Available online at www.sciencedirect.com

ScienceDirect

Transportation Research Procedia 25C (2017) 1164–1179

Transportation Research Procedia

www.elsevier.com/locate/procedia

World Conference on Transport Research - WCTR 2016 Shanghai. 10-15 July 2016

An emergency vehicles allocation model for major industrial disasters

Gianfranco Fancello[a], Simona Mancini[b], Claudia Pani[c,]*, Paolo Fadda[a]

[a]DICAAR, University of Cagliari, via Marengo 2, Cagliari 09123, Italy

[b]Polytechnic of Turin, Corso Duca degli Abruzzi 24, Turin 10129, Italy

[c] CIREM,University of Cagliari,via San Giorgio 12, Cagliari 09124, Italy

Abstract

One of the main issues in the event of a major industrial disaster (fire, explosion or toxic gas dispersion) is to efficacy manage emergencies by considering both medical and logistics issues. From a logistics point of view the purpose of this work is to correctly address critical patients from the emergency site to the most suitable hospitals. A Mixed Integer Programming (MIP) Model is proposed, able to determine the optimal number and allocation of emergency vehicles involved in relief operations, in order to maximize the number of successfully treated injured patients. Moreover, a vehicles reallocation strategy has been developed which takes into account the evolution of the patients health conditions. Alternative scenarios have been tested considering a dynamic version of the Emergency Vehicles Allocation Problem, in which patient health conditions evolves during the rescue process. A company located in Italy has been considered as case-study in order to evaluate the performance of the proposed methodology.

*Keywords:*industrial disaster; logistics relief operations; emergency vehicles allocation; mixed integer programming; reallocation strategy.

1. Introduction

The presented research is part of a broader project (DIEM-SSP - Disasters and Emergencies Management for Safety and Security in industrial Plants) aimed at managing major industrial emergencies by considering both medical and transport/logistics issues. The study of the scientific literature confirms that the severity of a disaster can be highly

* Corresponding author. Tel.: +39-070-675-5267; fax: +39-070-675-5267
E-mail address: claudia.pani@unica.it

2352-1465
10.1016/j.trpro.2017.05.134

influenced by the efficacy of the logistics operations during the disaster response phase (Yi and Özdamar, 2007; Berkoune at al., 2012; Holguin-Veras at al., 2012). Since in these circumstances time is crucial, one of the major issues in emergency conditions is to ensure a quick response of the rescue operations by an efficient vehicle fleet management (Pedraza-Martinez and Van Wassenhove, 2012). From a practical point of view, it is essential that Emergency Vehicles (EVs) be located so as to ensure an adequate coverage of the interested area and that logistics operations provide an effective response to the emergency. Normally, an EV call starts with a triage, where a qualified medical staff determines the severity of each injured patient and the urgency of the call. As a subsequent step, each vehicle has to be assigned to a patient and has to be sent to the call site where the patient is located. At this purpose, a large amount of information needs to be transferred from the Emergency Site (ES) to the various EV base locations. Moreover, it should also be considered that during the emergency response phase the operations have to be executed under challenging conditions like uncertainty of information, limited availability of resources, hospital congestion and so on (Najafi et al., 2014; Yi et al., 2010). For the above reasons, logistics relief operations are not trivial issues which can be successfully managed without the help of specific support tools. The majority of existing studies have dealt with three main problems:

- Emergency vehicles **location** problem. It implies finding vehicle bases within an area such that a certain response time is guaranteed to reach the potential ESs within this area (Brotocorne et al., 2003; Schmid and Doerner, 2010);
- Emergency vehicles **dispatching/allocation** problem. It consists of assigning EVs to answer the emergency calls in order to maximize the coverage throughout a planning horizon (Hanghani et al., 2003; Goldberg, 2004; Andersson and Varbrand, 2007). This problem is commonly solved in combination with the location problem (Toro-Diaz et al., 2013; Ibri et al., 2012; Schmid, 2012; Andersson and Varbrand, 2007) or with the routing problem (Jotshi et al., 2009)
- Emergency vehicles **routing** problem. It consists of finding a shortest (fastest) path from one location to another taking into account traffic conditions and the infrastructure damage caused by a disaster (Goldberg and Listowsky, 1994; Talarico et al., 2015).

This specific study focuses on the EV allocation problem, assuming that initial vehicles location is a priori known. The main goal of this research is to correctly address critical patients from the ES to the most suitable hospitals by deciding which vehicle has to be assigned to transport each injured patient in the most efficient way.

This work proposes a Mixed Integer Programming Model for the EV allocation able to define the optimal number and allocation of ambulances and helicopters which must be involved in relief operations, in order to maximize the number of successfully treated injured patients. Moreover, a dynamic vehicles reallocation approach has been considered, taking into account that patients health conditions can become worse during the rescue process and can be revaluated.

A fire/explosion within a company located in Italy, has been considered in order to evaluate the performance of the proposed methodology. Furthermore, three alternative scenarios have been developed in order to show the results of the first EV allocation plan and of the EV reallocation startegy as a result of the evolution of the patient health conditions during the rescue process. The first scenario deals with the first triage. In the second and third scenarios it is assumed that one yellow-code patient become a red-code patient and one green-code patient become a yellow-code patient at the 8^{th} minutes and 15^{th} minutes after the first patient health evaluation respectively.

