Ambulance Routing in Disaster Response Phase Considering Different Types of Ambulances

Hamid Tikani [a] and Mostafa Setak [a*]

[a] Department of Industrial Engineering
K.N.Toosi University of Technology, Iran, Tehran
Tel: (+98) 21 84063373, Fax: (+98) 21 88674858, E-mail: setak@kntu.ac.ir

Abstract

This paper studies the ambulance routing problem in disaster situations when a large number of injured people from various locations require to receive treatment and medical aid. In such circumstances, many people summoning the ambulance at the same time but the capacity and number of emergency vehicles are not sufficient enough to visit all the patients immediately. Therefore, a crucial part is to management the fleet of ambulances so as to mitigate human suffering. For this reason, we considered three different categories of patients with various requirements. Also the support ambulances are segmented to various classes based on their capabilities. A mathematical formulations is presented to obtain route plans with the aim of minimizing the latest service completion time among the patients. Since, disasters cause major damages to lifeline infrastructures such as refueling-stations, so provided model designs the ambulances routes in such way that overcome to difficulties that exist as a result of limited refueling. Proposed MIP problem is then implemented by GAMS software. Finally, a sensitivity analysis is provided to evaluate the relationship between the problem structures and achieved solutions.

Keywords:
Ambulance Classification, Vehicle Routing Problem, Disaster Response, Service Time, Patient Grouping

1. Introduction

A disasters can be considered as any unprecedented incidents which causes major damages, destruction, ecological disruption, loss of human life, human suffering, deterioration of health and health service on a scale adequate to warrant an extraordinary response from outside the affected area [1]. Some examples of disasters are earthquakes, hurricanes, tornadoes, fire, floods, blizzard, drought, terrorism, volcanic eruptions and generally all occurrences that have substantial devastating effects in terms of human lives and damage to a society's buildings and infrastructures. It has been widely investigated that the severity of a misadventure can be mainly influenced by the efficacy of the relief efforts during the response phase [2]. Unquestionably, the response and recovery phase must to be processed under acutely challenging conditions: Treatment capacity limitation (transportation vehicles, man power and hospital capacity), damaged roadways and transportation infrastructure, together with uncertain information about number and locations of injured people (see e.g., [3] and [4]). Thereupon, it is necessary to initiate the logistics relief operations quickly and managing and controlling the efficient flows of relief, and services to meet the urgent requirements of the affected people. Consequently, there is an indispensable need for decision support tools that provide solutions to the underlying optimization problems instantly [5]. There are several studies that address issues of locating, dispatching, and fleet of ambulances as emergency medical services. Brotcorne et al. [6] and Farahani et al. [7] introduced surveys of models and algorithms in locating ambulances where the aim is to deployment or establishment some sites for the vehicles within an urban area. Under this circumstances, we can be sure to reach the potential emergency sites in a certain response time. Knight et al. [8] formulate a model to locate ambulances in order to maximize the expected survival probability of heterogeneous patients. The patients are different regarded to targeted response time and in their medical conditions.

Some various models are developed with the purpose of capturing realistic planning situations like traffic-dependent traveling times and congestion phenomena. Schmid and Doerner [9] study travel times which vary in the course of a day for an ambulance location problem. By considering such variations, the coverage fulfilled throughout a day by a certain deployment of ambulances changes dynamically that calls for relocations. In dispatching, incoming emergency requests should assigned to ambulances. However it can be solved in combination with the ambulance location problem. Toro-DíAz et al. [10] present a model to integrate the location and dispatching investigates the response time and coverage the affected by queuing patients in congested server systems. Schmid [11] consider emergency service providers which wants to locate ambulances such that emergency patients can be reached in a time-efficient manner. In the proposed model after a request emerges an appropriate vehicle needs to be dispatched instantly and send to the requests' site. After having served a request the vehicle needs to be relocated to its next waiting location. Andersson and Värbrand [12] dispatch ambulances based on urgency of requests and the closeness of a vehicle to the site of an incident. The authors integrate the dispatching problem with a relocation of ambulances with the aim of maintain the coverage of the service such that some of the ambulances are busy serving patients.

Another field of research is focus on disaster relief routing. De la Torre et al. [13] provide a recent literature survey on this subject. Various routing problems have been studied in this research field. For example, Campbell et al. [14] formulate models and heuristics for traveling salesman and vehicle routing problems with the purpose of minimizing the latest arrival time or the average arrival time disaster response actions. Huang et al. [15] introduce a vehicle routing problem to distribute supplies from a depot with the aim of a fair allocation of not adequate supplies. Rath and Gutjahr [16] consider distribution planning combined with locating supply depots in order to minimize a cost measure and maximize the coverage. Yi and Özdamar [17] provide a model in order to minimize both weighted sum of unsatisfied demands and waiting times of injured people. They considered hospitals and some temporal emergency centers that patients have to be brought to them to cope with the disaster. Özdamar and Demir [18] present a similar model that minimizes the total vehicle travel time in order to ensure an efficient utilization of transport capacity and a fast delivery of supplies.

It can be conclude from literatures that disaster response management is a substantial active scope of researches. However, many researchers are mainly focuses on locating and dispatching of ambulances or on the distribution of supplies in response phase. Nonetheless, researches in the field of ambulance routing for disaster response operations is taken into consideration recently. To the best authors' knowledge, a few papers exist in the literature, studying vehicle fleet management in disaster response operations, see de la Torre et al. [13] and Pedraza-Martinez and van Wassenhove [19] and Talarico, Luca, et al. [5].

