RAIRO-Oper. Res. 54 (2020) 19–36
https://doi.org/10.1051/ro/2018095

RAIRO Operations Research
www.rairo-ro.org

A HYBRID ALGORITHM TABU SEARCH – GRASP FOR WOUNDED EVACUATION IN DISASTER RESPONSE

Mohamad Khorbatly[1,*], Hamdi Dkhil[1], Hassan Alabboud[2] and Adnan Yassine[1,3]

Abstract. Natural and triggered-disasters, have devastating and profound negative effects on human lives that require a speedy declaration of an emergency in order to minimize their severe consequences. Hence, a prompt disaster response, in addition to effective measures such as informed decision making, organized evacuation plan, right hospital selection, proper rescue vehicles, efficient resources assignment and timely vehicle scheduling are critical actions needed to organize successful secured operations that could, if well prepared, save many injured bodies and lessen the human distress. To reach this ultimate goal, a complicated procedure should be in place and any failure can potentially increase the number of causalities, thus a complete alertness and full caution should be exercised. In this paper, we treat the Integrated Problem of Ambulance Scheduling and Resource Assignment (IPASRA) in the case of a sudden disaster. The main resources to be assigned are the ambulances and the hospitals. While, the hospitals serving capacities might be considered or not according to the extent of disaster and particularly to the wounded bodies' total number. We formulate the (IPASRA) as a linear model, furthermore a novel hybrid algorithm based on Tabu Search (TS) and Greedy Randomized Adaptive Search Procedure (GRASP) is offered to tackle this complex problem. Simulation tests are also presented to prove the efficiency of our modelling and resolution approaches.

Mathematics Subject Classification. 90B06.

Received June 17, 2018. Accepted October 20, 2018.

1. Introduction

Over the last few years many natural disasters, wars and terrorist attacks occurred and led to hundreds and thousands of wounded and killed people.

During Tōhoku Earthquake and Tsunami (2011)[4], when an earthquake followed by a tsunami hit the east coast of Japan, 15 894 people were dead while 6152 injured and 2562 people missing. The Haiti Earthquake (2010)[5], the strongest earthquake to hit the country since 1770, led to over 200 000 deaths, 2 million homeless,

Keywords. Crisis management, secure organization, assignment problem, scheduling problem, GRASP, Tabu Search, linear programming.

[1] Normandie Univ, UNIHAVRE, LMAH, FR CNRS 3335, ISCN, 76600 Le Havre, France.

[2] Lebanese University, Laboratory of Informatics and Applications LIA, Doctoral School in Science and Technology DSST, Mitein street Tripoli, Lebanon.

[3] Normandie Univ, UNIHAVRE, Institut Supérieur d'Etudes Logistiques, 76600 Le Havre, France.

*Corresponding author: `mohamad.khorbatly@etu.univ-lehavre.fr; mouhamad.khorbatly@gmail.com`

[4] `https://www.livescience.com/39110-japan-2011-earthquake-tsunami-facts.html`

[5] `http://edition.cnn.com/2013/12/12/world/haiti-earthquake-fast-facts/index.html`

and 3 million people in need of emergency aid. Hurricane Katrina (2005)[6], struck the Gulf Coast of the US, this was the sixth strongest and fifth most destructive hurricane to ever hit the US. It killed 1833 people and left hundreds of wounded. In Iraq (2003)[7], US troops started the invasion of Iraq in March 2003, in coalition with the UK and other nations. By the 31st of August 2010, when the last US combat troops left, 4421 had been killed. Almost 32 000 had been wounded in action. Similarly, an enormous loss was reported in Syria since the beginning of the conflict in 2011[8], around 11.5% of the country's population have been killed or injured since the crisis erupted in March 2011, the report estimates that the number of wounded is put at 1.9 million. Life expectancy has dropped from 70 in 2010 to 55.4 in 2015. While in the Libyan armed conflict 2011[9], A total of 21 490 (0.5%) persons were killed and 19 700 (0.47%) were injured.

There is also another kind of disasters which are made by people like Terrorist attacks which hit multiple cities all over the world in different ways, such as car bomb, individual attacks etc. but all of them have the same consequences and common results revealed by a huge number of killed and wounded citizens. All these attacks are considered as terrorist acts and human disasters and treated as high-level crisis. For example: Paris attacks[10]: On the 13th of November 2015, six attacks in 33 min hit the capital of France, from France stadium to the capital center and caused the death for 129 citizens and hundreds of wounded spreads within this geographic area; most are seriously injured.

In this paper, we propose a mathematical tool for solving the Integrated Problem of Ambulance Scheduling and Resource Assignment in order to transport wounded as fast as possible to the available medical treatment centers. We present a mathematical modelling succeeded by a Branch and Cut under CPLEX solver and an efficient resolution that outperform metaheuristics methods and grounded on a hybrid algorithm based on Tabu Search and GRASP procedure.

This paper is organized as follows: the state of art is presented in Section 2, the problem description and mathematical formulation are presented in Section 3. In Section 4, we describe the adopted algorithms developed for solving our case study. Numerical experiments are presented and discussed in Section 5. And finally, the conclusion and perspectives are presented in Section 6.

2. Literature review

Supply Chain Management (SCM) is an essential element to operational efficiency, it requires the commitment of supply chain partners to work closely in coordinating order generation, order taking, and order fulfillment. In this section we present few works related to supply chain management and others dedicated to evacuation only.

Christopher *et al.* [4, 6, 7, 10] focused on the development of a managerial agenda for the identification and management of supply chain risk, with recommendations to improve the resilience of supply chains, their research has highlighted the risks to business continuity that lies in the wider supply chain. They defined the supply chain as a collected enterprises network that participates, upstream and downstream, to different process and activities for creating products and services to end-consumer.

In [8], Lummus *et al.* studied the relationship between information system and supply chain management (SCM) optimization. They define the supply chain as a network of entities in which the material flux passes through these entities, including providers, transporters, assembling sites, distribution centers, retailers and clients. To solve the supply chain problem, the authors offered a new strategy and some practical guidelines for successful supply chain management. They also described the competitive importance of linking a firm's supply

[6] https://www.livescience.com/22522-hurricane-katrina-facts.html

[7] http://www.bbc.com/news/world-middle-east-11107739

[8] https://www.theguardian.com/world/2016/feb/11/report-on-syria-conflict-finds-115-of-population-killed-or-injured

[9] https://www.sciencedirect.com/science/article/pii/S2211419X15000348

[10] http://www.lefigaro.fr/actualite-france/2015/11/14/01016-20151114ARTFIG00252-six-attaques-en-33-minutes-chronologie-d-un-massacre.php

chain strategy to its overall business strategy, but they didn't take into consideration the fact of optimizing the transportation time spent in order to accomplish tasks.

In [9], Tan *et al.* have developed a framework of supply chain management literature; they proposed various supply chain management strategies and the conditions conducive to supply chain management. Their contribution was illustrated by integrating the two bodies of literature (Purchasing and supply perspective of the industrial buyers and transportation and logistics perspective of the merchants) in the unification of supply chain management into a commonly accepted terminology that includes all the value creating activities along the value chain and finally they provided three distinct descriptions dominate prior literature:

- Supply chain management may be used as a handy synonym to describe the purchasing and supply activities of manufacturers.
- It may be used to describe the transportation and logistics functions of the merchants and retailers.
- It may be used to describe all the value-adding activities from the raw materials extractor to the end users and including recycling.

Silva *et al.* [11] worked on the distributed optimization problem of a logistic system and its providers. They improved the supply chain performance by introducing a new multi-agent approach for collaborative management of logistic and supply systems based on the ant colony optimization. The management methodology is defined as a set of distributed scheduling problems that exchange information during the optimization process. Each problem is solved by an ant colony agent that uses the pheromone matrix as the communication platform. Authors solved the whole problem by dividing it in several sub problems where each one is treated apart of the other. In our model the problem is treated as one entity and all sub problems (tasks) are executed in coherence and harmony to reach the final goal.