The model takes into consideration a variety of crucial information and data about both disaster severity (injured patients, injury type, injury severity, etc.) and medical resources availability (number of ambulance, helicopters, hospital specializations, etc.).

The remainder of the paper is structured as follows: Section 2 describes the methodological approach and proposes a Mixed Integer Programming Models for EV allocation, Section 3 describes the data collected to perform the analysis, Section 4 introduces the case-study and discusses the main results obtained for the various scenarios, Section 5 highlights conclusions and discusses future developments.

2. A Mixed Integer Programming Model

When a disaster occurs, it is necessary to immediately provide relief plans. Many decision must be made in very short time, which may have a relevant impact on the consequences of the disaster. An efficient and smart exploitation of available resources it is necessary to mitigate damages. Many applications of operations research methods to disaster response optimization may be found in the literature. Barbasoglu and Arda (2004) proposed a two-stage stochastic programming model for transportation planning in a disaster, while a multi-objective model for quick response to emergencies in logistics distribution has been proposed in Liu and Zhao (2007). In Balcik and Beamon (2008) the authors proposed a mixed integer programming model for facility location in humanitarian relief. Ozdamar and Yi (2008) dealt with vehicle dispatch plan for relief and evacuation. Other papers presented studies related to relief operations in specific type of disaster, such as in French (1996), where a decision support system, specific for emergency response in case of nuclear accident, has been presented and in Fiedrich et al. (2000) where the authors proposed an optimization model for allocating emergency resources after an earthquake. Similar issues may be found in ambulance allocation dispatching, where a limited fleet of ambulances must be allocated to real-time requests. A complete review on this subject may be found in Brotcorne et al. (2003).

This section describes the adopted methodological approach. It proposes a model for EV allocation problems in the case of a major industrial plant disaster and a reallocation policy which allow to optimally adjust the allocation plan after a change in a patient health conditions occurred.

2.1 A Mixed Integer Programming Model for Emergency Vehicles Allocation

In this sub-section we deal with ambulance/helicopter allocation. More in details, we consider a case in which, after an initial evaluation of injured people health conditions, we know:

- patient injury severity (red, yellow or green code);
- medical specialization required;
- a threshold time within which the patient should be treated;
- a further time threshold after what the medical service offered is considered not efficient.

We suppose to have a set of medical centers, for each one of which we know location, specialization, number and type of available emerging vehicles.

For each patient, we suppose to know by which vehicles he can be carried and to which medical centers he can be addressed. For patients belonging to the same class (having the same following characteristics: severity code and vehicles and hospitals compatibility) we define a priority order in which they must be addressed.

Each vehicle can carry only one patient at a time.

Each patient has a time penalty multiplier proportional to his injury severity. In fact, each minute of delay in addressing a seriously injured patient has a much higher specific weight respect to a minute of delay in addressing a slightly injured one. Further increasing penalties are added if the rescue time is higher than the prefixed thresholds.

We consider different dwell times for loading the patient into the EV, depending on the typology and severity of his injury. Dwell times for helicopters are fixed and they consider take off, patient loading and landing. We suppose to know travel times, both by road and by air, between each medical center and the site of the disaster.

The goal is to minimize an objective function given by the sum of all rescue times, weighted by their multiplier, plus the sum of additional penalties for inefficiency.

Before providing the mathematical formulation of the problem, the model parameters and sets and the involved variables are introduced below.

Model parameters:

- A_{ih}: Patient/Hospital compatibility, taking value 1 if patient i may be treated by hospital h and 0 otherwise;
- B_{iv}: Patient/Vehicle compatibility, taking value 1 if patient i may be carried by vehicle v and 0 otherwise;
- TR_h: travel time by road between hospital h and the site of the disaster;

- TE_h : travel time by air between hospital h and the site of the disaster;
- τ_{1i}: threshold for patient i rescue time, after which a penalty occurs;
- τ_{2i}: threshold for patient i rescue time, after which a further penalty occurs;
- p_i: unitary time penalty for patient i;
- π: priority level of patient i;
- ε: congestion penalty multiplyer;
- *classi*: parameter that identifies the class to which patient i belongs;
- r_{1i}: additional penalty if patient i rescue time is higher than τ_{1i};
- r_{2i}: additional penalty if patient i rescue time is higher than τ_{2i};
- σ_i: time necessary to load patient i into an ambulance;
- s: operational time for helicopters;
- l_{hv}: vehicle location parameter, taking value 1 if vehicle v is located at hospital h and 0 otherwise;
- $type_v$: vehicle type, equal to 1 if vehicle v is an ambulance and equal to 2 if it is an helicopter;
- M: a very large constant;
- E: a very small constant.

Model sets:

- I: set of patients;
- I_0: set of patients plus a dummy patient {0} (the role of this dummy patient will be explained hereafter);
- V: set of vehicles;
- H: set of hospitals.