In the current paper, we propose an extended model based on Talarico, Luca, et al. [5] so as to decision support approach for the routing of ambulances in response to a disaster. Presented extended model incorporates various types of ambulances with different capability and considers constraint on the route length due to the need for refueling. The major task of managing ambulances in a disaster response phase is to appoint first aid to slightly injured people and to transfer severely injured people to operating hospitals. Managing the plans of ambulances promptly aftermath of incidences a disaster is abundantly complicated and confusing owing to the dynamics and uncertainty in nature of relevant information that frequently change over the period of time. Add to the complexity of managing this issue that the managers should consider the availability of ambulances, the capacity of the nearby health centers, besides the accessibility of patient's locations because of the collapsed infrastructures and the potential traffic, see Edrissi et al. [20] and Jotshi et al. [21]. Ambulance routing problem in such a situation can be considered as a static or a dynamic problem. In the static version, at first property of emergencies needs is collected and afterwards, the vehicle routing problem is solved for this set of requests. While In the dynamic version, the routes of ambulances are updated by arriving new requests, which can decrease the response time. Whereas in dynamic approach communication with the ambulances is necessitous at all time, which might not be possible in a disaster condition and, moreover, the rescue teams may feel under pressure to quickly take action during the operations. Therefore, in this study, we consider a four-step response process to solve a static ambulance routing problem. As can be seen from Figure 1 the process is perform by a dispatching center that collects requests and manages ambulance operations. This process performs repeatedly to cover all emergency requests. The dispatcher collects several requests until a certain time limit has elapsed or a certain number of requests has been collected and, then in a second process step the requests should be categorized to different groups according to their severity. The availability of ambulances, the locations types of them should be recognized. Finally, the priority of patients is taken into account to manage the ambulances routings. Nevertheless, the time spent for the first three steps is too short, because requests are arrived in a short time in the case of a disaster event and the classification of requests can be carried out directly meanwhile answering an emergency call or automatically from the collected data.

This paper focuses on the fourth step of the response process and solve routing problem that occurs in the third step of the response process and send out the ambulances. Each ambulance carries medical personnel and medical first aid so as to help slightly injured people in the position of the patient. Meanwhile, patients with certain injuries should be transferred to the hospital for further treatments.

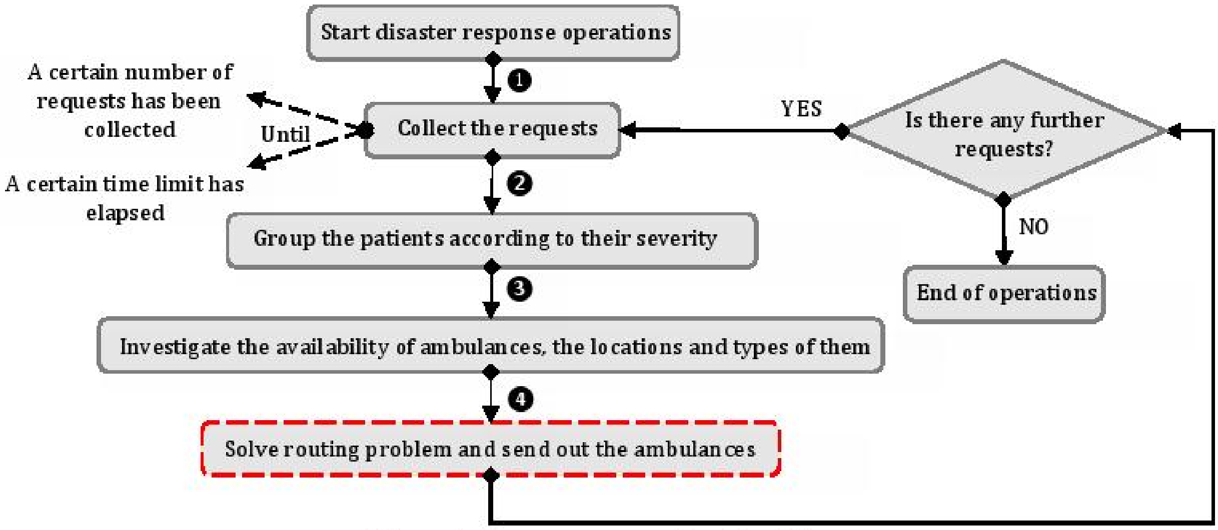

Figure 1. Disaster response flowchart [5]

In addition, emergency patients are accompanied by the medical staff on their way to the hospital to visit skilled doctors. According to this, we define three types of patients:

- Green code patient: An individual with green code classification is slightly injured patient which can be treated in place.
- Yellow code patient: A person with yellow code classification is moderately severe injured individual which should be transferred to the hospital for further treatments. Dedicated ambulance to this transportation does not need any special features.
- Red code patient: A person with red code classification is seriously injured and needs to be brought to a hospital by an ambulance which equipped with the medical equipment at least for basic life support.

There are various schemes for classifying patients and also several systems for categorizing and prioritizing patients in emergency situations with limited time and scarce medical resources. We refer the reader to study Thomas and Elaine [22] and Andersson and Peter [23] for further researches on mentioned subject. Due to the different needs of patients, ambulances are customized for using in different situations. In a general definition an ambulance is a transportation vehicle for carrying sick or injured people. In most cases, there are three general ambulance types with several subtypes. In the following we presented four types of ambulances that the first three of them are more common based on various standards:

- Type I- Patient transport ambulance: these types of ambulances should have a basic specialized equipment for first aid and nursing cares.
- Type II- Basic life support ambulance (BLS): these types of ambulances have to be equipped with the medical equipment. It is designed for patients who require medical transportation and continuous medical supervision.
- Type III- Advance Life Support Ambulance (ALS): These ambulances are operated by highly skilled and trained personnel and carry the essential medical equipment required to stabilize, treat and transport patients to a hospital.
- Type IV- Specialty care transport (SCT): These ambulances have been equipped to employ in hospital to hospital transportation. SCT is urgent when a beneficiary's condition requires ongoing care that must be equipped by one or more health professionals.