Chiu and Zheng *et al.* [12] described a linear program to deal with multi-priority group evacuation in sudden onset disasters. The authors' goal is to minimize the total travel time to outside the affected area, in their approach they didn't take into consideration the life expectancy of wounded and they have no plan to transport them to hospitals.

Yi and Ozdamar [13] studied the problem of commodities distribution and wounded evacuation to emergency units inside the disaster areas. The main objective was to minimize the delay between suppliers and distribution centers in the affected areas, to create temporarily medical facilities in addition to the permanent medical centers and to provide both of them with the necessary good and finally to transport the wounded to these medical centers. They are serving only severely and moderate injured people who are grouped in different places using different types of vehicles with different capacities to transport injured people.

Mete and Zabinsky [14] proposed a stochastic optimization approach for the storage and distribution problem of medical supplies to be used for disaster management under a wide variety of possible disaster types and magnitudes. They developed a stochastic programming model to select the storage locations of medical supplies and required inventory levels for each type of medical supply by maintaining balance between the preparedness and the risk despite the uncertainties of disaster events. In their proposed model they didn't optimize the time spent by routing vehicles. They were only concerned in optimal routing plan of vehicles with their loading amounts of medical supplies in an MIP model.

Sayyady and Eksioglu [16] used a mixed-integer linear program for evacuation plans of urban areas using public transit system, their objective is to minimize the total evacuation time and the number of casualties. The main difference between our model and their model is that all citizens are grouped in specific places (stations) and all transit vehicles had to collect citizens from the stations within its predefined lines to its closest shelter. Also, in their model they missed out the notion of priorities between stations and there is no plan to transport individual wounded to hospitals.

Ma *et al.* [18] presented a wounded transportation model based on multi type vehicles to solve the wounded transfer problem in large-scale disasters. In their approach, each vehicle is assigned to a single disaster area no matter how many wounded it contains and without taking into consideration the time spent in a disaster area which can cause that some vehicles which serve areas with little number of wounded will be free to serve again after some time, if opportunity is offered, meanwhile other vehicles which are serving areas with a huge number of wounded would stay busy for a longer time, as a result, as much as the number of wounded grows in areas as their evacuation time and their risk of death rise.

Coutinho-Rodrigues *et al.* [19] Presented a multi objective approach to generate urban evacuation plans where people are grouped inside a shelter and then they evacuate wounded to hospitals with different types of vehicles and there is no facilities capacities limitation. Using this strategy, they optimize the transport time but they risk the wounded life. Therefore, they are not reducing mortality rate because not all wounded can move to shelters which is not considered in their proposed model and which is the main objective in our proposed model.

Nordin *et al.* [20] studied the fact of finding the shortest path for ambulance routing starting from ambulance station and ending at emergency site. They focused on finding the best roads network for the area under study (with the total shortest distance) using A* algorithm, in their model, there is no transportation plan given to ambulances from their emergency sites to medical treatment centers.

Zhang *et al.* [21] studied the fact of a disaster inside a high-rise building and defined a new evacuation device for emergency evacuation problem but, as before, they assumed that all people are grouped in the same place and they should all use the same route the same device without taking into consideration the human medical situation and the time spent to perform these actions.

Chang *et al.* [22] studied the impact of large disasters on roads safety and suggested for this reason a nonlinear site distribution for vehicle routing problem on the affected points.

In his model, they focused on transporting materials to uncertain demand points according to three objectives ((1) Minimize vehicle total transportation cost, (2) Maximize the number of transported materials, (3) Maximize the poorest routes transportation capacities), but they didn't rely on service priority for demand points.

Yadollahnejad *et al.* [23] proposed a model based on earthquake disaster and focusing on transferring wounded to clinics and hospitals using air lines and ground transportation. They introduced a multi-objective approach to provide transportation on available routes, but they group a certain number of wounded with different injuries in one vehicle in each transportation cycle and most wounded are located near to each other.

Boonmee *et al.* [24] worked on finding solutions for facility location problem in case where disasters are happening or already happened. They intended to find the best facility's location depending on many factors such as distribution centers, hospitals, etc. Unlike our model, they did not focus on the transported injured and they didn't totally count on existent facilities (in our case: Hospitals) to which we intend to transport wounded, depending on many criteria.

As mentioned before, some previous works are interested in solving the transport optimization problem inside a supply chain by reducing the transportation cost of goods according to predefined constraints and the others ones are interested in evacuating groups of wounded to existing hospitals or to in site temporary created clinics, but none of them consider picking up wounded one by one from different places or take the facilities capacities limitation in consideration.

Our approach deals with a complicated case of crisis management where we have multiple dispersed wounded and multiple distant hospitals. Our goal is to reduce the overall wounded's transport time from their locations to hospitals by ambulances in order to reduce mortality rate. Two realistic scenarios were treated, the first one considers using hospitals with limited serving capacity. This scenario is applicable when we are facing an emergency situation with a small number of wounded and where the total hospitals capacities can cover this number. But when the wounded number increases, the first scenario become useless and the second scenario without capacity constraint is being applied. We solve the (IPASRA) by developing a new algorithm using hybridization between two metaheuristic methods (TS) and (GRASP). The efficiency of the proposed hybrid algorithm in term of solution quality and processing time is shown in Section 5.

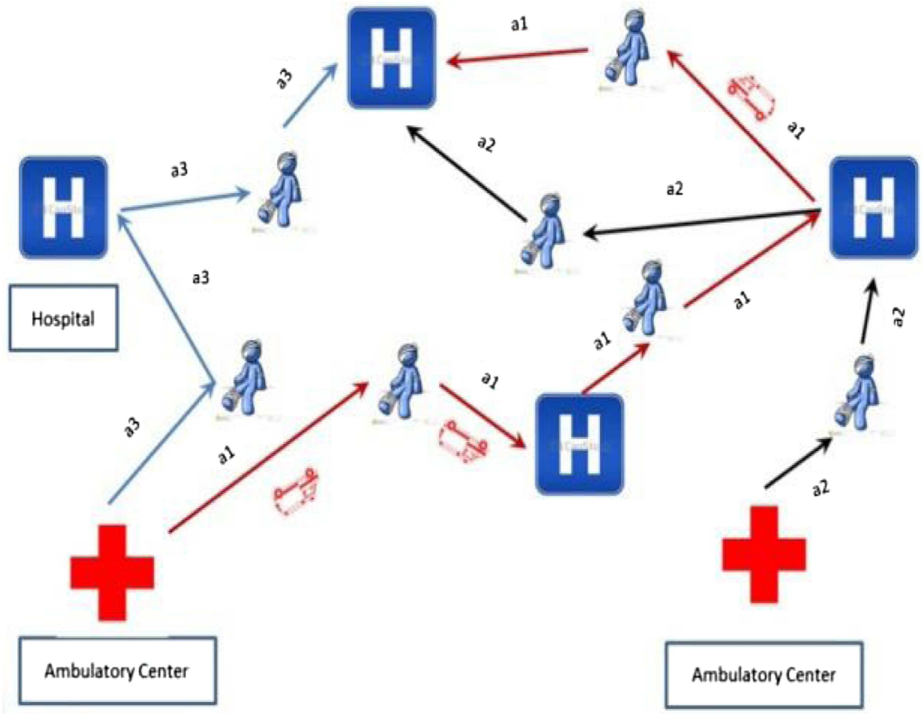

FIGURE 1. Problem description.

3. Problem description and mathematical modelling

3.1. Problem description

As explained before, we deal with the Integrated Problem of Ambulance Scheduling and Resource Assignment where the resource assignment concerns the allocation of hospitals and ambulances to wounded. The situation is described as follow: we have a finite number of dispersed wounded, a fleet of ambulances located in several ambulatory centers and several hospitals in distant areas, we intend to transport the set of wounded to the hospital sites with the fleet of ambulances (Fig. 1). Ambulance scheduling is defined by a sequence of tasks to be performed where each task has its own starting and ending locations. We consider two versions of the Integrated Problem of Ambulance Scheduling and Resource Assignment (IPASRA), the first one integrates a constraint of hospital capacity where each hospital treats a finite number of wounded and in the second one, that constraint is removed, in other terms with an infinite hospital capacity.