Involved variables:

- X_{ijv}: binary variable taking value equal to 1 if patient j is carried by vehicle $v$immediately after patient i, and 0 otherwise. If X_{0jv} is equal to 1, it means that patient j is the first patient addressed by vehicle v, while if X_{i0v} is equal to 1, it means that patient i is the last patient addressed by vehicle v;
- T_i: time within which patient i is rescued and carried to the hospital;
- Z_i: binary variable taking value equal to 1 if rescue time for patient i is higher than τ_{1i}, and 0 otherwise;
- W_i: binary variable taking value equal to 1 if rescue time for patient$i$ is higher than τ_{2i}, and 0 otherwise;
- Y_{ih}: binary variable taking value equal to 1if patient i is carried to hospital h.

The mathematical model for EVs Allocation is reported in the following:

$$min \sum_{iinI} T_i p_i + \sum_{i\ in\ I} Z_i r_i^1 + \sum_{i\ in\ I} W_i r_i^2 + \sum_{i\ in\ I} \varepsilon * cong_i\, p_i + \pi_i) \tag{1}$$

s.t.

$$\sum_{v\ in\ V} \sum_{i\ in\ I_0} X_{ijv} = 1 \qquad \forall j \in I \tag{2}$$

$$\sum_{v\ in\ V} \sum_{j\ in\ I} X_{ijv} \le 1 \qquad \forall i \in I \tag{3}$$

$$\sum_{jinI} X_{ijv} \le \sum_{j\ in\ I_0} X_{jiv} \quad \forall v \in V,\ \forall i \in I \tag{4}$$

$$\sum_{j in I} X_{0jv} \geq E \sum_{i in I} \sum_{j in I} X_{ijv} \ \forall v \in V \tag{5}$$

$$\sum_{j in I} X_{0jv} \leq 1 \ \forall v \in V \tag{6}$$

$$T_j \geq T_i + \sum_{h \ in \ H} Y_{ih} T_h^R + \sigma_j + \sum_{h \ in \ H} Y_{jh} T_h^R - M\left(1 - X_{ijv}\right) \forall j \in J, \ \ \forall i \in I, \forall v \in V \mid type_v = 1 \tag{7}$$

$$T_j \geq T_i + \sum_{h \ in \ H} Y_{ih} T_h^E + s + \sum_{h \ in \ H} Y_{jh} T_h^E - M\left(1 - X_{ijv}\right) \forall j \in J, \ \ \forall i \in I, \forall v \in V \mid type_v = 2 \tag{8}$$

$$T_i \geq -M(1 - X_{0iv}) + \sum_{h \ in \ H} l_{hv} T_h^R + \sigma_j + \sum_{h \ in \ H} Y_{ih} T_h^R \quad \forall i \in I, \forall v \in V \mid type_v = 1 \tag{9}$$

$$T_i \geq -M(1 - X_{0iv}) + \sum_{h \ in \ H} l_{hv} T_h^E + s + \sum_{h \ in \ H} Y_{ih} T_h^E \quad \forall i \in I, \forall v \in V \mid type_v = 2 \tag{10}$$

$$\sum_{h \ in \ H} Y_{ih} = 1 \ \forall i \in I \tag{11}$$

$$\sum_{i \ in \ I} Z_i \geq \varepsilon(T_i - \tau_i^1) \ \ \forall i \in I \tag{12}$$

$$\sum_{i \ in \ I} W_i \geq \varepsilon(T_i - \tau_i^2) \ \ \forall i \in I \tag{13}$$

$$cong_i \geq \sum_{\substack{j \ in \ I \\ i \neq j \\ j \ has \ been \ classified \ red \ or \ yellow \ code}} Y_{jh} - M(1 - Y_{jh}) \quad \forall i \in I \ \forall h \in H \tag{14}$$

$$Y_{ih} \leq A_{ih} \quad \forall i \in I \ \forall h \in H \tag{15}$$

$$\sum_{i \ in \ I_0} X_{ijv} \leq B_{jv} \ \ \forall j \in I \ \forall v \in V \tag{16}$$

$$X_{ijv} \ \in \ \{0{,}1\} \ \ \forall j \in J, \ \ \forall i \in I, \forall v \in V \tag{17}$$

$$Y_{ih} \ \in \ \{0{,}1\} \ \ \ \forall i \in I \ \forall h \in H \tag{18}$$

$$Z_i \ \in \ \{0{,}1\} \quad \forall i \in I \tag{19}$$

$$W_i \ \in \{0{,}1\} \quad \forall i \in I \tag{20}$$

$$T_i \ \in Z^+ \quad \forall i \in I \tag{21}$$

$$cong_i \ \in Z^+ \quad \forall i \in I \tag{22}$$

The objective function to be minimized is explained in (1).

Constraints (2) and (3) imply that all the patients must be addressed by a vehicle. Constraint (4) states that a customer j may be addressed by vehicle v immediately after customer i only if customer i has been assigned to the same vehicle. Patients can be addressed by a vehicle only if that vehicle is used in the solution (Constraint (5)). If a vehicle is used then there will be one patient which is carried as first patient by that vehicle (Constraint (6)). Constraints (7) and (8) allow to compute the rescue time for a patient which is not the first patient served by the vehicle, while the rescue time for patients who are addressed as first patient can be computed by means of constraints (9) and (10). Constraint (11) ensures that each patient is assigned to one and only one hospital. Constraints (12) and (13) imply that if the patient rescue time is higher than the prefixed threshold, the correspondent penalties are paid. Constraint (14) allows to take into account dwell times increment due to congestion. A patient may be carried by a vehicle only if that vehicle is compatible with his type of injury and can be assigned to an hospital only if that hospital may address his type of injury, as stated by constraints (15) and (16), respectively. Finally, constraints (17)-(22) specify variables domain.