When disaster occurs, we face the lack of professional and skilled personals, in addition, ambulances Type III and Type IV are expensive and available scarcely and using them for transportation is costly. So we assumed that the manager confines the system to employs first two types of ambulances. Concerning the routing of ambulances, both ambulances types one and two can be applied to visit green and yellow code patients. While, Red code patients must be visited by ambulance type two. Both of ambulances can carry one patient at a time and each patient is directly brought to a hospital after having been picked up. The decisions about caring which patient to which hospital is part of the routing problem and depends on the capacities of hospitals. Due to the structure of the problem, ambulance's route can be interpreted as a tour that begins at one hospital, visits one or more patients in a sequence, and ends in a hospital that could be either the starting one another hospital. The aim is to minimize the sum of the latest service completion time among the patients with different codes. Moreover we applied weights for the latest completion times of the patient groups that utilized to determine which code patients should be served sooner. Presented weighted objective function supports such a tradeoff of the priority of a help request and the medical resources required for it. An illustrating example together with model formulation is presented in the next section. The model is computationally tested in Section 3. Section 4 provided sensitivity analysis for proposed model. Section 5 concludes the paper and provide some guidelines for further researches.

2. Problem description: The ambulance routing problem

In all ambulance routing problems the model strives to acquire routes for a fleet of ambulances with the intention of giving aid to a set of patients. We modeled this issue by applying the notation presented in Table 1. Let R represent the set of red code patients. These patients have to be picked up by be brought to the hospitals in set H with proper ambulances (Type II or higher). Let Y denote the set of yellow code patients who should be transferred to the hospital directly for further treatments but it can be done even with simple patient transport ambulance (Type I). And G denote the set of green code patients which can be treated in place. Thereupon, the set of all patients is represented by P= R ∪ G ∪ Y.

We employ two types of ambulances in order to visit the patients (Type I and Type II). The set of available ambulances are denoted by K = Type I ∪ Type II. Each ambulance can carry at most one patient at a time and go directly to an available hospital. At the beginning of the response process, each ambulance is located at a hospital. We denote by K_h ⊆ K the subset of ambulances that are initially placed in hospital h ∈ H. Accordingly, a binary parameter f_h^k equals to one if ambulance k is initially placed in hospital h. Moreover, the set of relevant arcs that are existed for the routing problem is denote by A = {P × P} ∪ {H × P} ∪ {P × H}. And t_{ij} is the travel time between to node i and j by any ambulance type (i,j) ∈ A. For red and yellow code patients, d_i denotes the time required to some pre-hospital cares and the time to prepare the patient for transportation to a hospital. And for green code patients, d_i shows the time needed to give first aid to the patient in the place. A continues parameter d_h is also applied to represent needed time to drop off a patient at this hospital. This quantity is higher for red code patients compared with yellow code patients due to the sensitivity of patients. Lastly, c_h indicates the capacity of hospital h ∈ H. This value equates to in the maximum amount of patients that can be served in hospital h.

Table 1 - Notation used in the problem

Sets:	
$\mathcal{R}$	set of red code patients
$\mathcal{G}$	set of green code patients
$\mathcal{P}$	set of all patients, $\mathcal{P} = \mathcal{R} \cup \mathcal{G}$
$\mathcal{H}$	set of hospitals
$\mathcal{K}_h$	set of ambulances that are initially located at hospital h
$\mathcal{K}$	set of all ambulances, $\mathcal{K} = \cup_{h \in \mathcal{H}} \mathcal{K}_h$
$\mathcal{A}$	set of arcs in a problem, $\mathcal{A} = \{\mathcal{P} \times \mathcal{P}\} \cup \{\mathcal{H} \times \mathcal{P}\}$
$\mathcal{R}$	set of red code patients
$\mathcal{G}$	set of green code patients
$\mathcal{P}$	set of all patients, $\mathcal{P} = \mathcal{R} \cup \mathcal{G}$
Parameters:	
f_h^k	binary parameters, 1 if ambulance k is initially located at hospital h (i.e. $k \in \mathcal{K}_h$)
t_{ij}	travel time from i to j with $(i,j) \in \mathcal{A}$
d_i	service time of patient $i \in \mathcal{P}$
d_h^i	transfer time to drop off a red and yellow code patients at hospital $h \in \mathcal{H}$, $i \in \mathcal{R} \cup Y$
c_h	capacity of hospital $h \in \mathcal{H}$
w_R	priority given to red code patients
w_Y	priority given to green code patients
w_G	priority given to green code patients
Cap_k	fuel tank capacity of ambulance (type k)
P_k	ambulance (type k) fuel consumption per unit of distance
Decision variables:	
x_{ij}^k	binary, 1 if ambulance k serves patient i directly before patient j
u_{ih}	binary, 1 if red code patient i is brought to hospital h
v_{ih}	binary, 1 if yellow code patient i is brought to hospital h
b_i	visiting time of patient $i \in \mathcal{P}$, $b_i \geq 0$
e_R	latest service completion time among all red code patients
e_Y	latest service completion time among all red code patients
e_G	latest service completion time among all green code patients

Each one of the ambulances terminates its last route at any hospital. The objective function is formulated in such a way that minimizes a weighted linear combination of the latest service completion time among the patients of a group. In fact, we minimizes the worst case waiting time by considering the latest service completion time among the patients. In addition, weighted completion times are considered to describe the relative importance that a disaster response manager probably assigns to completion time of each patient groups. Since, disasters cause major damages to lifeline infrastructures such as refueling-stations, so provided model should overcome to difficulties that exist as a result of limited refueling. For this purpose we consider that each ambulance should finishes its assigned mission via non-stop refueling. Afterward it can refuel using specific sites in hospitals for fueling ambulances. To clarify the problem and its potential solutions, an illustrative example is provided in the next section.

