Operating room scheduling under unexpected events: the case of a disaster

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Abstract. Disaster like terrorist attack, earthquake, and hurricane, often cause a high degree of damage. Hundreds of people may be affected. Hospitals must be able to receive, in a short period, injured persons for medical and surgical treatment, using available resources and facilities. In such situations different disruptions widely perturb the execution of the established plans. Then medical resources optimization is fundamental to save human lives. Our works focus on operating rooms scheduling taking into account unexpected events. In this setting, we propose a reactive operating schedule. We consider two possible disruptions: the arrival of a new victim in the operating theatre and, the overflow of surgical processing time. The purpose is to treat all disruptions and so to save the maximum of human lives. The proposed approach is performed by the CPLEX solver. Computational experiments show that a substantial aid is obtained by using this approach which can be considered as a support decision for emergency manager.

Keywords: disaster; operating schedule; rescheduling; unexpected events

Introduction

In the case of a disaster, the need for medical treatment overwhelms the actual hospital treatment capacity (Noji, 1992). Hospitals must have a disaster plan, called white plan in several countries like France and Tunisia (Ministère de la santé et de la solidarité, France, 2006; Ministère de la santé publique, Tunisie, 2002). Emergency managers must find an optimal schedule for assigning resources. In USA, the Joint Commission on the Accreditation of Healthcare Organizations requires US hospitals to have a disaster management plan (DMP) (Lipp, 1998). In the case of a disaster, this plan is sets in motion (Kimberly, 2003).

Victims are evacuated to an immediate established pre-hospital, triage and dispatching structure which is set up near to the damaged zone. The triage allows classifying victims according to the urgency of the medical and/or surgical cares they need. Then this structure routes victims to the nearby admitting hospital. Before routing, a processing time and a ready date in the operating theatre are defined for the one who need surgical cares. Each victim is characterized by an emergency level which is defined by the latest start date of its surgical care. Therefore, the surgical care must be planned before the vital prognosis of the victim is being overaken.

A disaster situation is characterized by different disruptions. In this setting, we approach a reactive problem for optimization of surgical cares scheduling in the operating rooms. We consider two possible disruptions: the insertion of a new victim in the scheduling program and the overflow of assessed surgical processing time. Some unexpected victims can arrive to the admitting hospital at any time without being even spent by established pre-hospital, triage and

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dispatching structure (example: AZF disaster (Ministère de la santé, de la famille et des personnes handicapées, France, 2002). These unexpected events disrupt the established scheduling and need to be considered in a reactive way. In fact, these events have to be treated in real time and in coordination with the triage structure. Several works were interested in emergency logistics system, especially after the terrorist attack of September 11, 2001 and the Katrina hurricane in 2005. Many studies analyze what happened during the disaster and the resulting logistics problems (Kembell-cook and Stephenson, 1984) (Long and Wood, 1995) (Kimberly, 2003). These works are based on statistical studies. In order to resolve these problems, other works propose solutions for logistics organization (human and material resources) based on human experiences (Blackwell and Bosse, 2006) or on pragmatic approaches (Filoromo et al., 2003). Most of them treat transportation and distribution issues using linear programming (Rathi et al., 1992) (Sheu, 2007). However, all these works do not consider the optimisation of hospital critical resources such as operating theatres.

In normal situation, works focused on emergency problems (Hammami, 2002) (Hammami, 2004), are inspired from studies achieved on reactive problems in industrial application such as (1) the insertion of one or several jobs (Tadeuz, 2007) (Sun and Xue, 2001), in the pre-established planning, and (2) the scheduling of activities with uncertain length (Van de Vonder et al., 2007) (Bonfill et al., 2007).

Studies published in the literature address emergency problems in hospitals in normal working times. Most of them focus on operating theatres (Kuo et al. 2003) (Lamiri et al., 2006) (Roland et al., 2009) (Hammami, 2004) which are considered as a bottlenecks in the hospital system. These last two years, some works were interested in disaster situations (Nouaouri et al., 2008b) (Nouaouri et al., 2009) (Glaa, 2008). The optimization of operating theatres has become an important issue. All these works do not consider disaster situations in a reactive way.

