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# Multi-Objective Evolutionary for Multi-Skill Health Care Tasks Scheduling

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**Abstract:** Emergency health care services have a highly complex patient treatment system. This system is characterized by stochastic arrivals of patients which can lead in the case of activity to its services overload. In fact, the complexity of these medical exercises relays on assigning health care operations to medical staff members respecting constraints related to the uncertain environment. The objective is to minimize costs and delays and to increase the quality of care as well as patient satisfaction. In this article, a planning method is applied in the Pediatric Emergency Department of the Regional University Hospital of Lille (Northern France). The proposed approach is composed of two phases: the first one is an assignment procedure based on fuzzy logic and the second phase is based on an evolutionary method to solve the problem of medical staff scheduling. This approach improves the performance of the scheduling system in order to help physicians to better manage their organization and anticipate the overcrowding feature. This work is integrated into HOST project (Hospital: Optimization, Simulation and Crowding Avoidance) supported and financed by the French National Agency (ANR).

**Keywords:** Planning Method, Pediatric Emergency Department, Assignment, Fuzzy Logic, Evolutionary Method, Medical Staff Scheduling, Performance.

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## 1. INTRODUCTION

Health care facilities, which represent a growing sector, are confronted in recent decades to a mutation imposed by their providers and their consumers. It is essential that the offered services are of a good quality to best meet patients demand. Indeed, there is some patient dissatisfaction generally due to long waiting times or the mismatch between their needs and skills of human resources providing these services. These institutions have therefore a real need to develop a more efficient and rigorous human resources management system to improve the productivity and efficiency of their organization while ensuring the quality of health care provided to patients.

The main issue related to scheduling in health care institutions is to allocate human resources to health care tasks considering their availabilities and their skills. Human resources dimensioning is of highest importance for hospitals. These resources, usually related to high costs should be able to meet the objectives. A resource undersizing is a handicap to achieve these goals while oversizing leads to underutilization of available resources and therefore to additional costs. Besides, additional information about patients' pathologies received by the medical staff members during the health care process makes it difficult to determine the necessary medical treatments at the beginning of the handling process. Further, the duration of diagnosis and treatments are stochastic due to the specific characteristics of each patients. The immediate need for treatment in case of severe emergencies may also cause disturbances in the schedule and complications which can occur during a treatment are able to engender long waiting times and modify pathways for other patients.

Health care systems are thus complex systems facing a huge number of challenges related to production functions below the optimal and problems of information flow.

In this work, we consider the scheduling problem in emergency departments characterized by chaotic arrivals of patients. Several studies have shown that one of two emergency services works in overdrive, which means that all patients do not have the privilege of being supported in optimal conditions with extended waiting times [Bertrand, 2006]. Planning and resources scheduling has an impact on performance management and system control, typically based on a global evaluation of the existing system [Pham, 2002]. The objective is to provide diagnosis and anticipation of possible changes likely to affect its current functioning by the adjustment of some parameters [Canelon et al. 2009]. We are particularly interested in human resources planning in healthcare organizations. This planning aims to determine the best balance between patient demand and involved human resources in order to meet needs for treatment while minimizing waiting times, optimizing the quality of health care services and reducing costs.

This work belongs to HOST project (Hospital: Optimization, Simulation and Crowding Avoidance) supported and financed by the French National Research Agency (ANR). It targets to optimize the Pediatric Emergency Department functioning characterized by stochastic arrivals of patients which can lead to its overcrowding. It aims to better manage health care organizations, anticipate the overcrowding feature and establish avoidance proposals for it.

Our concerns focus on modeling the human resources allocation in the scheduling process and also searching for the existence of an assignment allowing the realization of a health care plan.

This paper is organized as follows: an analogy between job-shop scheduling and multi-skill health care tasks scheduling is presented in the second section followed by a mathematical modelling of the studied problem. Then, the proposed method will be described in the fourth section. A scenario of simulation is given in the fifth section. Finally, the last section is for conclusion and prospects.

## 2. ANALOGY BETWEEN JOB-SHOP SCHEDULING AND MULTI-SKILL HEALTH CARE TASKS SCHEDULING

Health care systems are similar to production systems which always try to meet demands (patients for the hospital and customers for industry). A health care system can be considered as a full production system, constrained by limited material and human capacity in order to deliver the best care at the lowest cost. Human resources planning is a central element of health institutions' management because of the cost and the constraints related to it (skills and availability). The numerous hazards such as the stochastic arrivals of patients and the complications that can occur during treatment process, the difficulty of standardization and the coordination of medical acts with the high number of actors make the planning a complex process. The implementation of generated plans requires sustained efforts.