2.1. Illustrative example

In this section, we clarify the model by an illustrative example on a small artificial case. In the current instance we considered three red code patients $R = \{r_1, r_2, r_3\}$ and two yellow code patients $Y = \{\mathcal{Y}_1, \mathcal{Y}_2\}$ and five green code patients $G = \{\mathcal{G}_1, \mathcal{G}_2, \mathcal{G}_3, \mathcal{G}_4, \mathcal{G}_5\}$. Also two hospitals $\mathcal{H} = \{h_1, h_2\}$ are ready to service the red and yellow code patients, each with 3 capacities. At the beginning of the horizon two type 1 ambulances a_1 and a_2 are initially located at hospital h_1 and one type 2 ambulance a_3 is located at hospital h_2. The locations of all patients and hospitals are depicted in Figure 2. We suppose that the travel time t_{ij} between to node i and j equals to the Euclidean distance between them. The service times d_i are assumed to be 30 time units for red code patients $i \in \mathcal{R}$ and to10 time units for remain code patients $i \in G \cup Y$. Dropping off a red cod patient at a hospitals is set to 10 time units for red code patients and 5 time units for yellow code patients. Figure 2 indicates a potential routes for the ambulances. In the current solution, ambulances a_1 and a_2 perform two routes and ambulance a_3 which is appropriate to carry red cod patients, performs three routes. Ambulance a_1 begins its first route at hospital h_1, and then picks up yellow code patient $\mathcal{Y}_1$ and brings this patient to hospital h_1. In the following on its second route, serves two green code patients $\mathcal{G}_4$ and $\mathcal{G}_5$. Ambulance a_2 in the first rout depart from h_1 to picks up yellow code patient $\mathcal{Y}_2$ and brings it to hospital h_2. Subsequently, it serves patient $\mathcal{G}_3$,and finally returns to hospital h_2.

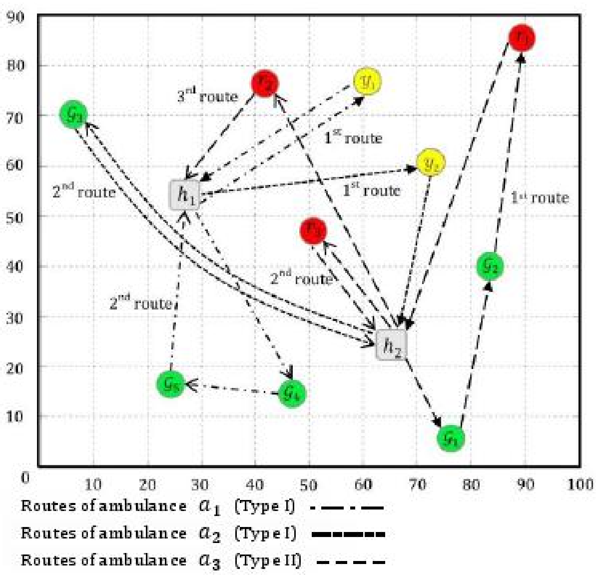

Figure 2. Illustration of all patients' and hospitals' locations and ambulances routs.

Ambulance a_3 which is type-II begins from hospital h_2 and joins the service of two green code patients $\mathcal{G}_1$ and $\mathcal{G}_2$with the service of red code patient r_1. Afterwards, it goes to bring r_3 to hospital h_2. And finally at last route ambulance a_3 depart from h_2 and brings patient r_2 to the hospital h_1. In order to assess the quality of obtained solution. The time-space diagram is shown in Figure 3. Provided diagram exerts the positions of all ambulances over the time of disaster response. Blue rectangles in the figure represent dropping off a patient at a hospital. .As can be seen from the Figure 3 the latest drop off of a red and yellow code patient at a hospital takes place at time e_R =410.52 and e_Y = 95.99 , respectively. The latest completion time of serving a green code patient is $\boldsymbol{e_G}$ = 182.80. As mentioned earlier a route can start and end at different hospitals, thereupon it would be accessible to achieve high quality solutions and serving patients as rapidly as possible. In presented example, it happens for the routes of ambulance $\boldsymbol{a_2}$ and $\boldsymbol{a_3}$.