Opposite to a normal situation where the aim is usually to reduce medical costs, in a disaster situation the purpose is to treat the maximum of victims in reactive way and so to save the maximum of human lives. In fact, in such situation, all possible means are used without thinking about cost. The important is to save human lives. In this paper, we deal with reactive operating schedule in the case of a disaster. Our purpose is to take into account disruptions. To achieve this, we propose an approach based on a several-stage model. In section 2 of this paper, we present the reactive problem we address in a disaster case. Section 3 and 4 detail the proposed approach and the problem modelling. Section 5 discusses the obtained numerical results. Finally, section 6 concludes the paper and presents possible extensions of this work.

The problem description

The pre-hospital and triage structure is set up near damage zone. This structure routes victims to the nearby hospital. It is important to note that this structure also routes victim’s data via information system to the admitting hospital. In hospital, some human and material resources are available. In this paper, we consider surgeons and operating rooms critical resources. The number and the ready dates in the operating theatre of surgeons are detailed in a pre-established emergency planning. Each surgeon is assigned to one operating room. In such situation, all operating rooms are considered to be polyvalent. Basing on these data, the admitting hospital achieves its predictive program (established operating schedule) at $t = t_0$. However, some disruptions can occur at any moment during the execution of this program.

In reaction to a disturbance at $t = t_p$, hospital must be able to respond quickly, in order to minimize the involved consequences. In the case of a disaster, date of arrival of victims, announced by the PMA, is widely variable and depends on type, location, transport capacities and site organization (Kimberly et al., 2003). Furthermore, some victims may arrive at hospitals at any time without passing by the pre-hospital, triage and dispatching structure (Ministère de la santé, de la famille et des personnes handicapées, France, 2002). Moreover, during the execution of a surgical care in the operating room, state of victims can deteriorate, thus lengthening the processing time of its surgical care. In this context, we handle the scheduling operating rooms problem while taking into account: the arrival of new (unexpected) victim requiring surgical cares, and the overflow of assessed surgical processing time. During a period $t$ we consider only one disruption.
Proposed approach

Before presenting our proposed approach, we will first introduce the following notations:

- \( S \) Number of operating rooms;
- \( N \) Number of victims;
- \( H \) Number of surgeons;
- \( T \) Time horizon;
- \( d_i \) Processing time of surgical care of victim \( i \);
- \( dl_i \) Latest start date of surgical care of victim \( i \);
- \( rv_i \) Ready date of victim \( i \);
- \( rc_h \) Ready date of surgeons \( h \) with respect to the hospital emergency planning;
- \( M \) Very big positive number.

We consider, that the number of rooms is equal to the number of surgeons \((H=S)\) and each surgeon is affected to only one operating room. So, we can use \( h \) as \( s \) and \( s \) as \( h \) \((h=s)\).

Arrival of new victim

At \( t = t_0 \) (date of disruption) a new victim is announced by the pre-hospital, triage and dispatching structure or, arrives directly to the hospital. In order to minimize disruption effect on \( P_0 \), we proceed in several stages. The first one, model \((P_1)\) is stated as follows: given the operating schedule \((P_0)\), \( P_1 \) tries to insert the new victim in an untapped (vacant) range. The model has to satisfy some constraints such as ready dates of surgeons and latest start date of the new victim. The surgical processing time of the new victim has to be lower or at more equal to one untapped range. If the new victim cannot be inserted by \((P_1)\), we compute for every operating room a free margin \( \Delta g \), from elementary margins \( \Delta \).

\[
\Delta g_s = \sum_{i=s}^{N} \Delta_i 
\]

(\text{I})

\[
\Delta_i = FD_{i-1} - FD_{e_i}
\]

(\text{II})

\[
\begin{array}{cccccccc}
SD_{i-2} & SD_{i-1} & FD_{i-1} & SD_{i} & FD_{i} & SD_{i+1} & FD_{i+1} \\
\hline
\text{i-2} & \text{i-1} & \text{i} & \text{i+1} \\
\end{array}
\]

Fig. 1. Pre-established schedule

We define:
- \( SD_i \) the start date of surgical care of victim \( i \),
- \( FD_i \) the finish date of surgical care of victim \( i \).