In this work, we assume that the following conditions are verified and respected.

- The estimated total wounded number is known in advance.
- We use one type of vehicles which is the ambulances.
- We will assume that the total number of ambulances to be used for wounded transportation purpose is less than the total number of wounded, moreover we will limit the ambulance capacity to one wounded at a time (standard capacity).
- We will set a finite capacity w_i for a hospital h_i (First scenario), this constraint is ignored in the second scenario.
- We will not consider the wasted time spent by the operation of picking up and putting down (Load/Unload) wounded.

- Each hospital is capable to treat all kind of injuries.

The disaster area is considered like a round field where all wounded are distributed. In reality, when an injury is critical, it means that the wounded have around 20–30 min to live, after that he will be most probably dead. Each tardiness second counts in losing an injured so the faster we provide results the fewer wounded are dead. Then we are interested in efficient solutions calculated with a processing time less than 10 min.

3.2. Mathematical formulation

We present below the data used in our modelling.

- H is the set of hospitals indexes and $|H|$ the number of hospitals.
- A is the set of ambulances indexes and $|A|$ the number of ambulances.
- P the set of wounded indexes and $|P|$ the number of wounded.
- H_{fic} and P_{fic} are respectively the set of fictive wounded and the set of fictive hospitals. Each vehicle a is associated to a pair (p_a, h_a), where p_a is a fictive wounded and h_a a fictive hospital and where the distance between p_a and h_a is nil. These elements are used to insure the starting of each vehicle missions. The distance between h_a (or p_a) and each hospital h represents the distance between the depot of ambulance a and the hospital h. In others terms, p_a and h_a represent the depot of ambulance a.
- w_h: Theoretical capacity of hospital h, it is the maximal number of wounded which hospital h can serve at the beginning of the operation.
- $T_{p,h}$: The total routing time spent in transporting the injured p to hospital h. This matrix is not symmetric in real cases.
- $T_{h,p}$: The total routing time spent in moving from the hospital h to the wounded p. We can consider here that h is the last visited hospital and p the next wounded to secure.
- G: A sufficiently large number.

In the following we introduce the variables of our model.

$C_{\max}$: the date of operation's ending called the makespan. This value is the objective to minimize in our modelling.

t_p: the time when the ambulance transporting wounded p arrive at hospital.

$X^a_{p,h,f}$: Binary variable defined as follow

$$X^a_{p,h,f} = \begin{cases} \bullet \quad 1 \text{ if ambulance } \boldsymbol{a} \text{ transfer wounded } \boldsymbol{f} \text{ directly before wounded } p \text{ to hospital } h. \\ \bullet \quad 0 \text{ if else.} \end{cases}$$

We present below the mathematical model of our problem. The objective function $C_{\max}$ seeks to minimize the total time spent by ambulance routing.

Minimize $C_{\max}$.

Subject to the following constraints:

$$\sum_{p\in P} X^a_{pa,ha,p} = 1, \qquad \forall a \in A \tag{3.1}$$

$$\sum_{a\in A}\sum_{p\in p}\sum_{f\in P, f\neq p} X^a_{p,h,f} = 1, \qquad \forall\ h \in H_f \tag{3.2}$$

$$\sum_{a\in A}\sum_{h\in H}\sum_{f\in P, f\neq p} X^a_{p,h,f} = 1, \qquad \forall p \in P \tag{3.3}$$

$$\sum_{a\in A}\sum_{h\in H}\sum_{f\in P, f\neq p} X^a_{f,h,p} = 1, \qquad \forall p \in P \tag{3.4}$$

$$\sum_{h\in H}\sum_{f\in P, f\neq p} = \sum_{l\in H}\sum_{g\in P, g\neq p} X^a_{g,l,p}, \qquad \forall p \in P,\ \forall a \in A \tag{3.5}$$

$$t_f \geq T_{p,h} + T_{h,f} + t_p + G(X^a_{p,h,f} - 1), \quad \forall a \in A,\ \forall p \in P,\ \forall f \in P \backslash P_f, f \neq p \tag{3.6}$$
$$C_{\text{Max}} \geq t_p, \quad \forall p \in P \backslash P_f. \tag{3.7}$$
$$X^a_{p,h,f} \in \{0,1\}, t_p \in R^+, \forall a \in A, \quad \forall p, f \in P,\ \forall h \in H. \tag{3.8}$$

Constraint (3.1) ensures the starting of each ambulance mission by associating it to a fictive couple of injured and hospital. Note that these two fictive elements are situated in the same location as the associated ambulance at the beginning of its mission. The distance between the fictive injured and the fictive hospital is nil and the distance between the fictive hospital and each injured is equal to the distance between the initial location of the ambulance and the injured which is initially known. Constraint (3.2) ensures that each fictive hospital is to be visited only once. Constraint (3.3) ensures that every injured has only one direct successor and constraint (3.4) ensures that he has only one predecessor. In other terms, constraints (3.3) and (3.4) ensure that each injured should be transported once. With constraint (3.5) we ensure that the successor and the predecessor of each injured are transported by the same ambulance. Constraint (3.6) ensure the temporal succession by considering the binary variable $X^a_{p,h,f}$ and the traveling times $T_{p,h}$ and $T_{h,f}$, with this constraint we evaluate the ending date of each securing mission denoted by t_p. Constraint (3.7) is used to evaluate the makespan which is the time spent by the last mission ending. The makespan in denoted by C_{Max}. Constraint (3.8) represents decision variable.

The evaluation of the makespan by constraints (3.6) and (3.7) represents a serious complication at simulation stage because of G which is a sufficiently large number. To improve the modelling, we replace constraints (3.6) and (3.7), respectively by constraints (3.9) and (3.10). We replace also $t_p\ by\ \ R_p$ which represents a number associated to wounded p and used to avoid sub-cycles.

$$R_f \geq 1 + R_p + |P| \left(X^a_{p,h,f} - 1\right), \ \forall a \in A,\ \forall p \in P,\ \forall f \in P \backslash P_{\text{fic}}, f \neq p. \tag{3.9}$$
$$C_{\text{Max}} \geq \sum_{p \in P} \sum_{h \in H} \sum_{f \in P \backslash P_{\text{fic}}} X^a_{p,h,f}(T_{p,h} + T_{h,f}),\ \forall a \in A. \tag{3.10}$$

Constraint (3.9) is imposed to avoid sub-cycles and with constraint (3.10) the makespan is reduced by the total traveling time of each ambulance. By adopting constraints (3.9) and (3.10) instead of constraints (3.6) and (3.7), we improved the efficiency of the modelling in terms of simulation results. Note that the use of G in constraint (3.9) does not affects the quality of simulation results as in the case of constraint (3.6). Note that we integrated the ambulance scheduling and hospital affectation in the same variable $X^a_{p,h,f}$ to avoid the use of a big number in constraint (3.10).

Considering the presented constraints, the capacity of hospitals is not taken into account. According to crisis extent, the problem can be considered with or without capacity constraint. In fact, for a major disaster, when the number of injured is larger than the total capacity of hospitals, the capacity constraint should be ignored. However, in other situation, when the number of injured is less than the total capacity of all hospitals, it is more realistic to consider the capacity constraint in the modelling in order to propose an adequate solution. Capacity constraint is modelled by the following inequality.

$$\sum_{a \in A} \sum_{p \in P} \sum_{f \in P, f \neq p} X^a_{p,h,f} \leq w_h,\ \forall h \in H \backslash H_{\text{fic}}. \tag{3.11}$$

Our linear model is solved using CPLEX solver 12.6.

3.3. Proof of NP-HARDNESS

Consider an instance of the TSP defined by an undirected graph $G = (V, E)$, in which each edge e has a weight $w(e)$. Now consider an instance of the IPASRA defined as follows. In this instance, each node of G corresponds to a hospital and to a wounded, that is, for each node $u\backslash in\ G$, we associated a hospital $h\_\{u\}$ and a wounded $p\_\{a\}$. Remark that here $|H| = |P| = |V|$. Also, suppose that the distance between two hospital $h\_\{u\}$ and $h\_\{v\}$ is equal to the weight $w(u, v)$, and the distance between wounded $p\_\{u\}$ and hospital $h\_\{u\}$ is very small with respect to weights $w(e)$. In other words, in an optimal solution, a wounded $p\_\{u\}$ will be assigned to hospital $h\_\{u\}$. Finally, we consider that we have only one ambulance, and consider any node of G as the depot. It is not hard to see that a solution of IPASRA is optimal if and only if it is optimal for the TSP. As the TSP is NP-hard, the IPASRA is also NP-hard.