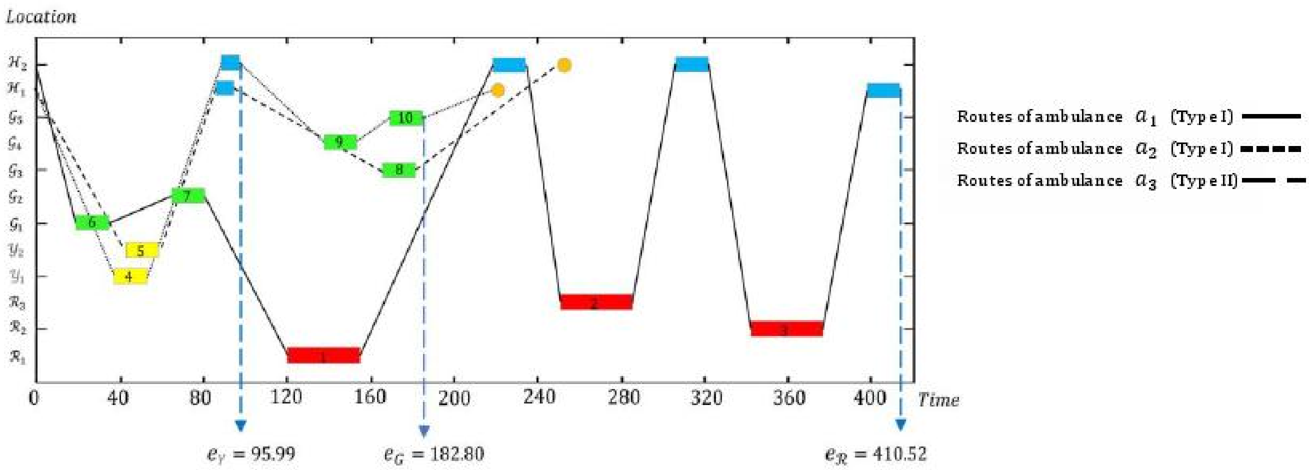

Figure 3. Time-space demonstration of the provided instance

Mazandaran University of Science and Technology

Available online at www.iiec2017.com

13th International Conference on Industrial Engineering (IIEC 2017)

Iran Institute of Industrial Engineering

IIEC (2017) 000–000

2.2. Model formulation

In this section we propose a mathematical formulation for ambulance routing problem. The model is formulated using binary decision variables x_{ij}^{k} , which imply the sequence of vising patients and take value 1 if ambulance k serves patient i directly before patient j and 0 otherwise. Also Binary variables u_{ih} and v_{ih} take value 1 if red and yellow code patient $i \in \mathcal{R}$ is brought to hospital h, respectively, and 0 otherwise. A positive continuous variable bi is defined to represented arrival time of the ambulance to the patient i. We can obtain the problem formulation as follows:

$$\text{Min} \quad w_R \cdot e_R + w_Y \cdot e_Y + w_G \cdot e_G \tag{1}$$

$S.t.$

$$\sum_{j\in\mathcal{P}\cup\mathcal{H}} x_h^k = f_h^k \qquad \forall h \in \mathcal{H}; k \in \mathcal{K} \tag{2}$$

$$\sum_{k\in\mathcal{K}}\sum_{j\in\mathcal{P}\cup\mathcal{H}} x_{ji}^k = 1 \qquad \forall i \in \mathcal{P} \tag{3}$$

$$\sum_{j\in\mathcal{P}\cup\mathcal{H}} x_{ji}^k = \sum_{j\in\mathcal{P}\cup\mathcal{H}} x_{ij}^k \qquad \forall i \in \mathcal{P};\ k \in \mathcal{K} \tag{4}$$

$$\sum_{h\in\mathcal{H}} u_{ih} = 1 \qquad \forall i \in \mathcal{R} \tag{5}$$

$$\sum_{h\in\mathcal{H}} v_{ih} = 1 \qquad \forall i \in Y \tag{6}$$

$$\sum_{i\in\mathcal{R}} u_{ih} + \sum_{i\in\mathcal{R}} v_{ih} \le c_h \qquad \forall h \in \mathcal{H} \tag{7}$$

$$\sum_{k\in Type\ II}\sum_{i\in\mathcal{P}} x_{ij}^k = 1 \qquad j \in \mathcal{R} \tag{8}$$

$$b_i + d_i + t_{ij} \le b_j \cdot \sum_{K\in\mathcal{K}} x_{ij}^k \qquad \forall i \in \mathcal{G}\cup\mathcal{H}; j\in\mathcal{P} \tag{9}$$

$$b_i + d_i + t_{ih} + d_h + t_{hj} \le b_j \cdot \sum_{k\in\mathcal{K}} x_{ij}^k \cdot u_{ih} \qquad \forall i \in \mathcal{R}; j \in \mathcal{P}; h \in \mathcal{H} \tag{10}$$

$$b_i + d_i + t_{ih} + d_h + t_{hj} \le b_j \cdot \sum_{k\in\mathcal{K}} x_{ij}^k \cdot v_{ih} \qquad \forall i \in Y; j \in \mathcal{P}; h \in \mathcal{H} \tag{11}$$

$$\sum_{j\in\mathcal{P}}\sum_{i\in G} x_{ij}^k . t_{ij} + \sum_{h\in\mathcal{H}}\sum_{j\in\mathcal{P}}\sum_{i\in Y} x_{ij}^k . v_{ih} . (t_{ij} + t_{ih} + t_{hi}) + \sum_{h\in\mathcal{H}}\sum_{j\in\mathcal{P}}\sum_{i\in R} x_{ij}^k . u_{ih} . (t_{ij} + t_{ih} + t_{hi}) \le \frac{Cap_k}{p_k} \qquad k \in \mathcal{K} \tag{12}$$

$$e_G \ge b_i + d_i \qquad \forall i \in G \tag{13}$$

$$e_R \ge b_i + d_i + u_{ih} \cdot (t_{ih} + d_h^i) \qquad \forall i \in \mathcal{R}; h \in \mathcal{H} \tag{14}$$

$$e_Y \ge b_i + d_i + v_{ih} \cdot (t_{ih} + d_h^i) \qquad \forall i \in Y; h \in \mathcal{H} \tag{15}$$

$$0 \le b_i \qquad \forall i \in \mathcal{P}\cup\mathcal{H} \tag{16}$$

$$u_{ih} \in \{0,1\} \qquad \forall i \in \mathcal{R}; h \in \mathcal{H} \tag{17}$$

$$v_{ih} \in \{0,1\} \qquad \forall i \in Y; h \in \mathcal{H} \tag{18}$$

$$x_{ij}^k \in \{0,1\} \qquad \forall (i,j) \in \mathcal{A}; k \in \mathcal{K} \tag{19}$$