The latest finish date of surgical care of victim \( i \) is given by the equation (III).

\[
FD_{i} = \min (dl_i + d_i, SD_{i+1})
\]

(\text{III})

The earliest finish date (date as soon as possible) of surgical care of victim \( i \) is given by the equation (IV).

\[
FD_{e_i} = FD_{i-1} + d_i
\]

(\text{IV})

If the new victim cannot be inserted by \((P_1)\), the model \((P_2)\) tries to reschedule, from disruption date, the victims (including the new victim) belonging to the operating room which possesses the biggest \( \Delta g \). Current surgical cares won’t be interrupted. If the new victim has not been inserted, the model \((P_3)\) tries to reschedule, from disruption date.
date, all surgical cares in all operating rooms. If no solution is found, the new victim can’t be inserted and is proposed for a reorientation to another hospital. We present in figure 2, the proposed reactive approach in the case of insertion of a new victim in the operating schedule.

\[
\text{Start}
\]

- **P₀**: pre-established schedule \((t = t₀)\)
- **P₁**: insert the new victim in an untapped range.
  - Is the victim inserted?
    - yes
    - no
  - Calculate for every operating room the free margin \(\Delta g\).
- **P₂**: Reschedule surgical cares in the operating room who possesses the biggest \(\Delta g\).
  - Is the victim inserted?
    - yes
    - no
  - **P₃**: Reschedule surgical cares in all operating rooms
    - yes
    - no
      - Victim reoriented to another hospital

**Fig. 2.** Reactive approach in the case of insertion of a new victim

**Overflow of assessed surgical processing time**

In this case, \(t_p\) is the date for which surgical care exceeds the assessed surgical processing time. We proceed in several stages. In the first stage, we apply “shift right” algorithm \((P₄)\) in order to shift all surgical cares following victim whose state needs more time in operating room, lengthening so its surgical processing time. The shift is equal to the foreseen delay. If \((P₄)\) eliminates other victims from operating schedule, \((P₅)\) tries to reschedule, from disruption date, victims belonging to the same operating room. If disruption cannot be treated, \((P₆)\) reschedule, from disruption date, all surgical cares in all operating rooms. If no solution is found, the least urgent victims, eliminated from operating room, will be oriented to other hospitals. Indeed, these victims have the largest latest start date. We expose in figure 3, the proposed reactive approach in the case of overflow of assessed surgical processing time.
Fig. 3. Reactive approach in the case of overflow of assessed surgical processing time

**Problem modelling**

**Arrival of new victim**

We propose a three-stage mathematical model. For each stage, an integer linear programming model is developed using ILOG OPL 6.1 Studio. According to the pre-established schedule ($P_0$) (Nouaouri et al., 2008a), we define:

- $t_{is}$: the start date of surgical care of the victim $i$ in the operating rooms $s$.
- $y_{js}$: $= 1$ if the surgical care of the victim $j$ follows the surgical care of the victim $i$ in the same operating room $s$, 0 otherwise.
- $t_p$: Disruption date which is generated in stochastic way.
NR Number of new victims (we consider NR = 1, because we treat only one disruption at a given instant).

Besides, we define the following decision variables:

\[ Z_{kts} \] = 1 if the new victim \( k \) is assigned to an operating room \( s \) at time \( t \), 0 otherwise.

\[ st_k \] Start time of surgical care of victim \( k \);

**Model 1: Insertion of the new victim in an untapped range**

In the first stage, we address the optimization problem \((P_1)\). Thus, using the previous notations, we propose the following integer linear program:

- The objective function (1) maximizes the number of new inserted victims in the operating schedule. In our case the objective function consist to insert the new victim in the operating schedule.

\[
\text{Maximize } \sum_{k} \sum_{i} \sum_{s} Z_{kts}
\]

(1)

- Constraints (2) ensure that each victim is treated only once during the horizon \( T \).

\[
\sum_{i} \sum_{s} Z_{kts} \leq 1 \quad \forall k \in \{1..NR\}
\]

(2)

- Constraints (3) grantee, for every untapped range, one victim is assigned at most at time \( t \).

\[
\sum_{t} Z_{kts} \leq y_{ijs} \quad \forall s \in \{1..S\} \forall i, j \in \{1..N\} \forall k \in \{1..NR\}
\]

(3)

- Constraints (4) impose to satisfy the emergency level of each new victim.

\[
st_k - dl_k \sum_{s} \sum_{t} Z_{kts} = M(1 - \sum_{t} \sum_{s} Z_{kts}) \leq 0 \quad \forall k \in \{1..NR\}
\]

(4)

- Constraints (5) Ensures that the duration of surgical care of a new victim is lower or equal to the duration of the untapped range.

\[
t_{js} y_{ijs} - (t_{is} + d_i) y_{ijs} \geq d_k \sum_{t} Z_{kts} \quad \forall s \in \{1..S\} \forall i, j \in \{1..N\} \forall k \in \{1..NR\}
\]

(5)

- Constraints (6) and (7) verify that surgical care can be realized only when victim and surgeon are present in the hospital.