In order to avoid symmetry the following constraint has been added:

$$T_j \geq T_i \ \ \forall j \in J, \ \ \forall i \in I \mid class_j = \ class_i \ and \ \pi_j > \pi_i \tag{23}$$

The following set of valid inequalities has been added to strengthen the formulation:

$$T_i \ \ \geq Tmin_i \forall i \in I \tag{24}$$

Where $Tmin_i$ is a lower bound on the rescue time of patient i, which is equal to the optimal rescue time for i if he would be the only patient to be rescued, which can be computed in a polynomial time.

2.2 Emergency Vehicles Reallocation

Emergency vehicles allocation is a typical dynamic problem. In fact, the allocation plan is performed basing on information related to an initial patient situation, without considering that patients conditions may dynamically change during the rescue process and that borderline clinical situations may negatively evolve. For this reason, we propose a reallocation policy which allow to optimally adjust the allocation plan after a change in a patient conditions occurred. The reallocation problem has been rarely addressed, since most published papers consider the static ambulance location problem. This can be explained mainly by the limitations of past technology which did not allow for real-time solutions of dynamic large-scale problems. The development of new computer technologies now make the reallocation problem tractable, since the required data can be obtained and processed in real-time Brotcorne et al (1999). For instance, the positions of vehicles are always available through a Geographic Positioning System (GPS) and can be reported on a computerized map managed by a Geographic Information System (GIS). Interesting examples of vehicles reallocation can be found in the area of dynamic vehicle dispatching, for example Gendreau et al.(1999).

We consider that a certain time α, a worsening of the clinical conditions of patient j occurs, and the rescue of patient i becomes of top priority. The goal is to choose which vehicle assign to this task (delaying its remaining tasks), in order to minimize the objective function, (expressed in (1)), increment. If we define as ρ_v the increment on the objective function obtained assigning the new urgent task to vehicle v, the reallocation becomes the minimization over v in V of ρ_v, which can be expressed as follows:

$$\rho v = \sum_{i\ served\ by\ v\ after\ \alpha} \delta iv\, pi + Ziri1 + Wiri2 + \ \varepsilon\, cong(pi + \ \pi i) \tag{25}$$

Being:

$$\delta_{iv} = \tau_{j\,+}\theta_v \tag{26}$$

and

$$\tau_j = T_j - T_{pred} \tag{27}$$

i.e. the time needed to address the task "rescue patient j", which can be computed as patient j rescue time minus its processor (pred(*j*)) rescue time. Θ_v indicates the time needed by vehicle v to complete is current task, before to become available for the new task. This depend on its geographical location at instant α and if, at that moment, it is empty or it is carrying a patient.

3. Data description

The proposed methodology has been validated considering a company located in the center of Italy as case-study. With the practical assistance of the University of Cassino, data have been collected and they have been divided into three main classes.

3.1 Data providing information about the hospital

For each hospital the following information were required:

- *name and location*. The hospitals located at distance within 35 km from the ES have been taken into consideration (Table 1);
- *distance* (km). Distances from each hospital to the ES (Table 1);
- *specializations*. For each hospital the various departments by which it is composed have been collected. They indicates then the possibility of a hospital in treating a given injury type (Table 1).

Table 1. Data related to the hospital.

name	location	distance	Neuro Surgery	Traumatology	Burn Unit
FabrizioSpaziani	Frosinone	3,4	1	1	1
San Benedetto	Alatri	16,8	0	0	1
SS Trinità	Sora	34,9	0	0	1

3.2 Data on EV features

For the various EVs the following information have been collected:

- *type and number*. These data specify the different type and number of the available EVs which may be used in order to carry injured people to the hospitals and to evacuate the external population (Table 2);
- *location.* This variable specifies the EVs initial location, in particular the location of: (i) ambulance sites; (ii) helicopter bases (Table 3a, 3b);
- *distance* (km). Distances between EV initial location and the ES have been computed (Table 3a, 3b);
- *capacity*. This information indicates the maximum number of patients that each EV can carry at a time (Table 2);

- *travel time*. EV travel times have been estimated from each EV initial location to the ES and from the ES to each hospital. Times have been estimated considering the travel distance (km) and the EV average speed without traffic congestion. It is assumed that: (i) an ambulance run at 50 km/h average speed (when driving in emergency mode with lights and sirens activated); (ii) a helicopter can cover in 5 minutes a distance of 20 km (iii) .