The objective function (1) strives to minimize the weighted sum of the latest service completion time among all patients. Constraints (2) guarantee that each ambulance starts from the hospital where it is initially located. Constraints (3) state that each patient is visited exactly once by one of the ambulances. Constraints (4) ensure that an ambulance visiting a patient also has to leave that patient's location. Constraints (5) and (6) enforce that each red and yellow code patient is assigned to exactly one hospital. Constraints (7) specify that the number of patients which assigned to a hospital should be less than capacity of that hospital. Constraints (7) specify that the number of patients which assigned to a hospital should be less than capacity of that hospital. Constraints (8) ensure that red code patients, needs to be brought to a hospital by a type II ambulance. Constraints (9-11) express the arrival times of ambulances at the patient locations. Constraints (12) State that the determination of fleets should be provided by considering fuel capacity of each class of ambulances. Constraints (13) state the latest service completion time e_G between all green code patients. Constraints (14-15) state the latest service completion time e_R and e_Y of all red and yellow code patients, respectively. It is Notable that the completion service time of a red and yellow code patient equals to the time when the patient is dropped off at the dedicated hospital. Constraints (16)-(19) define the domains of the decision variables.

Since the constraints (9-12) are nonlinear. We obtain the linear version of formulation as follows (The parameter M is sufficiently large):

$$b_i + d_i + t_{ij} \le b_j + \left(1 - \sum_{K\in\mathcal{K}} x_{ij}^k\right) . \text{M} \qquad \forall i \in \mathcal{G}\cup\mathcal{H}; j \in \mathcal{P} \tag{20}$$

$$b_i + d_i + t_{ih} + d_h + t_{hj} \le b_j + \left(2 - \sum_{k\in\mathcal{K}} x_{ij}^k - u_{ih}\right).\text{M} \qquad \forall i \in \mathcal{R}; j \in \mathcal{P}; h \in \mathcal{H} \tag{21}$$

$$b_i + d_i + t_{ih} + d_h + t_{hj} \le b_j + \left(2 - \sum_{k\in\mathcal{K}} x_{ij}^k - v_{ih}\right).\text{M} \qquad \forall i \in Y; j \in \mathcal{P}; h \in \mathcal{H} \tag{22}$$

$$\sum_{j\in\mathcal{P}}\sum_{i\in G} x_{ij}^k . t_{ij} + \sum_{h\in\mathcal{H}}\sum_{j\in\mathcal{P}}\sum_{i\in Y}(t_{ij} + t_{ih} + t_{hi}) + \left(2 - \sum_{k\in\mathcal{K}} x_{ij}^k - v_{ih}\right).(-\text{M}) + \sum_{h\in\mathcal{H}}\sum_{j\in\mathcal{P}}\sum_{i\in R}(t_{ij} + t_{ih} + t_{hi}) + \left(2 - \sum_{k\in\mathcal{K}} x_{ij}^k - u_{ih}\right)(-\text{M}) \le \frac{Cap_k}{p_k} \qquad k \in \mathcal{K} \tag{23}$$

In order to achieve linear mixed integer program, constraints (9-12) should be replaced by constraints (20-23). In the next section, we reported the computational results of the discussed model on various problem instances.

3. Model implementation

In this section we presented the obtained results for some different instances. For this purpose the problem is implemented by the GAMS 24.1.3 with ILOG CPLEX 12.5 64-Bit optimization routines, then the MIP solver is employed to solve the instances. All tests were executed on a personal computer equipped with Intel core i5-3337U (1.8 GHz) with 6 GB of RAM. We solve various problem with different sizes and different combinations of weights which reflect the priority of various code patients. In Table 2 the first three columns describe the instances. The optimum solutions are presented in column four. Then, the latest completion time of each code patients is presented in the next three columns.

As can be seen from Table 2, changes in number of patients, number of vehicles and weight of patients' codes, affect the solutions. Thus, in the next section we perform a brief sensitivity analysis to figure out the relationship between the structure of a problem instance and its solution.

4. Sensitivity analysis

We investigate the impact of having a low, a medium, or a high percentage of red code patients. The generated instances with their code patients are represent in Table 3. In the first example we consider that red code patients are more than other code patients. In the second example we study the problem when the red code patients equally important as green and yellow code. And finally the third one indicates that a green cod patients are more important than others.

The relative importance of red code patients in a solution is controlled by parameter w_R. It is shown in Figure 4 that a larger value w_R indeed reduces the latest service completion time e_R of red code patients and increase the latest service completion time e_G of green code patients and e_Y of yellow code patients.

Also the average waiting time of all patients is provide in Figure 4 which is calculated by the following equation (N equals to total number of patients):

$$\bar{b} = \sum_{i \in \mathcal{P}} b_i \Big/ N \tag{24}$$

The average waiting time value for this instance, decreases with a larger value of w_R. But in practice, it also depends on the structure of the problem and other parameters.

In Figure 5 we analyze the benefits and drawbacks resulting from various number of vehicles. According to Figure 5, a larger number of ambulances clearly helps serving red code patients by reducing the trip duration to transport them to a hospitals while lack of adequate vehicles increase the latest completion time of each groups.