\[
st_k + M(1 - \sum_{t} \sum_{s} Z_{kts}) \geq rv_k \quad \forall k \in \{1..NR\}
\]

(6)

\[
st_k - rc_s \sum_{t} Z_{kts} - M(1 - \sum_{t} \sum_{s} Z_{kts}) \geq 0 \quad \forall s \in \{1..S\} \forall k \in \{1..NR\}
\]

(7)

- Constraints (8) Grantees that surgical care of the new victim cannot be inserted before disruption date \( t_p \).
\[ s_t + M (1 - \sum_{t_p}^{T} \sum_{s}^{S} Z_{its}) \geq t_p \quad \forall k \in \{1..NR\} \tag{8} \]

- Constraints (9) ensure that every victim \( k \) is assigned to an untapped range.

\[ (t_{is} + d_i) \sum_{t_p}^{T} Z_{its} \leq s_t \leq t_{js} \sum_{t_p}^{T} Z_{its} \quad \forall s \in \{1..S\} \forall k \in \{1..NR\} \forall i, j \in \{1..N\} \tag{9} \]

- Constraints (10) give the start times of surgical cares.

\[ s_t = \sum_{t_p}^{T} \sum_{s}^{S} t Z_{ks} + (1 - \sum_{t_p}^{T} \sum_{s}^{S} Z_{ks}) M \quad \forall k \in \{1..NR\} \tag{10} \]

- Constraints (11) ensure the integrality of the variables.

\[ Z_{its} = \{0,1\} \quad \forall k \in \{1..NR\} \forall t \in \{t_p..T\} \forall s \in \{1..S\} \tag{11} \]

If the new victim has not been inserted, we try to treat it with the model \((P_2)\).

**Model 2: Reschedule surgical cares in the operating room which possesses the biggest free margin \( \Delta g_s \)**

Before solving this problem, we have to compute: (1) the free margin \( \Delta g_s \) of each operating room \( s \), and (2) the date \( (A_s) \) from which operating room \( s \) (surgeon \( h \)) is available after \( t_p \). So it is possible to compute the date of the availability \( A_s \) of operating room \( s \) possessing the biggest margin. The room \( s \) as well as the surgeon \( h \) are known beforehand. The mathematical formulation of this combinatorial optimization problem \((P_2)\) is given by the following linear integer program.

\( W \) set of waiting victims (including the new victim) for surgical cares.

The decision variables are defined as follow:

- \( X_{its} \) = 1 if the victim \( i \) is assigned to an operating room \( s \) at time \( t \), 0 otherwise.
- \( st_i \) Start time of surgical care of victim \( i \);  

- The objective function (12) maximizes the number of treated victims in the operating room \( s \) after the disruption date \( t_p \).

\[ \text{Maximize} \sum_{i}^{W} \sum_{t=t_p}^{T} X_{its} \tag{12} \]

- Constraints (13) ensure that each victim is treated only once during the horizon \( T \).

\[ \sum_{t=t_p}^{T} X_{its} \leq 1 \quad \forall i \in W \tag{13} \]

- Constraints (14) guarantee that one victim at most is assigned at time \( t \) in the operating room \( s \).

\[ \sum_{i}^{W} X_{its} \leq 1 \quad \forall t \in \{t_p..T\} \tag{14} \]

- Constraints (15) impose to satisfy the emergency level of each victim.
\[ st_i - dl_i \sum_{t=t_p}^{T} X_{its} - M (1 - \sum_{t=t_p}^{T} X_{its}) \leq 0 \quad \forall i \in W \]  

(15)

- Constraints (16) and (17) verify that surgical care are realized only when victim and surgeon are present in the hospital.

\[ st_i + M (1 - \sum_{t=t_p}^{T} X_{its}) \geq r v_i \quad \forall i \in W \]  

(16)

\[ st_i - r c_s \sum_{t=t_p}^{T} X_{its} - M (1 - \sum_{t=t_p}^{T} X_{its}) \geq 0 \quad \forall i \in W \]  

(17)

- Constraints (18) verify the availability of the operating room \( s \) after the disruption date.

\[ st_i \geq A_s . X_{its} - M (1 - \sum_{t=t_p}^{T} X_{its}) \quad \forall i \in W \]  

(18)

- Constraints (19a), (19b) and (20) are disjunctive precedence constraints.

\[ \sum_{j \neq i}^{W} y_{ij} \leq 1 \quad \forall i \in W \]  