Table 2. Data related to the vehicle.

type	description	number	capacity	average speed
ambulance type I	ambulance used to transport patients that only require Basic Life Support (BLS) features	31	1 patient	50 km/h
ambulance type II	ambulance equipped with medical staff for Advance Life Support (ALS) for seriously injured patients	12	1 patient	50 km/h
Helicopter	vehicle that may be used only for seriously injured patients	3	1 patient	20 km/5 min

Table 3a. EV initial location description (hospitals, medical centers and helicopter bases).

vehicle	type	location type	location	distance
1	BLS	Hospital	Alatri	17
2	BLS	Medical Center	Anagni	23,1
3	BLS	Medical Center	Arpino	36,3
4	BLS	Medical Center	Atina	54,8
5	BLS	Hospital	Cassino	54,7
6	BLS	Hospital	Cassino	54,7
7	BLS	Medical Center	Ceccano	7,4
8	BLS	Medical Center	Ceprano	27,2
9	BLS	Medical Center	Ferentino	3,1
10	BLS	Hospital	Frosinone	3,2
11	BLS	Hospital	Frosinone	3,2
12	BLS	Medical Center	Isola del Liri	30,6
13	BLS	Medical Center	Pontecorvo	46,8
14	BLS	Hospital	Sora	34,9
15	BLS	Medical Center	Veroli	23,9
16	ALS	Medical Center	Anagni	23,1
17	ALS	Medical Center	Ceccano	7,4
18	ALS	Medical Center	Ceprano	27,2
19	ALS	Medical Center	Fiuggi	42,4
20	ALS	Medical Center	Pontecorvo	46,8
21	ALS	Hospital	Sora	34,9
22	Helicopter	Helicopter base	Roma	42
23	Helicopter	Helicopter base	Latina	80
24	Helicopter	Helicopter base	Viterbo	134

Ambulances may be located across different hospitals (Table 3a), medical centers (Table 3a) and red cross bases (Table 3b). Medical centers and red cross bases are places in which EVs are located but which cannot offer medical assistance. A set of three helicopter bases has been considered. where helicopters are located (Table 3a).

Table 3b. EV initial location description (red cross bases).

vehicle	Type	location type	location	distance
25	BLS	red cross base	Cassino	53,3
26	BLS	red cross base	Cassino	53,3
27	BLS	red cross base	Cassino	53,3
28	BLS	red cross base	Frosinone	4,6
29	BLS	red cross base	Frosinone	4,6
30	BLS	red cross base	Frosinone	4,6
31	BLS	red cross base	Frosinone	4,6
32	ALS	red cross base	Frosinone	4,6
33	BLS	red cross base	Amaseno	23,5
34	BLS	red cross base	Ferentino	13,8
35	BLS	red cross base	Paliano	40,4
36	ALS	red cross base	San Germano	45,9
37	BLS	red cross base	Piglio	37,2
38	BLS	red cross base	San Donato	61,8
39	BLS	red cross base	Sant'Elia	60,2
40	BLS	red cross base	Serrone	40,7
41	BLS	red cross base	Latina	49,5
42	BLS	red cross base	Latina	49,5
43	ALS	red cross base	Latina	49,5
44	ALS	red cross base	Latina	49,5
45	ALS	red cross base	Latina	49,5
46	ALS	red cross base	Latina	49,5

3.3 Data related to the patient

The requested information for each patient are the following:

- *number*. A number of employees involved by the fire/explosion has been suggested (see Section 5). In particular: (i) 1 dead; (ii) 3 red codes; (iii) 5 yellow codes; (iv) 13 green codes; (v) 20 white codes (Table 4);
- *injury severity*. Injury severity is used to determine the patient's priority for treatment. Four types of patients have been distinguished: (i) Red code patient: very critical injured who needs to be brought to a hospital by an ALS ambulance. The red code patient has maximum priority and immediate access to treatment. (ii) Yellow code patient: fairly critical injured who needs to be brought to a hospital by an ALS ambulance. The yellow code patient is characterized by an high level of risk, and the treatment cannot be delayed. (iii) Green code patient: slightly injured who is delivered to the hospital by a BLS ambulance. (iv) White code patient: a person which does not require assistance (Table 4);
- *injury type*. Considering a fire/explosion the injury types take into consideration, thanks to the assistance of medical experts, are: (i) burn; (ii) major trauma; (iii) intoxication; (iv) head trauma; (v) minor trauma. This information is essential in order to know the medical specialization required by each patient (Table 4).

Table 4. Data related to the patient.

patient	injury severity	injury type	Neuro Surgery	Traumatology	Burn Unit
1	Red	Major Trauma	0	1	0
2	Red	Head Trauma	1	1	0
3	Red	Burns	0	0	1
4	Yellow	Fracture	0	1	0
5	Yellow	Intoxication	0	0	0
6	Yellow	Intoxication	0	0	0
7	Yellow	Burns	0	0	1
8	Yellow	Burns	0	0	1
9	Green	Intoxication	0	0	0
10	Green	Intoxication	0	0	0
11	Green	Intoxication	0	0	0
12	Green	Intoxication	0	0	0
13	Green	Intoxication	0	0	0
14	Green	Intoxication	0	0	0
15	Green	Minor Trauma	0	0	0
16	Green	Minor Trauma	0	0	0
17	Green	Minor Trauma	0	0	0
18	Green	Minor Trauma	0	0	0
19	Green	Minor Trauma	0	0	0

4. A case-study

In this work, the proposed methodology has been validated considering a company on the waste oils regeneration sector located in the center of Italy. In particular, it is assumed a fire/explosion within the company, during a daily working hour (14:00) , in which several workers remain injured.