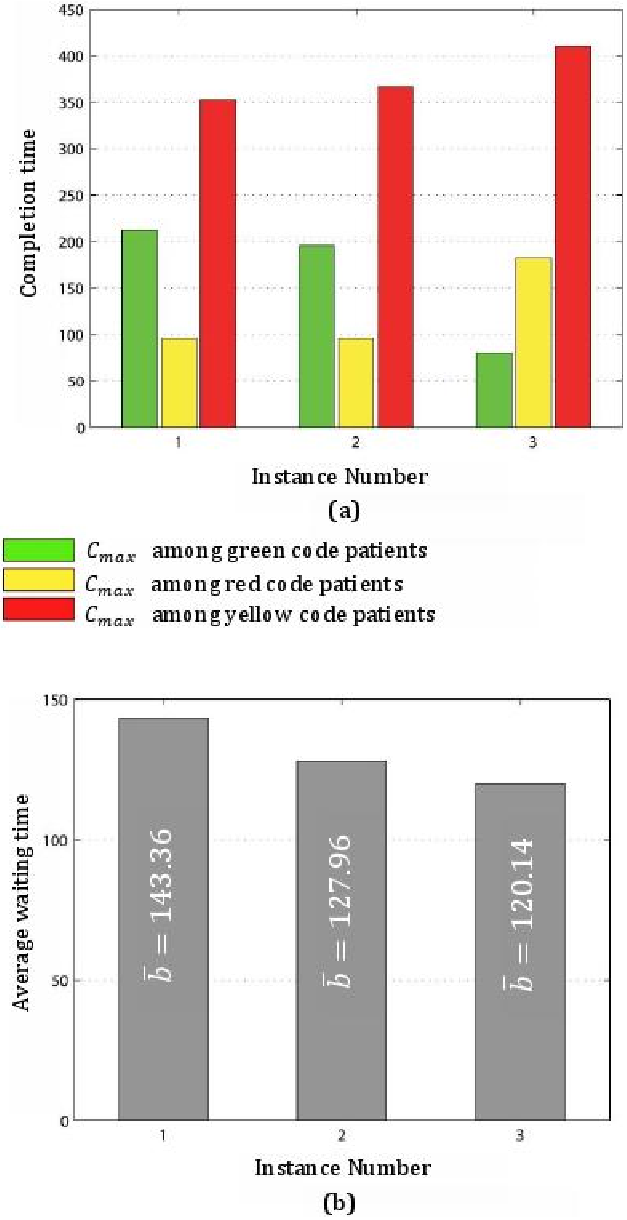

Figure 4. Impact of patient weights on the completion times (a) and average waiting time of all patients (b)

Figure 6 investigates the impact of the total hospital capacity on the objective function. The capacity of hospitals affect the achieved solutions slightly and no specific reduction results in the latest service completion times here. However, in a higher capacity there is a much chance to find free capacity at a surrounding hospital for patients.

The commentary is that in the current instance the most red and yellow code patients find a hospital around themselves even if the overall capacity is low.

Table 2: Results of proposed model for different instances

patients	hospitals	vehicles	Obj	e_G (w_G)	e_Y (w_Y)	e_R (w_R)
9	2	2	230.14	133.37(0.3)	140.43(0.3)	370.01(0.4)
9	2	3	209.51	117.93(0.1)	126.40 (0.2)	344.89(0.5)
10	2	3	215.68	131.53 (0.3)	95.99 (0.3)	368.56 (0.4)
10	2	2	232.14	286.50(0.2)	118.99 (0.5)	384.48(0.3)
10	2	2	259.25	217.37(0.3)	121.43(0.3)	394.01(0.4)
11	2	3	268.22	118.42(0.3)	171.55(0.3)	453.06(0.4)

Table 3: Patients weights taken for sensitivity analysis

Instance	w_G	w_Y	w_R
1	0.1	0.3	0.6
2	0.33	0.33	0.33
3	0.5	0.2	0.3

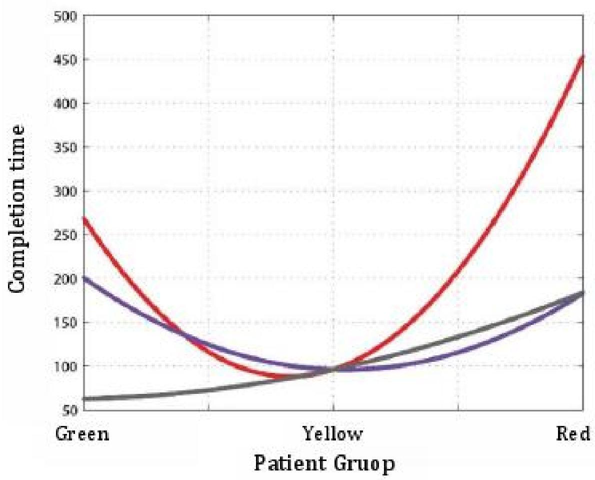

Figure 5. Impact of the number of ambulances on completion times.