The search for industrial excellence in corporate comes near to the concept of optimization of the quality of health care facilities. The specific feature of health care systems is that they cannot speculate on human suffering and for which the objective of profit must be dismissed.

The most commonly discussed programming policies in previous works are those included in workshops. A classification scheduling problems in a workshop can be made according to the number of machines and the order of their use to make a product, which depends on the nature of the considered workshop. A workshop is characterized by the number of machines it contains and its type. We distinguish three types of workshops: flow-shop, job shop and open-shop. We compare in this paper, the scheduling problem in the PED to a job-shop scheduling problem in industry.

Job-shop problems called also Multipath workshops are workshops where operations are carried out in a fixed order, vary according to the task. The flexible job-shop is an extension of the classical job-shop model. Its uniqueness lies in the fact that several machines are potentially capable of achieving a subset of operations. Basically, it is a problem of planning and organization of a set of tasks to be performed on a set of resources with variable performance [Gotha, 1993]. Similarly, multi-skill health care tasks scheduling corresponds to assign health care tasks to medical staff members who are characterized by their skills and availabilities in order to satisfy patients' needs while respecting their emergency degrees and taking into account their length of stay in the PED.

Given a set of tasks and a set of resources, resolving a scheduling problem corresponds to program tasks and allocate resources to optimize one or more goals (corresponding to objective performance criteria), respecting a set of constraints. The problem of job-shop scheduling consists in organizing the realization of  $N$  jobs on  $M$  machines and a job  $j$  represents a number of  $n_j$  non preemptable ordered operations. In multi-skill health care tasks scheduling, jobs corresponds to treatment tasks (a treatment task for each patient), machines are the medical staff members and health care operations being executed are also non preemptable. In both cases, the execution of each operation involves one resource selected from the set of available resources and at a given time, a resource can only execute one operation: it becomes available to other operations once the operation currently assigned is accomplished (resource constraints). The assignment of an operation to a resource entails the occupancy of this resource during a processing time. So, for each flexible job-shop problem, we can associate a processing time to each operation. However, because the most important target of health organizations is to ensure a high quality of care, durations are not given importance while scheduling in health care process. In fact, durations of health care operations are uncertain and not known in advance. They depend on care providers' skills and patients' states. On the other hand, health care demands can occur unexpectedly. We cannot, in any circumstances know when the request arises. Requests are prioritized and scheduled according to emergency degrees. Some requests are less urgent than others; they can be delayed without endangering patients' lives. However, most of the requests in the PED and the emergency departments in general require immediate intervention. According to the legal structure of the hospital, this latter has to accept all patients. In such a situation, it is necessary to insert urgent patients in the planning already established, which sometimes causes malfunctions and usually additional operating costs. This makes the duration of a treatment operation, which is determinist in job-shop scheduling problems, undergoes significant variations depending on the type of operation, the level of expertise of care provider, the patient and his pathology, etc. The variability of processing times often leads to changes in the schedule of the PED activity which may cause a decline in quality concerning services provided to patients. The consequences include long waiting times and additional costs due to overtime.

Hence, treatment tasks durations should be disintegrated while resolving human resources affectation for health care operations execution. In fact, durations of treatment tasks in emergency department are difficult to calculate and cannot be known in advance. So we chose to define the Demand Load (DL) of healthcare treatment in the PED to quantify patient treatment load. The more progression is, the less healthcare treatment demand will be. This reflects the progression of health care process for each patient and gives us an idea about health care operations already executed and the ones which remain to be done.

In job-shop scheduling a resource (machine) becomes available to other tasks once the task which is currently assigned to is completed. Task's completion time can be

calculated in advance. But, in health care treatment process, the availabilities of medical staff members depend on their skills and experience, patient's health state, pathology severity degree and the evolution of the current medical treatment task. To set the availability date, it is hard for experts to afford exact values due to the uncertainty involved. Besides, the evaluation is not the same in the eyes of the decision-makers [Issai and Singh, 2000], it depends on human feeling and recognition. So, health care providers cannot make the single judgment [Abbod, 2001].

For the objectives to achieve, it is to minimize the overall completion time (makespan), the total workload of the machines in job-shop scheduling, etc. However, in our study, we aim also to minimize patients waiting time in addition to balancing workload between all medical staff members and minimizing the response time as well as the workload of all the medical staff in the PED.