4.1 First Scenario

Thanks to the assistance provided by the company and considering that the number of employees in a daily shift (8:00-18:00) is about 86 people, it is assumed that the number of involved persons is equal to 42. Following the indication of fire brigade, when an accidental event, or a maxi-emergency, occurs, the percentage of *injury severity* is usually distributed as follows:

- 5-7% of the victims – red code;
- 12-15% of the victims - yellow code;
- 33-35% of the victims - green code;
- 50-57% of the victims - white code.

Observing the above percentages, in this work it is assumed that the involved patients are divided as follows:

- 1 dead;
- 3 red codes: 3 burns (7% of the victims);
- 5 yellow codes: 2 burns, 2 intoxicated and 1 concussion (12% of the victims);

- 13 green codes: 5 burned, 6 intoxicated and 2 affected by minor trauma (33% of the victims);
- 20 white codes, which do not require assistance (50% of the victims).

The goal of the problem is to allocate EVs in order to assist all the injured patients (red, yellow and green codes) in the most efficient way. Table 4 summarizes injury severity, injury type and specialization required by each patient. The fleet of available EVs is composed by 46 vehicles:

- 31 BLS ambulances (which can assist green code patients only);
- 12 ALS (which can assist all type of patients);
- 3 Helicopters (which can be used for red and yellow code patient only).

A complete list of vehicles, with indication of the category they belong to and of the medical center/red cross site where they are located, is reported in Tables 3a and 3b.

Two time thresholds after which a significant penalty is added have been considered: τ_1 and τ_2.

The first threshold is equal to 20, 40 and 60 minutes, while the second one is equal to 30, 60 and 90 minutes, for red, yellow and green code patients, respectively

Time elapsed to load the patient inside the ambulance is considered equal to 7,5 and 2 minutes for red, yellow and green code patients respectively.

Helicopter operational time is equal to 30 minutes, including take off, landing and patient loading.

In the first scenario, which correspond to the first triage, two cases have been carried out. In the first one, no hospital congestion is considered, while in the second one we have added to each patient a congestion penalty, proportional to the number of red and yellow code patients assigned to the same hospital. The resulting optimal vehicles allocation plans for both cases are reported in Table 8 and in Table 9, respectively.

Table 8. EVs Allocation Plan without considering congestion.

patient	time	vehicle	location	hospital
1	20	17	Ceccano	Frosinone
2	35	17	Frosinone	Frosinone
3	20	7	Ceccano	Frosinone
4	41	22	Roma	Frosinone
5	44	18	Ceprano	Frosinone
6	50	17	Frosinone	Frosinone
7	39	16	Anagni	Frosinone
8	35	7	Frosinone	Frosinone
9	10	10	Frosinone	Frosinone
10	10	9	Ferentino	Frosinone
11	10	11	Frosinone	Frosinone
12	10	28	Frosinone	Frosinone
13	10	29	Frosinone	Frosinone
14	10	30	Frosinone	Frosinone
15	10	31	Frosinone	Frosinone
16	10	34	Frosinone	Frosinone
17	20	10	Frosinone	Frosinone
18	20	9	Frosinone	Frosinone
19	20	11	Frosinone	Frosinone

More in details, we report, for each patient:

- the rescue time (arrival time at the hospital);
- the specific vehicle which assists it;
- the location from which the vehicle started;
- the hospital in which the patient is carried.

Table 9. EVs Allocation Plan considering congestion.

patient	time	vehicle	location	hospital
1	20	17	Ceccano	Frosinone
2	35	17	Frosinone	Frosinone
3	20	7	Ceccano	Frosinone
4	**41**	**22**	**Roma**	**Alatri**
5	44	18	Ceprano	Frosinone
6	**55**	**23**	**Latina**	**Alatri**
7	39	16	Anagni	Frosinone
8	35	7	Frosinone	Frosinone
9	10	10	Frosinone	Frosinone
10	10	9	Ferentino	Frosinone
11	10	11	Frosinone	Frosinone
12	10	28	Frosinone	Frosinone
13	10	29	Frosinone	Frosinone
14	10	30	Frosinone	Frosinone
15	10	31	Frosinone	Frosinone
16	10	34	Frosinone	Frosinone
17	20	10	Frosinone	Frosinone
18	20	9	Frosinone	Frosinone
19	20	11	Frosinone	Frosinone

We can notice that, without considering congestion, the optimal solution consists into carry all the patients at Frosinone hospital which is the nearest and the most equipped one. This solution will yield to an overcharge of this hospital with consequently delay of the assistance services to the patients. To avoid that, we inserted a congestion penalty as described above. As shown in Table 9, to limit congestion, the optimal solution consists into addressing patients n. 4 and n. 6 to the second nearest suitable hospital, Alatri. These patients are both carried by helicopter, such that the increment of travel time is lower than if they were carried by ambulance.

In the second and in the third scenarios, the emergency vehicles reallocation strategy has been tested. It takes into account that, in realistic conditions, patient health conditions can evolve and change during the rescue process. In these cases, patients may become critical and therefore their priority may grow. Since we are interested into analyzing the impact of this event on the patients rescue order, we analyzed only the case without congestion. In fact, congestion would not change the priority of patients but only the hospital to which they are assigned. The results of the reallocation strategy are provided in the following sections.