4. Resolution methods

As proven in Section 3.3, our problem is NP-Complete and then exact solutions obtained by CPLEX of large-scale instances are not practical. In this section we develop our hybrid algorithm. For this part, we consider that the problem without capacity constraint is equivalent to the problem with infinite hospital capacity. In this section we present (GRASP), (TS) and their hybridization and we discuss their adaption to our problem.

4.1. Greedy Randomized Adaptive Search Procedure (GRASP)

GRASP is a fast-randomized heuristic used to solve combinatorial optimization problems. It was first proposed by Feo and Resende [5], it consists of two phases, the first one is a repetitive randomized construction and the second one is a local search phase in which the constructed solution is subject to many improvements.

We discuss now the adaptation of (GRASP) algorithm to solve our problem. As shown in next diagram, we start the algorithm by initializing randomly the initial solution. Then we apply an iterative randomized procedure to construct a feasible solution. At each iteration of the randomized procedure, we treat the subsequent injured to secure and we select randomly, with probability one of the nearest ambulances and one of the nearest hospitals having sufficient capacity. Then we update the distances between the set of injured and the selected ambulance at this iteration. We update also the capacity of the selected hospital. When we finish the treatment of all wounded, we check if the constructed solution is better than all of the previous constructed solutions, if it was the case then we save it as the best solution and then we reinitialize the parameters of the randomized procedure and we restart it again. The number of randomized constructions named K_{Max} is initially predefined, when it is reached, the procedure is stopped and the best solution found is returned.

Note here that we use the normal uniform law in the random distribution.

4.2. Tabu Search (TS)

In [1, 2], Glover was the first who developed a Tabu Search algorithm which has been effectively powerful and useful for solving combinatorial optimization problems. This technique relies on two phases: (a) Adaptive memory; (b) Responsive exploration; the first one record ancient search information depending on four important references: occurrence, recently visited, quality and influence. The second one is capable to make tactical selections to achieve effectiveness. The main role of using an adaptive memory is to record the pre-visited good candidates, this record is called tabu list (forbidden list), its main purpose is to restrict choosing redundant candidates (marked as Tabu active) for some time, depending on the user pre-fixed Tabu list size, when the list size exceeds the user predefined limit, the first record is removed (aspiration method). The main importance of this adaptive memory is to avoid entering in a local optimum and to enhance the search by using intensification or diversification strategies, the intensification strategy allows the algorithm to exploit more the good found candidates while the diversification strategy lead to explore unvisited candidates inside the solution space. We present in the next paragraph the adaptation of Tabu Search approach to our problem.

We provide a detailed explanation for neighborhood construction after this general description. At first, let us define a negative iteration as an iteration that does not improve the best solution found. After that, we use the number of successive negative iterations as a diversification criterion, an intensification criterion and a stopping criterion. Before launching the Tabu Search procedure, an initial solution is generated and all of the required parameters are initialized such as: the tabu list, the current solution, the best solution and the number of successive negative iterations. Next, we start the iterations of our algorithm. At each iteration, the

TABLE 1. Parameters value.

Family	K_{Max}	I_{Max}	Z_{Max}
F1	1000	100	300
F2	10000	200	1000
F3	1000000	300	2000

neighborhood of the current solution is constructed. The size of this neighborhood depends on the number of successive negative iterations at the current iteration. The current solution is updated by the best non tabu neighbor, if this neighbor is better than the best explored solution, then the best solution will be updated and the neighbor is injected to the tabu list. If the maximal size of tabu list is reached, the oldest element is removed. When the number of successive negative iterations is equal to a fixed integer which we denote by I_{Max}, the Tabu Search is stopped and the best solution is returned.

The neighborhood of each constructed solution is divided into three sub neighborhoods where each one is constructed according to a particular vision. For the first sub-neighborhood construction, the method is done by selecting a vehicle and replacing it with another one. The wounded is being inserted in the other vehicle associated cycle. For the second sub-neighborhood construction, we select a vehicle and we switch only the associated wounded with another wounded, in other term we switch service order between its associated wounded. For the construction of the third sub-neighborhood, we select a vehicle and we replace only the associated hospital with another available one and update their capacities.

4.3. Hybrid algorithm

Hybrid algorithms are popular and well known for their efficiency compar to classic meta-heuristics. By using hybridization, we can avoid falling in some problems like the stagnation under local optima, also we can efficiency reduce the required processing time spent in calculating an optimal solution or an acceptable solution. Many hybridization strategies are developed in literature but we can identify two-man classes of hybridization. The first one is the hybridization by parallelization or by threading and it is a strategy based on the exploitation of concurrence and cooperation benefits when many meta-heuristic processes are launched in parallel. The second approach is the sequential hybridization and is based on the alternate between two meta-heuristics or more and on a cooperation technique like the communication among some parameters. The hybrid algorithm which we propose is a sequential hybridization of (GRASP) algorithm and (TS) procedure. This approach is based on restarting the Tabu Search from different initial solutions generated by (GRASP) algorithm for a specific iteration number denoted by Z_{Max}.

Note here that the values of I_{Max}, K_{Max} and Z_{Max} are subject to modifications depending on the instances size. We present in the next Table 1, the values of theses iterations according to instances size.

With the following diagrams in Figures 2 and 3, we present respectively our (GRASP) procedure and hybrid algorithm with the integrated Tabu Search procedure.

5. Experimental results and discussions

This section presents the obtained results for the instances of the IPASRA. All Algorithms are coded using java, the computer used for simulation has a CPU Core I7 2.4 GHZ, 16 GB of RAM, 2 GB dedicated VGA RAM and 500 GB SSD hard disk.

In Table 2, we present instances generated for simulation tests and for each one we give the number of wounded, the number of ambulances, the number of hospitals and the capacity of each hospital. Note that for every instance two other data are defined, the distances between hospitals and injured and the distances between ambulances and injured at the beginning of the secure operation. Instances are classified in three families F1,