(19a)

\[ \sum_{j \neq i}^{W} y_{ij} \leq 1 \quad \forall i \in W \]  

(19b)

\[ \sum_{i}^{W} \sum_{j \neq i}^{W} y_{ij} = \sum_{i}^{W} \sum_{t=t_p}^{T} X_{its} - 1 \]  

(20)

- Constraints (21) give the start times of surgical cares.

\[ st_i = \sum_{t=t_p}^{T} t . X_{its} + (1 - \sum_{t=t_p}^{T} t . X_{its}) M \quad \forall i \in W \]  

(21)

- Constraints (22) impose no overlapping between two successive cares made in same operating room.

\[ st_j \geq st_i + y_{ij} d_i - M (1 - y_{ij}) \quad \forall i, j \in W \]  

(22)

- Constraints (23) and (24) ensure the integrality of the variables.

\[ X_{its} = \{0,1\} \quad \forall i \in W \quad \forall t \in [\lfloor t_p \rfloor, T) \]  

(23)

\[ y_{ij} = \{0,1\} \quad \forall i, j \in W \]  

(24)

If the new victim has not been inserted, we try to treat it with the model \((P_j)\).
Model 3: Reschedule surgical cares in all operating rooms

The objective function (25) maximizes the number of treated victims in all operating rooms.

\[
\text{Maximize } \sum_{i} \sum_{t=1_p}^T \sum_{s} X_{its}
\]

(25)

Under the same kind of constraints used in model 2 but taking into account all operating rooms. For example constraints (2) and (3) become (26) and (27):

\[
\sum_{t=1_p}^T \sum_{s} X_{its} \leq 1 \quad \forall i \in W
\]

(26)

\[
\sum_{i} X_{its} \leq 1 \quad \forall t \in \{1_p, T\} \quad \forall s \in \{1..S\}
\]

(27)

Overflow of assessed surgical processing time

In order to minimize disruption effect on \(P_0\), we start with applying “shift right” algorithm \(P_4\). This program is activated after the delay \(R\) has been estimated during the surgical process of current surgical care. If \(P_4\) excludes other victims from operating schedule, we go to the model \(P_5\).

Shift right algorithm

1/ Initialization:
   \(s\) : operating room which present overflow of assessed current surgical processing time.
   \(k\) : surgical care exceeds the assessed surgical processing time.
   \(I_s\) : Number of waiting victims for surgical cares in the operating room \(s\).

2/ Shift right all surgical cares following victim whose state needs more time in the operating room, lengthening so its surgical processing time. The shift is equal to the recorded delay \(R\) :

\[
R = \text{concrete spending time of surgical care } k \text{ – assessed time } (d_k).
\]

For \((i = k+1 ; i < I_s ; i++)\)

\[
st_i = st_i + R \quad \text{if } st_i \geq dl_i
\]

Then

Return to initial operating schedule \(P_0\) and go -to 3/

3/ End

Model 4: Reschedule surgical cares in the operating room \(s\) which present an overflow of assessed surgical processing time

\(W\)  set of waiting victims for surgical cares.

The objective function (28) maximizes the number of treated victims in operating room \(s\).

\[
\text{Maximize } \sum_{i} \sum_{t=1_p}^T X_{its}
\]

(28)

Under the same constraints used for model 2: (13), (14), (15), (16), (17), (18), (19a), (19b), (20), (21), (22), (23) and (24). If \(P_3\) eliminates other victims from operating schedule, we go to the model \(P_6\).
Model 5: Reschedule surgical cares in all operating rooms

The objective function (29) maximizes the number of treated victims in all operating rooms, taking into account the most urgent cases.

\[
\text{Maximize } \sum_{i} \sum_{t} \sum_{s} \frac{dl^{-1}}{X_{its}}
\]  

(29)

Under the same constraints used for model 3. If no solution is found, the least urgent victims, eliminated from operating room, will be oriented to other hospitals.

Computational experiments

In this section, we present the realized computational experiments using the CPLEX solver. We run programs on a Cluster consist of 6 workstations Bixeon® of 3.00 GHz processor and 2-4 Go RAM. We evaluate the performances of the proposed reactive approach with different scenarios described on the following.

Problem tests

Different disaster situations are considered by varying the number of victims (N=25, 50 and 70) and the duration of surgical cares (given between 30 minutes and 2 hours). Moreover 10 surgeons are available with different ready dates (\( R = (rc_1, ..., rc_{10}) \), \( H = 10 \)) according to the hospital emergency planning (table 1). The instance label \( PN.S.R \) means the problem \( P \) involves \( N \) victims, \( S \) operating rooms and ready dates \( R \) of surgeons.