4.2 Second Scenario

Thanks to the assistance of the medical staff, in the second scenario it is assumed that 8 minutes after the first triage patient n. 5, affected by a concussion, becomes worse moving from a yellow to a red severity code.

The resulting optimal vehicles reallocation plan is reported in Table 10.

Also in this case, we report, for each patient: the rescue time, the specific vehicle which assists it with the location from which the vehicle started and the hospital in which the patient is carried.

Table 10. EVs Reallocation Plan after 8 minutes without considering congestion.

patient	time	vehicle	location	hospital
1	20	17	Ceccano	Ceccano
2	35	17	Frosinone	Frosinone
3	20	7	Ceccano	Ceccano
4	41	22	Roma	Roma
5	**35**	**7**	**Forsinone**	**Forsinone**
6	50	17	Frosinone	Frosinone
7	39	16	Anagni	Anagni
8	**44**	**18**	**Ceprano**	**Ceprano**
9	10	10	Frosinone	Frosinone
10	10	9	Ferentino	Ferentino
11	10	11	Frosinone	Frosinone
12	10	28	Frosinone	Frosinone
13	10	29	Frosinone	Frosinone
14	10	30	Frosinone	Frosinone
15	10	31	Frosinone	Frosinone
16	10	34	Frosinone	Frosinone
17	20	10	Frosinone	Frosinone
18	20	9	Frosinone	Frosinone
19	20	11	Frosinone	Frosinone

As we can notice in this case the total rescue time for the patients is not changed because patient n. 5 and patient n. 8 scheduling are just exchanged between each others. The increment on the objective function is only given by the augmented penalty of patient n. 5 that now has a penalty equal to the other red-code patients.

4.3 Third Scenario

In the third scenario it is assumed a change of the health patients conditions 15 minutes later from the first triage. In particular, it is considered that one patient affected by a minor trauma, patient n. 13, got worse moving from a green to a yellow major trauma severity-code.

The resulting optimal vehicles reallocation plan is reported in Table 11.

Table 11. EVs Reallocation Plan after 15 minutes without considering congestion.

patient	time	vehicle	location	hospital
1	20	17	Ceccano	Frosinone
2	35	17	Frosinone	Frosinone
3	20	7	Ceccano	Frosinone
4	41	22	Roma	Frosinone
5	44	18	Ceprano	Frosinone
6	50	17	Frosinone	Frosinone
7	39	16	Anagni	Frosinone
8	**50**	**7**	**Frosinone**	**Frosinone**
9	10	10	Frosinone	Frosinone
10	10	9	Ferentino	Frosinone
11	10	11	Frosinone	Frosinone
12	10	28	Frosinone	Frosinone
13	**35**	**7**	**Frosinone**	**Frosinone**
14	10	30	Frosinone	Frosinone
15	10	31	Frosinone	Frosinone
16	10	34	Frosinone	Frosinone
17	**10**	**29**	**Frosinone**	**Frosinone**
18	20	9	Frosinone	Frosinone
19	20	11	Frosinone	Frosinone

Results reported in table 11 show that patient n. 13 is scheduled before patient n. 8 which is postponed but 13 let free a non medical vehicle that can be used only for green patients which can be immediately reallocated to serve another patient. Therefore the increment of time elapsed to serve 8, is partially balanced by the reduction of time elapsed to serve 17.

5. Concluding Remarks and Future Developments

The state of the art underlines that, when a major disaster occur, it is necessary to immediately provide relief plans. An efficient and smart exploitation of available resources it is necessary to mitigate damages. From a transport/logistics point of view, the most important decisions that should be made by EV managers during a disaster response phase are related with the allocation of the vehicles (ambulances and helicopters) in order to assist all the injured patients. Moreover, it is important to consider that from a medical point of view patients health conditions can evolve during the rescue process. For that reason a dynamic version of the Emergency Vehicles Allocation Problem has been considered and an EVs reallocation strategy has been proposed.

Considering the big number of involved data and the challenging conditions characterizing the logistics rescue operations, the EVs allocation problem is not a trivial issue which can be successfully managed by hand. This work proposes a Mixed Integer Programming Model and develop a vehicles reallocation approach considering three alternative scenarios of a fire/explosion within an industrial plant located in Italy.

The model takes into consideration a variety of crucial information and data, in particular:

- data related to the patient (number of casualties, injuries severity, injury type,..);
- data providing information about the hospital (location, hospital availability and specializations,..);
- data related to the available emergency vehicle fleet (type, availability, location..);

From an operational point of view, the main goal of the developed approach is to ensure a quick response of the rescue operations by an efficient vehicle fleet management. At this scope, the proposed strategy finds the best allocation/reallocation plan for ambulances and helicopters in order to maximize the number of successfully treated patients. More in details, the MIP model allows to correct address injured patients from the emergency site to the most suitable hospital taking into account a possible revaluation of patients health conditions during the rescue operations.

This research also provides basis for further studies. One of the main lines of research that results directly from this work concerns the study of the dynamic traffic congestion evolution and the possibility to modify the initial EV allocation, basing on real time information on traffic conditions. Moreover, it could be interesting to develop an evacuation strategy to assist the population in the nearby, which can be affected by the disaster. In this case an interesting aspect to be investigated is the evaluation of direction and speed of the toxic gas dispersion through a specific function of propagation.