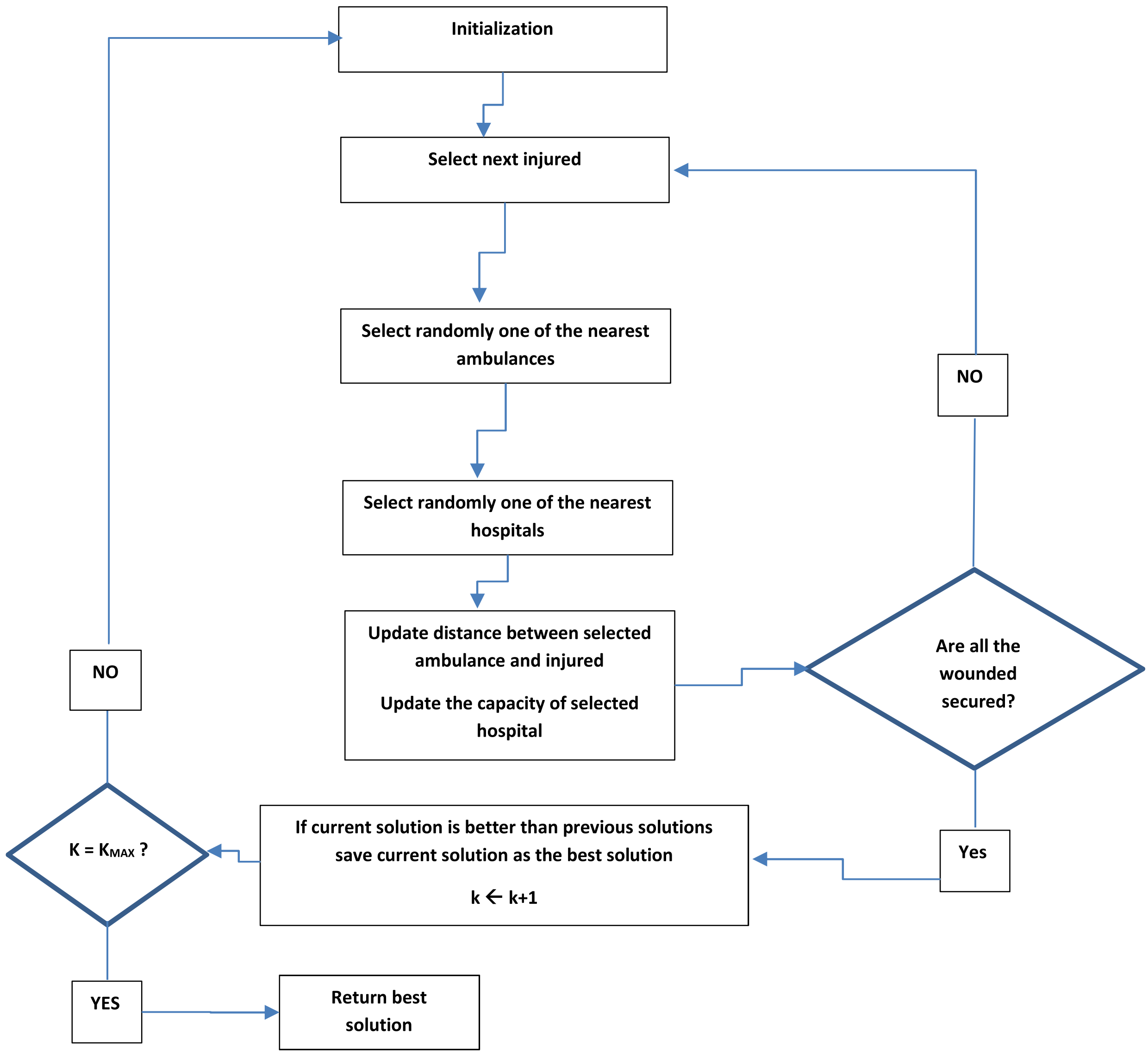

FIGURE 2. GRASP procedure.

F2 and F3. F1 contains instances with a number of injured equal to 10 or 15 wounded, F2 contains instances of 20, 30 or 50 injured and F3 is the family containing instances of more than 50 wounded. The deviation between the CPLEX solution and the solution given by hybrid algorithm is calculated by:

$$\text{Gap} = \frac{\text{V.H.A} - \text{V.C}}{\text{V.C}}.$$

V.H.A: Value given by Hybrid Algorithm
V.C: Value given by CPLEX.

In Table 3, we present the numerical results for capacitated (IPASRA). The simulation tests of non-capacitated (IPASRA) are presented in Table 4.

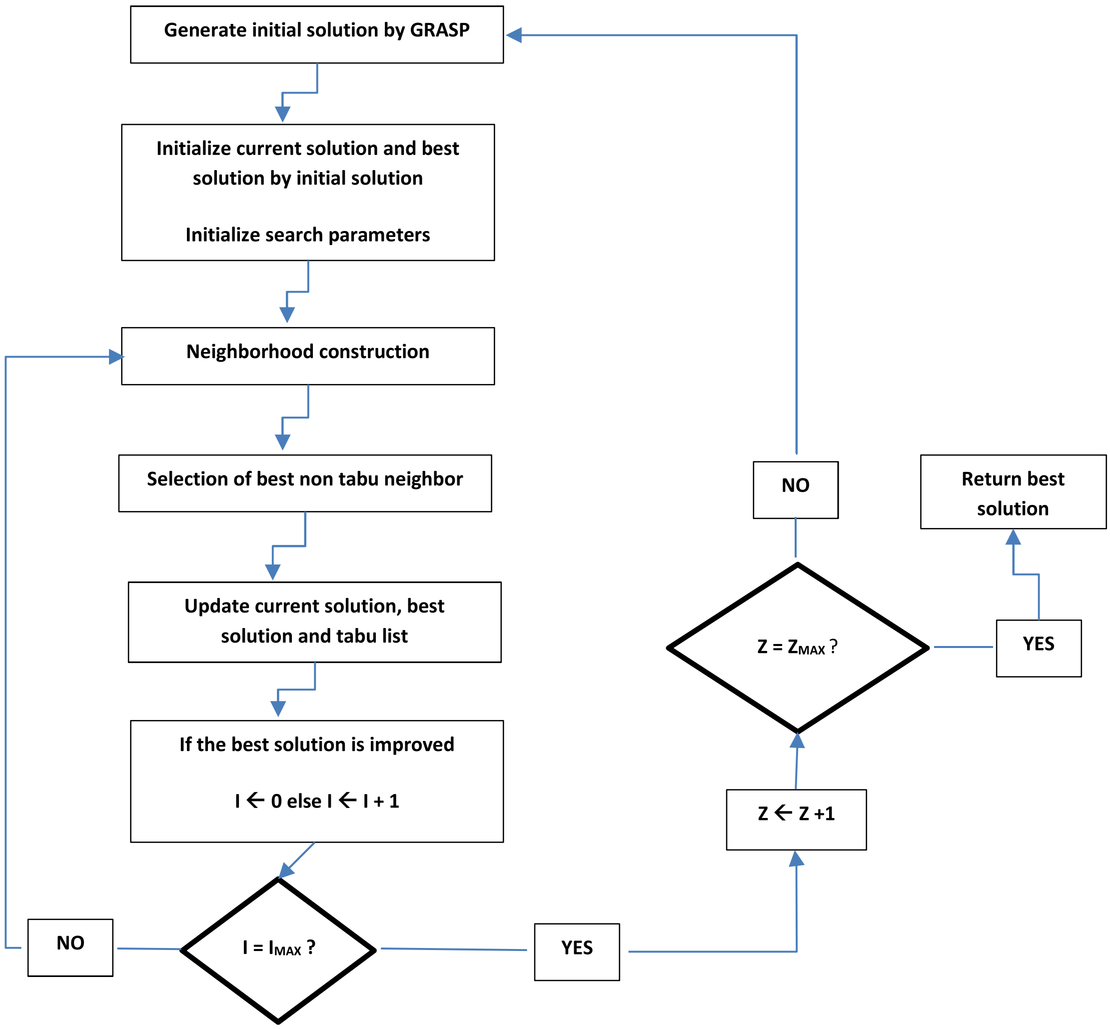

FIGURE 3. Hybrid algorithm.

Consider now the capacitated (IPASRA). For instances of family F1, the gap is between 0% and 0.94% and the processing time is less than 6 min. All the solutions given by CPLEX are optimal. From a total of 12 instances, 9 solutions calculated by hybrid algorithm are optimal and 8 from them are given in less than 8 s. For Family F2, Inst13, Inst14, Inst15 and Inst16 are solved optimally by CPLEX and the deviation between CPLEX solution and solution given by hybrid algorithm is less than 2%. These solutions are given in less than 23 s. For the others instances of F2 the processing time is limited to 3600 s and excepting Inst27 and Inst30, the CPLEX gap is less than 6%. For Inst27 and Inst30 the CPLEX gaps are respectively equals to 9.59% and 20.88%. The deviation between these solutions and solutions given by hybrid algorithm is between −13% and 12%. For the instances of Family F3, the CPLEX gaps of inst31, inst32 and int33 are respectively 6.11%, 9.73% and 12.62 %. The deviations between CPLEX solutions and the solutions of hybrid algorithm are respectively 5.13%, 3.62% and −1.97%. These deviations are reached after 10 800 s of running time. For instances from Inst34 to Inst40 no solution is given by CPLEX solver after 10 800 s of processing time. For Inst41, Inst42 and Inst43 no solution is returned because of the “out of memory”.

Table 2. Problem characteristics.