Table 1. Ready dates of surgeons according to hospital emergency planning.

<table>
<thead>
<tr>
<th>R</th>
<th>rc_1(mn)</th>
<th>rc_2(mn)</th>
<th>rc_3(mn)</th>
<th>rc_4(mn)</th>
<th>rc_5(mn)</th>
<th>rc_6(mn)</th>
<th>rc_7(mn)</th>
<th>rc_8(mn)</th>
<th>rc_9(mn)</th>
<th>rc_10(mn)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R_1 )</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>60</td>
<td>60</td>
<td>120</td>
<td>120</td>
</tr>
<tr>
<td>( R_2 )</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>60</td>
<td>60</td>
<td>60</td>
<td>120</td>
</tr>
<tr>
<td>( R_3 )</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>30</td>
<td>30</td>
<td>60</td>
<td>60</td>
<td>60</td>
<td>120</td>
<td>120</td>
</tr>
<tr>
<td>( R_4 )</td>
<td>0</td>
<td>0</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>60</td>
<td>60</td>
<td>60</td>
<td>120</td>
<td>120</td>
</tr>
<tr>
<td>( R_5 )</td>
<td>0</td>
<td>0</td>
<td>30</td>
<td>30</td>
<td>60</td>
<td>60</td>
<td>60</td>
<td>120</td>
<td>120</td>
<td>120</td>
</tr>
</tbody>
</table>

For example \( P70.10.R_3 \) denotes a problem of 70 victims and 10 surgeons (10 operating rooms) which ready dates in minutes (mn) are given by \( R_3 \), thus \( rc_1 = 0, rc_2 = 0, rc_3 = 0, rc_4 = 30, rc_5 = 30, rc_6 = 60, rc_7 = 60, rc_8 = 60, rc_9 = 120, rc_{10} = 120 \). For each instance, we generate a predictive program \( P_0 \) (pre-established operating schedule) (Nouaouri et al., 2008a). We apply for every instance:

- 20 scenarios by inserting a new victim requiring surgical cares in the operating schedule. Each scenario is characterized by the ready date, the processing time and the emergency level of the new victim.
- 20 scenarios by varying surgical processing time and the victim whose state needs more time in the operating room.

The computational experiments are performed while fixing time horizon \( T = \max_{i=1, ..., N} (dl_i + d_j) \). Indeed, after this date, no victim can be treated. \( T \) is decomposed in elementary periods.

Experimental results

Arrival of new victim

In order to assess the performance of the proposed approach, we calculate for a set of scenarios belonging to one instance, the rate of insertion of the new victims in the operating schedule (\( V.I. (%) \)). We also compute, the percentage of cases for which disruptions are treated and resolute by the program \( P_k \) (\( V.I.P_k \) (%)). Scenarios are generated in a stochastic way. We note \( Sc_j \) the scenario \( j \).
\[
V.I(\%) = \frac{\sum_{j} \text{Inserted new victim } j}{\sum_{i} \text{New victim } i}
\]

(V)

\[
V.I.P_k(\%) = \frac{\sum_{j} \text{New victim } j \text{ inserted by the model } p_k}{\sum_{i} \text{New victim } i}
\]

(VI)

The results presented in Tables 2 are obtained by solving Model \((P_1)\), Model \((P_2)\) and Model \((P_3)\). We report for each instance the rate of insertion of new victims in the operating schedule \((V.I(\%))\), the percentage of cases for which disruptions are treated and resolved by the program \(P_k\) \((V.I.P_k(\%))\), the minimum CPU time \((Tmin)\) and the maximum CPU time \((Tmax)\). For each instance, we compute \(TM(\%)\) the mean occupancy rate of operating rooms for pre-established operating schedule.

\[
TM(\%) = \frac{\sum_{i=1}^{N} d_i}{C_{\max}.S}
\]

(VII)

where, \(C_{\max}\) is the Makespan given by the pre-established operating schedule.

Table 2. Numerical results in the case of arrival of a new victim.