Acknowledgements

The research project is part of a broader project DIEM-SSP - Disasters and Emergencies Management for Safety and Security in industrial Plants financed by the Italian Ministry of Education and Research. The authors would like to thank all the involved operating units for supporting the research by providing data and relevant information, in particular the department of Industrial Engineering of the University of Cassino and the department of Diagnostic & Surgical Sciences of the University of Genoa.

References

Andersson, T., & Värbrand, P., 2007. Decision support tools for ambulance dispatch and relocation. Journal of the Operational Research Society 58 (2), 195-201.

Balcik, B., Beamon, B. M., 2008. Facility location in humanitarian relief.. International Journal of Logistics, 11(2), 101-121.

Barbarosoglu, G., Arda, Y., 2004. A two-stage stochastic programming framework for transportation planning in disaster response. Journal of the Operational Research Society 55 (1), 43-53.

Berkoune, D., Renaud, J., Rekik, M., Ruiz, A., 2012. Transportation in disaster response operations. Socio-Economic Plannning Sciences 46 (1), 23–32.

Brotcorne, L., Farand, L., Laporte, G., Semet, F, 1999. Impacts des nouvelles technologies sur lagestion des systèmes de véhicules d'urgence. Ruptures 6, 149-168.

Brotcorne, L., Laporte, G., Semet, F., 2003. Ambulance location and relocation models. European Journal of Operational Research 147, 451-463.

Chen, C.Y., Chen, P.Y., Chen, W.T. 2013. A Novel Emergency Vehicle Dispatching System. In Vehicular Technology Conference (VTC Spring), IEEE 77th (pp. 1-5). IEEE.

Farahani, R.Z., Asgari, N., Heidari, N., Hosseininia, M., Goh, M., 2012. Covering problems in facility location: A review. Computers & Industrial Engineering 62(1), 368-407.

Fiedrich, F., Gehbauer, F., Rickers, U., 2000. Optimized resource allocation for emergency response after earthquake disasters. Safety Science 35 (1), 41-57.

French, S., 1996. Multi-attribute decision support in the event of a nuclear accident. Journal of Multi-Criteria Decision Analysis 5 (1), 39-57.

Gendreau, M., Guertin, F., Potvin, J.-Y., Taillard E., 1999. Parallel tabu search for real-time vehicle routing and dispatching. Transportation Science 33, 381-390.

Goldberg, R., Listowsky, P., 1994. Critical factors for emergency vehicle routing expert systems. Expert systems with applications 7 (4), 589-602.

Holguín-Veras, J., Jaller, M., Van Wassenhove, L.N., Pérez, N., Wachtendorf, T., 2012. On the unique features of post-disaster humanitarian logistics. Journal of Operations Management 30 (7), 494-506.

Ibri, S., Nourelfath, M., Drias, H., 2012. A multi-agent approach for integrated emergency vehicle dispatching and covering problem. Engineering Applications of Artificial Intelligence 25 (3), 554-565.

Jotshi, A., Gong, Q., & Batta, R., 2009. Dispatching and routing of emergency vehicles in disaster mitigation using data fusion. Socio-Economic Planning Sciences 43 (1), 1-24.

Liu, M., Zhao, L, 2007. A composite weighted multi-objective optimal approach for emergency logistics distribution. In IEEE International Conference on Industrial Engineering and Engineering Management, December. 2007, (pp. 968-972). IEEE.

Najafi, M., Eshghi, K., de Leeuw, S., 2014. A dynamic dispatching and routing model to plan/re-plan logistics activities in response to an earthquake. OR spectrum 36 (2), 323-356.

Ozdamar, L., Yi, W., 2008. Greedy neighborhood search for disaster relief and evacuation logistics. Intelligent Systems, IEEE 23(1), 14-23.

Schmid, V. and Doerner, K.F., 2010. Ambulance location and relocation problems with time-dependent travel times. European Journal of Operational Research 207 (3), 1293-1303.

Pedraza-Martinez, A.J., & Van Wassenhove, L.N., 2012. Transportation and vehicle fleet management in humanitarian logistics: challenges for future research. EURO Journal on Transportation and Logistics 1 (1-2), 185-196.
Schmid, V., 2012. Solving the dynamic ambulance relocation and dispatching problem using approximate dynamic programming. European Journal of Operational Research 219 (3), 611-621.
Talarico, L., Meisel, F., Sörensen, K., 2015. Ambulance routing for disaster response with patient groups. Computers & Operations Research 56, 120-133.
Toro-Díaz, H., Mayorga, M.E., Chanta, S., McLay, L. A., 2013. Joint location and dispatching decisions for Emergency Medical Services. Computers & Industrial Engineering 64 (4), 917-928.
Yi, P., George, S.K., Paul, J.A., Lin, L., 2010. Hospital capacity planning for disaster emergency management.. Socio-Economic Planning Sciences 44 (3), 151-160.
Yi, W., Özdamar, L., 2007. A dynamic logistics coordination model for evacuation and European Journal of Operational Research 179 (3), 1177–1193.