of the ground and aerial vehicles in the second problem

Table 2 shows the travel time of the assigned aerial vehicles to the selected hospitals. “Hospital no.” illustrates the hospital number and “Travel time” shows the total travel time of the aerial vehicle assigned to each hospital.

Table 2. Total travel times of each aerial vehicles

Hospital no.	Travel time	Hospital no.	Travel time
2	782.1845	24	77.0321
3	570.6739	27	194.5914
4	1205.1408	28	1045.0013
5	590.7761	29	361.2708
8	139.5910	33	663.0100
10	698.8661	38	295.8835
12	45.0462	40	375.8193
14	443.5188	41	499.9818
15	391.7271	44	182.0422
20	335.8850	45	177.4319

Table 3 depicts the travel time of the assigned ground vehicles to the selected hospitals. "Hospital no." illustrates the hospital number and "Travel time" shows the total travel time of the ground vehicle assigned to each hospital.

Table 3. Total travel times of each ground vehicles

Hospital no.	Travel time	Hospital no.	Travel time	Hospital no.	Travel time
1	2570.7286	18	1519.5870	33	962.7194
2	429.7706	19	2011.0188	34	920.9978
3	1379.1171	21	614.7942	35	1171.7515
6	1025.0647	22	1065.6489	38	1730.4726
7	2403.1255	23	972.2442	41	714.8020
9	364.1426	26	2398.1563	43	561.7763
11	1683.4727	28	657.9383	46	1284.2496
12	1412.8445	30	1140.0711	47	820.6388
13	1246.7623	31	1585.2342	48	789.9216
16	537.7710	32	1530.7763	50	2209.7733

The chart of the best cost function values acquired in each iteration is illustrated in Figure 23.

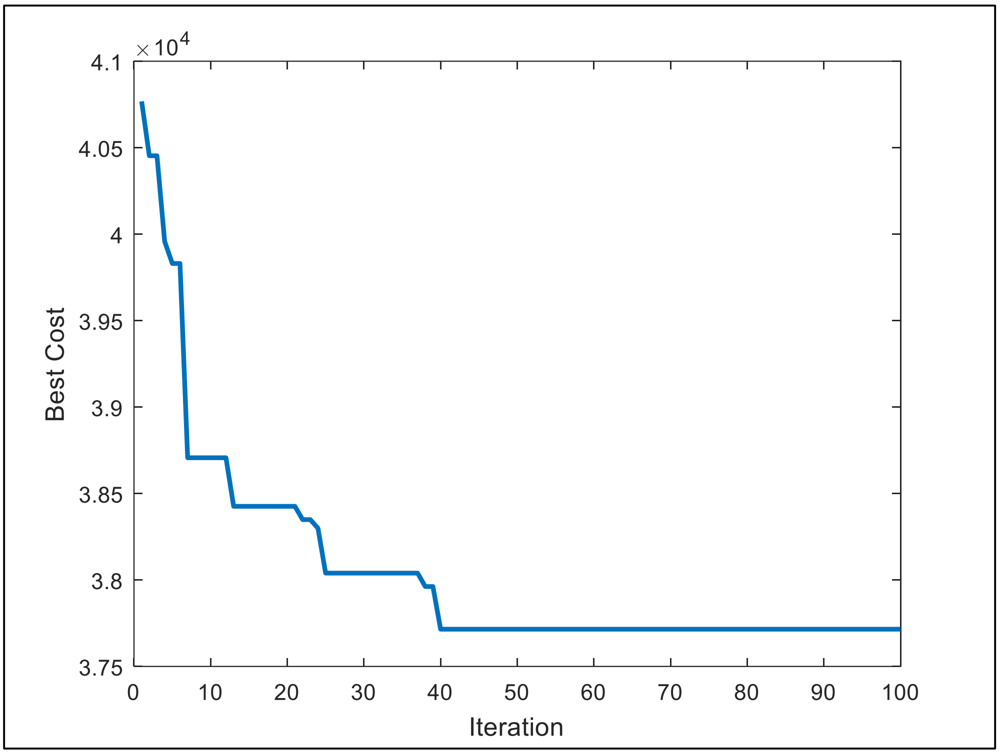

Figure 23. The best cost function values found in each iteration of the second problem

Chapter 5

CONCLUSIONS

In this thesis, we dealt with two different real-life medical emergency service problems. A city with its known hospitals or medical care center locations was considered. In the first problem we wanted to assign a given number of aerial vehicles to some of the hospitals or medical service centers in a way that the total response time to the patients was minimized. In the second problem, additional to the aerial vehicles, a given number of the ground vehicles were also considered to be assigned to the hospitals aiming the same minimization as the previous problem. Two different mathematical formulations were proposed for the problems. Additionally, two metaheuristic algorithms based on the genetic algorithm were proposed to solve the considered problems. A case study including 1000 medical service demands, such as accidents or emergency cases was considered. The locations of all the 50 hospitals or medical care centers were distinguished and plotted. 20 number of aerial vehicles were considered for the both problems and 30 number of ground vehicles were considered for only the second problem. As it was expected, the runtime of solving the first problem was less than the runtime needed for solving the second problem, which was about 7.3 seconds for the first problem and 13.4 seconds for the second one.

For the future studies there are many different related problems to do, that some of them are implied here. Except of considering real case problems and applying the mentioned and proposed solution methods, different types of vehicles, helicopters and drones may be considered for the problem modifications. Different solution methods such as heuristic and metaheuristic algorithms can also been considered. These problems can be modified as multi objective problems by adding a different and opposite objective function in relation with the minimization of the response time or the minimization of the total travelled distances.

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