<table>
<thead>
<tr>
<th>Instances</th>
<th>V.I (%)</th>
<th>V.I.P₁(%)</th>
<th>V.I.P₂(%)</th>
<th>V.I.P₃(%)</th>
<th>CPU time</th>
<th>Tmax (s)</th>
<th>TM(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>P25.4.R₁</td>
<td>25</td>
<td>5</td>
<td>10</td>
<td>10</td>
<td>26</td>
<td>295</td>
<td>81.25</td>
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<tr>
<td>P25.6.R₃</td>
<td>85</td>
<td>10</td>
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<td>40</td>
<td>47</td>
<td>352</td>
<td>53.17</td>
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<td>80</td>
<td>10</td>
<td>40</td>
<td>30</td>
<td>43</td>
<td>281</td>
<td>53.33</td>
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<tr>
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<td>10</td>
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<td>0</td>
<td>10</td>
<td>524</td>
<td>682</td>
<td>94.82</td>
</tr>
<tr>
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<td>25</td>
<td>0</td>
<td>0</td>
<td>25</td>
<td>609</td>
<td>752</td>
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</tr>
<tr>
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<td>90</td>
<td>15</td>
<td>40</td>
<td>35</td>
<td>43</td>
<td>350</td>
<td>63.79</td>
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<td>0</td>
<td>15</td>
<td>869</td>
<td>973</td>
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<tr>
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<td>5</td>
<td>30</td>
<td>826</td>
<td>1239</td>
<td>85.55</td>
</tr>
<tr>
<td>P70.10.R₃</td>
<td>70</td>
<td>5</td>
<td>25</td>
<td>40</td>
<td>76</td>
<td>1120</td>
<td>59.41</td>
</tr>
</tbody>
</table>

Fig. 4. Percentage of treated cases per instance
The proposed approach has allowed inserting new victims in 48% of cases. The solution is obtained between 26 seconds (minimum) and 21 minutes (maximum). Table 2 shows that the rate of insertion of new victims varies according to the mean rate of operating rooms occupancy (for pre-established operating schedule) ($TM\ (%)$) (example: $VI\ (%) = 25$ for $TM\ (%) = 81.25$ (P25.4.R$_1$) beside $VI\ (%) = 85$ for $TM\ (%) = 53.17$ (P25.6.R$_3$)). In most cases, new victims are inserted by using rescheduling model ((P$_2$) and (P$_3$)) (example: in the case of $P70.10.R_3$, $VI.P_4\ (%) = 25$ and $VI.P_6\ (%) = 40$). In fact, reschedule models give good results. Figure 4 shows when the capacity increases (the mean occupancy rate is low) the rate of insertion of new victims is much important.

**Overflow of assessed surgical processing time**

We compute for each scenario, the rate of treated victims for which surgical care exceeds the assessed surgical processing time ($V.S\ (%)$). We also compute, the percentage of cases for which disruptions are treated and resolute by the program $P_k$ ($V.S.P_k\ (%)$).

$$V.S(\%) = \frac{\sum_{j}^{\text{treated victim } j}}{\sum_{i}^{\text{planned victim } i}} \tag{VIII}$$

$$V.I.P_k(\%) = \frac{\sum_{j}^{\text{disruption of victim } j \text{ treated by the model } p_k}}{\sum_{i}^{\text{planned victim } i}} \tag{IX}$$

The results presented in Tables 3 are obtained by solving Model (P$_2$), Model (P$_3$) and Model (P$_6$). We report for each instance the rate of treated victims for which surgical care exceeds the assessed surgical processing time ($V.S\ (%)$), the percentage of cases for which disruptions are treated and resolute by the program $P_k$ ($V.S.P_k\ (%)$), the minimum CPU time ($T_{min}$) and the maximum CPU time ($T_{max}$). Also, we compute $TM\ (%)$ the mean occupancy rate of operating rooms for pre-established operating schedule.