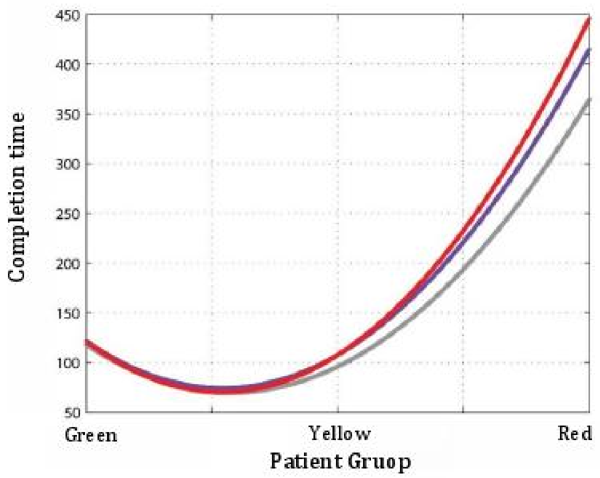

Figure 6. Impact of the capacity of hospitals on completion times

5. Conclusions

In this paper, we have formulated and solved an ambulance routing problem for disaster response phase where patients are classified to different groups with various requirements. We consider three groups of patients: slightly injured people who can be assisted directly in the field, moderately severe and severely injured individuals which should be transferred to the hospital for further treatments. The ambulances are applied to transport medical personnel and patients. Since, ambulances is recognized as a scarce resource in disaster situations, their efficient usage is utmost vital. For this reason, we distinguish various types of ambulance with different capabilities. Therefore, we should adapt the type of ambulance and the patients' needs to increase the total service quality. The aim of proposed model is minimizing the latest service completion time among the people waiting for help. Proposed model is implemented by the GAMS 24.1.3 and MIP solver is employed to solve the instances. The results of the model have been provided in the related tables. We also performed a brief sensitivity analysis to figure out the relationship between the structure of a problem instance and its solution.

One of the interesting direction for future study is consideration of time windows. Since in many disaster events (for example when an earthquake strikes), buildings lacking sufficient structural stability are susceptible to collapse and residents are at risk of getting injured and requiring medical attention and humanitarian supplies, addressing the model which incorporates the travel time reliability, capacity reliability and reliability of critical links can be a valuable future research.

6. References

[1] Barbarosoğlu, Gulay, and Yasemin Arda. "A two-stage stochastic programming framework for transportation planning in disaster response." *Journal of the*

operational research society 55, no. 1 (2004): 43-53..

[2] Berkoune, Djamel, Jacques Renaud, Monia Rekik, and Angel Ruiz. "Transportation in disaster response operations." *Socio-Economic Planning Sciences* 46, no. 1 (2012): 23-32.

[3] Najafi, Mehdi, Kourosh Eshghi, and Wout Dullaert. "A multi-objective robust optimization model for logistics planning in the earthquake response phase." *Transportation Research Part E: Logistics and Transportation Review* 49, no. 1 (2013): 217-249.

[4] Edrissi, Ali, Mehdi Nourinejad, and Matthew J. Roorda. "Transportation network reliability in emergency response." Transportation research part E: logistics and transportation review 80 (2015): 56-73.

[5] Talarico, Luca, Frank Meisel, and Kenneth Sörensen. "Ambulance routing for disaster response with patient groups." Computers & Operations Research56 (2015): 120-133.

[6] Brotcorne, Luce, Gilbert Laporte, and Frederic Semet. "Ambulance location and relocation models." European journal of operational research 147.3 (2003): 451-463.

[7] Farahani, Reza Zanjirani, et al. "Covering problems in facility location: A review." Computers & Industrial Engineering 62.1 (2012): 368-407.

[8] Knight, Vincent Anthony, Paul Robert Harper, and Leanne Smith. "Ambulance allocation for maximal survival with heterogeneous outcome measures." Omega 40.6 (2012): 918-926.

[9] Schmid, Verena, and Karl F. Doerner. "Ambulance location and relocation problems with time-dependent travel times." European journal of operational research 207.3 (2010): 1293-1303.

[10] Toro-DíAz, Hector, et al. "Joint location and dispatching decisions for emergency medical services." Computers & Industrial Engineering 64.4 (2013): 917-928.

[11] Schmid, Verena. "Solving the dynamic ambulance relocation and dispatching problem using approximate dynamic programming." European journal of operational research 219.3 (2012): 611-621.

[12] Andersson, T., and Peter Värbrand. "Decision support tools for ambulance dispatch and relocation." Journal of the Operational Research Society 58.2 (2007): 195-201.

[13] Luis, E., Irina S. Dolinskaya, and Karen R. Smilowitz. "Disaster relief routing: Integrating research and practice." Socio-economic planning sciences 46.1 (2012): 88-97.

[14] Campbell, Ann Melissa, Dieter Vandenbussche, and William Hermann. "Routing for relief efforts." Transportation Science 42.2 (2008): 127-145.

[15] Huang, Michael, Karen Smilowitz, and Burcu Balcik. "Models for relief routing: Equity, efficiency and efficacy." Transportation research part E: logistics and transportation review 48.1 (2012): 2-18.

[16] Rath, Stefan, and Walter J. Gutjahr. "A math-heuristic for the warehouse location–routing problem in disaster relief." Computers & Operations Research 42 (2014): 25-39.

[17] Yi, Wei, and Linet Özdamar. "A dynamic logistics coordination model for evacuation and support in disaster response activities." European Journal of Operational Research 179.3 (2007): 1177-1193.

[18] Özdamar, Linet, and Onur Demir. "A hierarchical clustering and routing procedure for large scale disaster relief logistics planning." Transportation Research Part E: Logistics and Transportation Review 48.3 (2012): 591-602.

[19] Pedraza-Martinez, Alfonso J., and Luk N. Van Wassenhove. "Transportation and vehicle fleet management in humanitarian logistics: challenges for future research." EURO Journal on Transportation and Logistics 1.1-2 (2012): 185-196.

[20] Edrissi, Ali, et al. "A multi-agent optimization formulation of earthquake disaster prevention and management." European Journal of Operational Research 229.1 (2013): 261-275.

[21] Jotshi, Arun, Qiang Gong, and Rajan Batta. "Dispatching and routing of emergency vehicles in disaster mitigation using data fusion." Socio-Economic Planning Sciences 43.1 (2009): 1-24.

[22] Thomas, A., and Elaine Wodzin Gennarelli. "The Abbreviated injury scale 2005." Des Plaines, IL Update (2008).

[23] Andersson, T., and Peter Värbrand. "Decision support tools for ambulance dispatch and relocation." Journal of the Operational Research Society 58.2 (2007): 195-201.