Family	Instance	$\|P\|$	$\|H\|$	$\|A\|$
F1	*Inst1*	10	2	1
	Inst2	10	3	1
	Inst3	10	2	2
	Inst4	10	3	2
	Inst5	10	2	3
	Inst6	10	3	3
	Inst7	15	2	1
	Inst8	15	3	1
	Inst9	15	2	2
	Inst10	15	3	2
	Inst11	15	2	3
	Inst12	15	3	3
F2	Inst13	20	2	1
	Inst14	20	3	1
	Inst15	20	4	1
	Inst16	20	2	2
	Inst17	20	3	2
	Inst18	20	4	2
	Inst19	20	2	3
	Inst20	20	3	3
	Inst21	20	4	3
	Inst22	20	2	4
	Inst23	20	3	4
	Inst24	20	4	4
	Inst25	30	4	4
	Inst26	30	5	4
	Inst27	30	6	4
	Inst28	50	4	4
	Inst29	50	6	4
	Inst30	50	8	4
F3	Inst31	70	5	4
	Inst32	70	8	4
	Inst33	70	9	4
	Inst34	100	5	5
	Inst35	100	8	5
	Inst36	100	10	5
	Inst37	150	8	5
	Inst38	150	10	5
	Inst39	150	12	5
	Inst40	200	10	5
	Inst41	200	15	5
	Inst42	200	20	5

Notes. Italic: It means that hybrid method produces better solution than the one produced by exact method.

Note that deviation between CPLEX solutions and hybrid algorithm solutions is negative when the solution given by hybrid algorithm is better than the one given by CPLEX. Note also that solutions given by CPLEX are not optimal for some instances because of memory limit or processing time limitation.

Consider now the non-capacitated IPASRA given in Table 4. Starting with instances of family F1, the CPLEX gap is between 0.8% and 1.78%, 10 of 12 instances were optimal, 8 of them were given in less than 3 min and the

Table 3. Comparison of obtained results of applied methods with capacity constraint.

	Instance ID	C-VAL (s)	H-VAL (s)	C-CPU (s)	H-CPU (s)	C-GAP	H-GAP
	Inst1	11503	11503	<1	<1	0%	0%
	Inst2	3975	3975	<1	2	0%	0%
	Inst3	**2782**	**2782**	**2.8**	**48**	**0%**	**0%**
	Inst4	**3776**	**3776**	**0.81**	**6**	**0%**	**0%**
	Inst5	**4870**	**4870**	**1.2**	**5**	**0%**	**0%**
	Inst6	**2943**	**2943**	**7.64**	**317**	**0%**	**0%**
F1	*Inst7*	**4675**	**4675**	**0.52**	**88**	**0%**	**0%**
	Inst8	**13023**	**13023**	**0.31**	**32**	**0%**	**0%**
	Inst9	**2328**	**2328**	**172.29**	**234**	**0%**	**0%**
	Inst10	8719	8721	123.07	48	0%	0.02%
	Inst11	3023	3024	53.13	104	0%	0.03%
	Inst12	1801	1818	355.7	313	0	0.94%
	Inst13	16816	16816	<1	387	0%	0%
	Inst14	23487	23487	<1	99	0%	0%
	Inst15	2892	2948	<1	71	0%	1.94%
	Inst16	3497	3499	23	24	0%	0.06%
	Inst17	6733	6792	3600	195	1.26%	0.88%
	Inst18	8594	8753	3600	164	0.02%	1.85%
	Inst19	*10467*	*10463*	*3600*	*5*	*2.52%*	*–0.04%*
	Inst20	1762	1777	3600	54	0.51%	0.85%
	Inst21	2384	2413	3600	163	0.34%	1.22%
F2	*Inst22*	*8095*	*8085*	*3600*	*376*	*1.17%*	*–0.12%*
	Inst23	*6210*	*6165*	*3600*	*38*	*0.81%*	*–0.72%*
	Inst24	*6150*	*6113*	*3600*	*94*	*3.84%*	*–0.6%*
	Inst25	6450	6487	3600	329	1.01%	0.57%
	Inst26	*3572*	*3541*	*3600*	*111*	*5.49%*	*–0.87%*
	Inst27	3325	3444	3600	108	9.59%	3.58%
	Inst28	8949	9664	3600	387	1.74%	7.99%
	Inst29	4270	4762	3600	245	3.09%	11.52%
	Inst30	*6590*	*5779*	*3600*	*242*	*21.88%*	–12.31%
	Inst31	*8433*	*8866*	*10800*	*61*	*6.11%*	5.13%
	Inst32	*7490*	*7761*	*10800*	*188*	*9.73%*	3.62%
	Inst33	7926	7770	10800	200	12.62%	–1.97%
	Inst34	N.S	15552	10800	40		
	Inst35	N.S	4924	10800	279		
	Inst36	N.S	9498	10800	570		
F3	*Inst37*	N.S	15438	10800	734		
	Inst38	N.S	17249	10800	305		
	Inst39	N.S	10159	10800	634		
	Inst40	N.S–O.M	20197	9673	866		
	Inst41	N.S–O.M	16017	<1	625		
	Inst42	N.S–O.M	7874	<1	820		

Notes. Bold: It means that both exact and hybrid methods reach optimal. Italic: It means that hybrid method produces better solution than the one produced by exact method.

remaining 2 were given in less than 44 min, Inst7 and Inst11 did not attain optimality after a fixed processing time of 1 hour with a gap equals to 1.78% and 0.17%, respectively. With the hybrid algorithm, from a total of 12 instances, 9 were optimal in less than 3 min. For both Inst7 and Inst1 the hybrid algorithm produces exactly the same value as CPLEX in less than 5 s. Finally, for Inst11, a deviation of 0.14% was given by hybrid algorithm

Table 4. Comparison of obtained results of applied methods without capacity constraint.

	Instance ID	C-VAL (s)	H-VAL (s)	C-CPU (s)	H-CPU (s)	C-GAP	H-GAP
	Inst1	11275	11275	<1	<1	0%	0%
	Inst2	948	948	<1	<1	0%	0%
	Inst3	2259	2259	<1	<1	0%	0%
	Inst4	3595	3595	<1	<1	0%	0%
	Inst5	4839	4839	2595	<1	0%	0%
	Inst6	1878	1878	3	<1	0%	0%
F1	*Inst7*	3487	3487	3600	<1	1.78%	0%
	Inst8	9856	9856	<1	<1	0%	0%
	Inst9	2325	2325	69	5	0%	0%
	Inst10	8602	8614	1018	38	0%	0.14%
	Inst11	2950	2950	3600	5	0.17%	0%
	Inst12	1799	1799	151	170	0%	0%
	Inst13	11338	11338	2.64	<1	0%	0%
	Inst14	9030	9030	1.39	<1	0%	0%
	Inst15	2826	2844	3600	145	0.07%	0.64%
	Inst16	2398	2398	3600	9	0.54%	0%
	Inst17	1131	1131	41	<1	0%	0%
	Inst18	7971	7971	3600	51	0.84%	0%
	Inst19	10463	10463	3600	12	4.73%	0%
	Inst20	852	852	66	<1	0%	0%
	Inst21	1213	1213	299	345	0%	0%
F2	*Inst22*	7123	7123	3600	4	3.47%	0%
	Inst23	*6122*	*6101*	*3600*	*63*	*1.08%*	–0.34%
	Inst24	4077	4099	3600	237	1.03%	0.54%
	Inst25	*5158*	*5133*	*3600*	*281*	*3.76%*	–0.48%
	Inst26	732	732	43	45	0%	0%
	Inst27	992	1023	96	13	0%	3.13%
	Inst28	6045	6126	3600	287	0.88%	1.34%
	Inst29	*3904*	*3748*	*3600*	*241*	*10.91%*	–4%
	Inst30	*3416*	*3288*	*3600*	*317*	*5.50%*	–3.75%
	Inst31	1732	1832	10800	314	0.06%	2.86%
	Inst32	2198	2210	10800	113	1.91%	0.55%
	Inst33	9465	3709	10800	121	64.68%	–60.81%
	Inst34	N.S	9564	10800	317		
	Inst35	N.S	1610	10800	25		
	Inst36	N.S	7480	10800	216		
F3	*Inst37*	N.S	2110	10800	274		
	Inst38	N.S	17249	10800	305		
	Inst39	N.S	3564	10800	709		
	Inst40	N.S	2629	10800	414		
	Inst41	N.S – O.M	12912	1499	511		
	Inst42	N.S – O.M	1926	<1	619		