**Table 3.** Numerical results in the case of overflow of assessed surgical processing time.

<table>
<thead>
<tr>
<th>Instances</th>
<th>$V.S\ (%)$</th>
<th>$V.S.P_4\ (%)$</th>
<th>$V.S.P_5\ (%)$</th>
<th>$V.S.P_6\ (%)$</th>
<th>$CPU\ time$</th>
<th>$T_{min}$ (s)</th>
<th>$T_{max}$ (s)</th>
<th>$TM\ (%)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>P25.4.R$_1$</td>
<td>60</td>
<td>0</td>
<td>30</td>
<td>30</td>
<td>214</td>
<td>785</td>
<td>81.25</td>
<td></td>
</tr>
<tr>
<td>P25.6.R$_3$</td>
<td>100</td>
<td>0</td>
<td>60</td>
<td>40</td>
<td>71</td>
<td>324</td>
<td>53.17</td>
<td></td>
</tr>
<tr>
<td>P25.6.R$_5$</td>
<td>100</td>
<td>0</td>
<td>60</td>
<td>40</td>
<td>117</td>
<td>245</td>
<td>53.33</td>
<td></td>
</tr>
<tr>
<td>P50.4.R$_1$</td>
<td>50</td>
<td>0</td>
<td>20</td>
<td>30</td>
<td>309</td>
<td>796</td>
<td>94.82</td>
<td></td>
</tr>
<tr>
<td>P50.6.R$_3$</td>
<td>50</td>
<td>0</td>
<td>30</td>
<td>20</td>
<td>312</td>
<td>782</td>
<td>78.73</td>
<td></td>
</tr>
<tr>
<td>P50.8.R$_3$</td>
<td>80</td>
<td>0</td>
<td>50</td>
<td>30</td>
<td>82</td>
<td>243</td>
<td>63.79</td>
<td></td>
</tr>
<tr>
<td>P70.4.R$_1$</td>
<td>40</td>
<td>0</td>
<td>20</td>
<td>20</td>
<td>539</td>
<td>984</td>
<td>98.30</td>
<td></td>
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<tr>
<td>P70.6.R$_3$</td>
<td>60</td>
<td>0</td>
<td>20</td>
<td>40</td>
<td>571</td>
<td>1127</td>
<td>85.55</td>
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<tr>
<td>P70.10.R$_3$</td>
<td>90</td>
<td>0</td>
<td>60</td>
<td>30</td>
<td>739</td>
<td>890</td>
<td>59.41</td>
<td></td>
</tr>
</tbody>
</table>
The solution is obtained between 71 seconds (minimum) and 19 minutes (maximum). The proposed approach treats disruptions in 70% of cases (Table 3). We note that these disruptions are treated only by models $P_5$ and $P_6$. $P_4$ didn't resolve any disruption. So, in this case, we can ask the following question: is it necessary to keep $P_4$ in the proposed heuristic? Figure 5 shows that the rate of insertion of new victims varies according to the rate of the mean occupancy rate of operating rooms for pre-established operating schedule ($TM\,\%$) (example: $V.S\,\% = 40$ for $TM\,\% = 98.30$, $P70.4.R_1$) beside $V.S\,\% = 90$ for $TM\,\% = 59.41$, $P70.10.R_3$). Disruptions are treated by using rescheduling models ($P_5$ and $P_6$). In some cases we can treat 100% of disruptions ($P25.6.R_3$, $P25.6.R_5$).

In both proposed approaches, the execution time is relatively long in several cases. It reduces the chance for some victims to be saved in time. In fact, the time of arrival of one victim to the admitting hospital can be estimated between 15 minutes and 1 hour. It is according to the nature of disaster, the distance between the triage structure and the admitting hospital, and the means of transportation used during the disaster. Nevertheless, when the program execution time is important, we can stop execution and get an approached result.

**Conclusions**

In this work, we have addressed a reactive approach in the case of a disaster in order to optimize the operating rooms scheduling taking into account disruptions: (1) insertion of a new victim in the established operating schedule, (2) surgical care exceeds the assessed processing time. Both proposed approaches are based on a three-stage model. In the case of insertion of a new victim in the established operating schedule, the first model tries to insert the new victim in an untapped range. If the victim cannot be treated, the second model tries to reschedule, from disruption date, the victims belonging to the operating room that possesses the biggest free margin. If the new victim has not been inserted, the third model reschedules all surgical cares in all operating rooms. If no solution is founded the victim will be reoriented to another hospital.

In the case of one surgical care exceeds the assessed processing time, the first model “shift right” shifts all surgical cares following the concerned victim. If this model excludes other victims from operating schedule, we apply rescheduling models: (1) rescheduling of one operating room and (2) rescheduling of all operating rooms. The proposed Heuristic approach allows hospital to decide how to take into account disruption, and so to treat a maximum of victims (save the maximum of human life). It is a support decision used before the arrival of victim(s) at hospital in order to take the best decision quickly and efficiently. Another interesting advantage of this approach is that it tries to resolve the problem in several stages in order to minimize the disruption of pre-established operating schedule.

This approach has been tested on different disaster situations with various scenarios. Further research works should focus on decreasing execution time by improving the proposed approach and dealing with auxiliary services (recovery room, post anaesthesia care unit, etc.) as well as sharing critical resources.
References