Notes. Italic: It means that hybrid method produces better solution than the one produced by exact method.

with a processing time equal to 38 s. Continuing with F2 family, Inst13, Inst14, Inst17, Inst20, Inst21, Inst26 and Inst27 were solved optimally by CPLEX in less than 345 s and the deviation between CPLEX solutions and the solutions given by hybrid algorithm is equal to 0% for all instances except for Inst27 where the deviation is equal to 3.13%, all these solutions are given in less than 6 min. For instances Inst15, Inst16, Inst18, Inst19, Inst22, Inst23, Inst24, Inst25, Inst28, Inst29 and Inst30 the CPLEX gap is between 0.07% and 10.91%. The

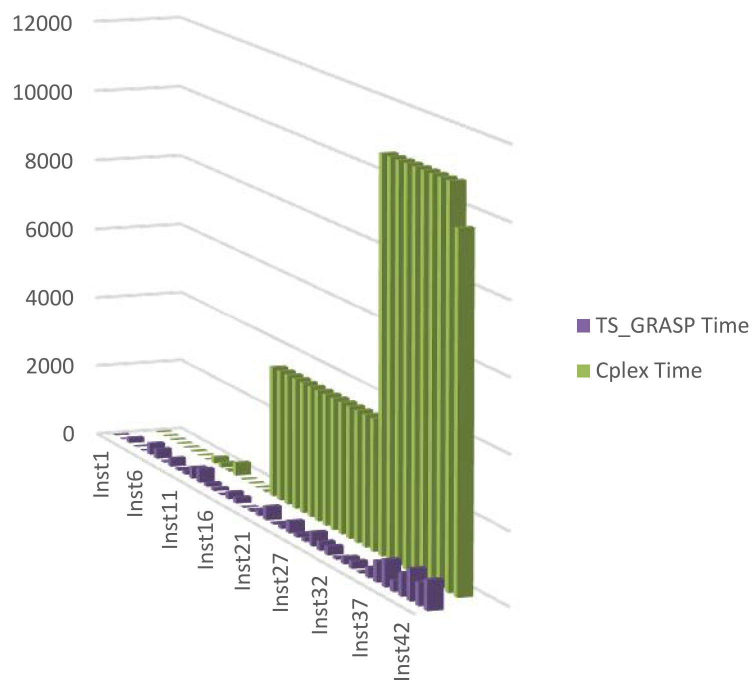

FIGURE 4. CPLEX *vs.* Hybrid Algorithm – comparison of processing time/with capacity constraint.

deviation between these solutions and solutions given by hybrid algorithm is between −3.75% and 4%. Ending with instances of family F3, the CPLEX gaps of Inst31 and Inst32 are respectively 0.06% and 1.91%. For Inst33 the CPLEX gap is equal to 64.68%, these solutions were attained after 10 800 s of CPU Consuming time. The deviations between these solutions and the solutions produced by the hybrid algorithm are equal to 2.86%, 0.55% and −60.81%, respectively. These solutions are reached in less than 6 min of processing time. For instances Inst34, Inst35, Inst36, Inst37, Inst 38, Inst39 and Inst40 there is no solution given by CPLEX after 10 800 s and finally for Inst41 no solution is returned due to "out of memory" but with a processing time equal to 1499 s, meanwhile for inst42 the "no solution out of memory" is returned directly.

We should note here that when the deviation between CPLEX solutions and Hybrid solutions is negative, it means that the produced solutions by hybrid algorithm is better than the ones produced by CPLEX which are not optimal due to processing time limitation or due to memory limitation.

In Figures 4 and 5 we can clearly recognize the huge difference in CPU consuming Time between CPLEX and (TSGRASP) in both scenarios.

In Figures 6 and 7 we can clearly distinguish, in both scenarios, the values convergence between CPLEX and (TSGRASP), also we can visually notice the CPLEX limitations due to time or memory limitations. Starting from instance Inst34 (in both scenarios), CPLEX stops providing feasible solutions.

6. Conclusion

In this paper, we study a real-life case of wounded carrying toward hospitals via ambulances throughout a crisis in the case of sudden disaster. This Integrated Problem of Ambulance Scheduling and Resources Assignment (IPASRA) has been treated and formulated as a linear model that minimize the total time spent by routing ambulances picking up wounded from their locations to distant hospitals. We applied an effective hybrid metaheuristic algorithm based on the Tabu Search and (GRASP). We also offered a methodology that can be adopted to provide an efficient evacuation plans under various circumstances. Two scenarios were treated and

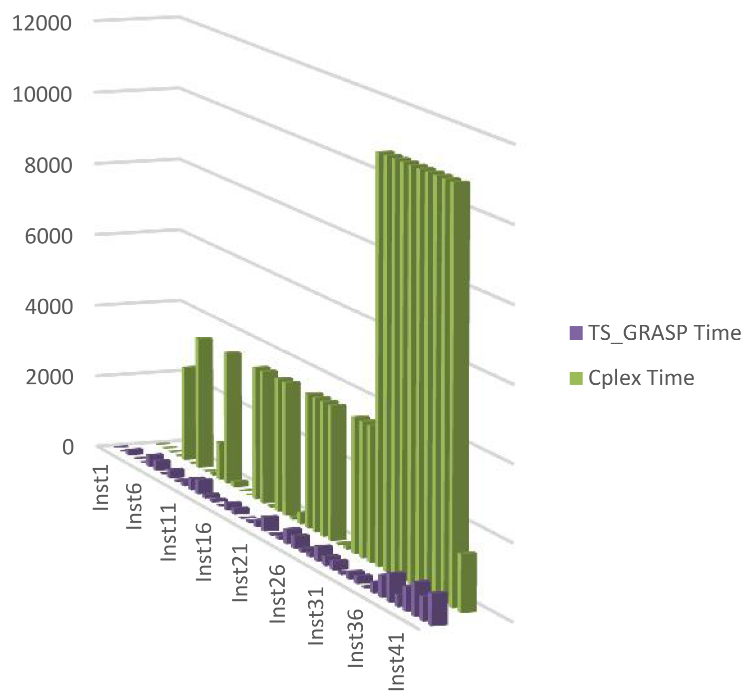

FIGURE 5. CPLEX *vs.* Hybrid Algorithm – comparison of processing time/without capacity constraint.

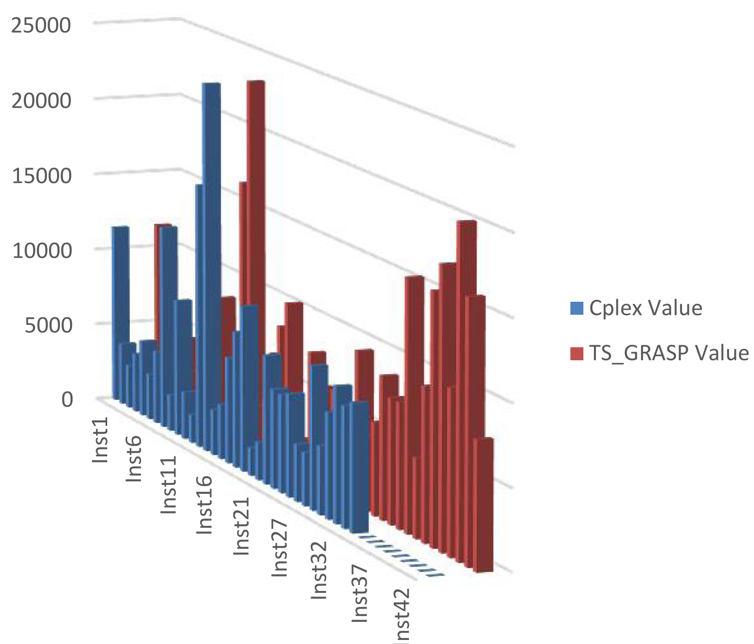

FIGURE 6. CPLEX *vs.* Hybrid Algorithm – comparison of solution value/with capacity constraint.

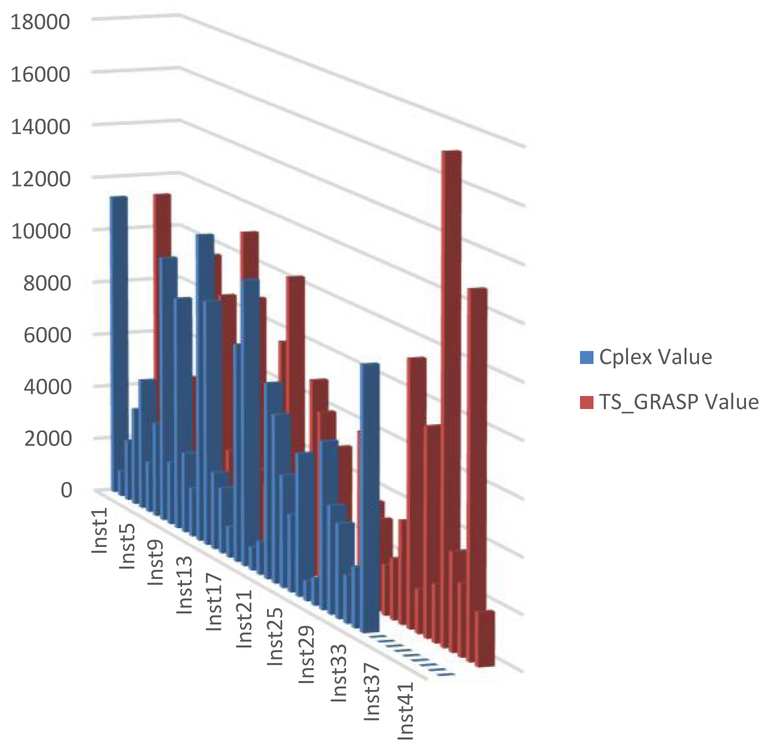

FIGURE 7. CPLEX *vs.* Hybrid Algorithm – comparison of solution value/without capacity constraint.

for both of them, the offered model has proved his capability of evacuating wounded from their positions to hospitals within reasonable time.

After discussing the obtained results for both scenarios in Section 6, and depending on the situation, we can notice the huge importance of choosing between the two scenarios especially with large instances, the choice should be based on the on-site provided information, especially wounded number and hospitals theoretical capacities, before taking the final decision. Both exact and hybrid versions of algorithms have been extensively tested on randomly generated instances of the (IPASRA). Our algorithms provide in both scenarios' optimal solutions for instances with wounded number up to 50, ambulance number up to 8 and hospitals number up to 4. Also, it gives an efficient solution for instances with more than 70 wounded, 8 ambulances and 4 hospitals in less than 5 min of execution time, and even when it deals with an instance with 200 wounded, 15 ambulances and 5 hospitals or more, it continues providing feasible solutions in less than 10 min of CPU consuming time which prove its efficiency in term of quality and time.

At the end, the results of the proposed hybrid algorithm are compared with those obtained with the exact method of CPLEX solver. The comparison of the execution time illustrates the efficiency of our proposed model; its results show clearly that it is capable of generating optimal solutions within seconds. The CPLEX resolution, based on our modelling, also proves its efficiency but with more precious time wasted. However, the efficiency of the exact method decreases as the number of instances grows; it is only effective with a medium number of instances.

For the future work, we believe that there is a need of further improvements by:

(1) Dynamic hospital capacity.
(2) Implementing the use of firefighter truck.
(3) Implementing the notion of wounded urgency and transportation priority.

References

[1] F. Glover, Tabu search – Part I. *ORSA J. Comput.* **1** (1989) 190–206.

[2] F. Glover, Tabu search – Part II. *ORSA J. Comput.* **2** (1990) 4–32.

[3] M. Laguna and J.L. González-Velarde, A search heuristic for just-in – time scheduling in parallel machines. *J. Intel. Manuf.* **2** (1991) 253–260.

[4] M. Christopher, Logistics and Supply Chain Management, 1st edition. Pitmans, London (1992).

[5] T. Feo and M. Resende, Greedy randomized adaptive search procedures. *J. Global Optim.* **6** (1995) 109–133.

[6] M. Christopher, From brand values to customer value. *J. Market. Prac. Appl. Market. Sci.* **2** (1996) 55–66.

[7] M. Christopher, L. Magrill and G. Wills, Educational development for marketing logistics. *Int. J. Phys. Distr. Logist. Manage.* **28** (1998) 234–241.

[8] R.R. Lummus, R.J. Vokurka and K.L. Alber, Strategic supply chain planning. *Prod. Inventory Manage. J.* **39** (1998) 49–58.

[9] K.C. Tan, A framework of supply chain management literature. *Eur. J. Purchasing Supply Manage.* **7** (2001) 39–48.

[10] M. Christopher and H. Peck, Building the resilient supply chain. *Int. J. Logist. Manage.* **15** (2004) 1–13.

[11] C.S. Silva, Distributed optimization of a logistic system and its suppliers using ant colonies. *Int. J. Syst. Sci.* **37** (2006) 503–512.

[12] M. Chen, L. Chen and R. Miller-Hooks, Traffic signal timing for urban evacuation. *J. Urban Planning Dev.* **133** (2007) 30–42.

[13] W. Yi and L. Ozdamar, A dynamic logistics coordination model for evacuation and support in disaster response activities. *Eur. J. Oper. Res.* **179** (2007) 1177–1193.

[14] H.O. Mete and Z.B. Zabinsky, Stochastic optimization of medical supply location and distribution in disaster management. *Int. J. Prod. Econ.* **126** (2010) 76–84.

[15] C. Blum, Hybrid metaheuristics. *Comput. Oper. Res.* **37** (2010) 430–431.

[16] F. Sayyady and S.D. Eksioglu, Optimizing the use of public transit system during no-notice evacuation of urban areas. *Comput. Ind. Eng.* **59** (2010) 488–495.

[17] M. Lozano and C. García-Martínez, Hybrid metaheuristics with evolutionary algorithms specializing in intensification and diversification: overview and progress report. *Comput. Oper. Res.* **37** (2010) 481–497.

[18] X. Ma, Y. Song and J. Huang, Min-max Robust Optimization for the Wounded Transfer Problem in Large-scale Emergencies. IEEE, Chinese Control and Decision Conference (CCDC), Xuzhou (2010).

[19] J. Coutinho-Rodrigues, L. Tralhão and L. Alçada-Almeida, Solving a location-routing problem with a multiobjective approach. *Eng. Sci. Technol. Int. J. Des. Urban Evacuation Plans* **22** (2012) 206–218.

[20] N.A.M. Nordin, Z.A. Zaharudin, M.A. Maasar and N.A. Nordin, Finding Shortest Path of the Ambulance Routing: Interface of A* Algorithm Using C# Programming. IEEE Symposium on Humanities, Science and Engineering Research, Kuala Lumpur, Malaysia (2012) 1569–1573.

[21] X. Zhang, Study on rapid evacuation in high-rise buildings. *Eng. Sci. Technol. Int. J.* **20** (2017) 1203–1210.

[22] K. Chang, H. Zhou, G. Chen and H. Chen, Multiobjective location routing problem considering uncertain data after disasters. *Discrete Dyn. Nat. Soc.* **2017** (2017) 1703608.

[23] V. Yadollahnejad, Allocation and vehicle routing for evacuation operations: a model and a GRASPHeuristic. *J. Urban Planning Dev.* **143** (2017) 04017018.

[24] C. Boonmee, M. Arimura and T. Asada, Facility location optimization model for emergency humanitarian logistics. *Int. J. Dis. Risk Reduct.* **24** (2017) 485–498.

[25] J.A. Díaz, D.E. Luna, J.-F. Camacho-Vallejo and M.-S. Casas-Ramírez, GRASP and hybrid GRASP-Tabu heuristics to solve a maximal covering location problem with customer preference ordering. *Expert Syst. App.* **82** (2017) 67–76.