### 3. MATHEMATICAL MODELING

#### Notation

$M$ :	number of available medical staff members,
$k$ :	index of medical staff member $M_k$ ,
$j$ :	index of treatment task $T_j$ ,
$n_j$ :	number of operations of treatment task $T_j$ ,
$r_j$ :	earliest starting date of task $T_j$ ,
$i$ :	index of a health care operation,
$O_{i,j}$ :	$i^{\text{th}}$ operation of task $T_j$ ,
$r_{i,j}$ :	the earliest availability date of operation $O_{i,j}$ ,
$N_i$ :	total number of operations to execute, $N_i = \sum_j n_j$ ,
$P_i$ :	total number of patients waiting for health care treatment $P_i = \sum_j P_j$ ,
$d_{i,j,k}$ :	execution time of the operation $O_{i,j}$ ,
$C_{i,j,k}$ :	the skill of the medical staff member $M_k$ needed for the execution of the operation $O_{i,j}$ ,

The problem is to organize the execution of  $N$  health care operations by  $M$  medical staff members. The set of medical staff members is  $U$ . Each task  $T_j$  corresponds to a patient waiting for treatment in the PED and is a sequence of  $n_j$  health care operations. Each operation  $i$  of a task  $T_j$  (noted  $O_{i,j}$ ) may be performed by a set of medical staff members  $U_{i,j} \subseteq U$ .

The affectation of an operation  $O_{i,j}$  to a medical staff member  $MS_k \in U_{i,j}$  leads to the occupancy of this medical staff member for a period  $d_{i,j,k}$  (we assume that  $d_{i,j,k} \in \mathbb{N}^*$ ).

In this issue, we make the following assumptions:

- Each treatment task  $T_j$  can be started at the time  $t = r_j$ ;
- Each medical staff member can execute at a time a single operation (resource constraint);
- The total number of operations to be performed is higher than that of medical staff members.

#### Performance Indicators

To evaluate functioning quality of the PED, we define three performance indicators:

- Minimize the total load of all medical staff members:

The total load is equal to the sum of the lengths of all health care operations executed according to any assignment. However, for each operation  $O_{i,j}$ , the length of execution time is greater than the minimum length  $\gamma_{i,j}$  where:

$$\gamma_{i,j} = \min_k (d_{i,j,k})$$

With  $\gamma_{i,j}$  the minimum length of the health care operation execution for a treatment task  $T_j$  and  $O_{i,j}$  is the  $i^{\text{th}}$  operation.

So, this criterion corresponds to minimize  $Cr_1 = \sum_j \sum_i \gamma_{i,j}$

- Reduce waiting time of each patient

It corresponds to minimize  $Cr_2 = \sum_{j=1}^l \max(0, c_j - d_j)$

With:

$c_j$  = the completion time of the treatment task  $T_j$ ,

$d_j$  = the theoretical treatment time for the task  $T_j$ ,

$l$  = the total number of treatment tasks.

- Minimize response time to health care tasks

It corresponds to minimize  $Cr_3 = \max \left( r_j + \sum_i \gamma_{i,j} \right)$

The proposed optimization method presented in this work will focus on balancing the workload of medical staff members ( $k \in [1 \dots M]$ ) as well as minimizing the response time for patients' treatment.

### 4. METHOD

The studied multi-skill health care tasks scheduling presents two difficulties. The first one is to assign each operation  $O_{i,j}$  to a medical staff member  $M_k$  (selected from the set  $U$ ). The second one is the calculation of the starting times  $t_{i,j}$ .

The proposed method consists in two stages of resolution.

#### 4.1 First stage

- **Assignment Algorithm**

It allows us to assign each health care operation to the suitable medical staff member taking into account his availability date and workloads of health care providers to whom operations have been already assigned. To compute the availability date of each  $MS_k$  a simple application of fuzzy logic is proposed. Calculation is based on analysing the affordable skills, the evolution of the current treatment task, patient's health state and pathology severity degree. These are the inputs. Then, we define for each input three sub-sets {"Low", "Medium" and "High"}.

Each subset is characterized by its trapezoidal Membership Functions (MF) meanwhile the state varies gradually. After the definition of MF of the variables or *Inference* which is based on decision rules depending on experts' views and historical data.

Example of rules:

**if** (the medical staff is "high qualified") **and** (the evolution of the current act is "high") **and** (the pathology is "serious") **and** (patient's health state is "improves") **then** (the medical staff is "highly available").

The result which is a fuzzy value undergoes a defuzzification to obtain an exact number as final output using the Center Of Area method (COA). For the assignment, we choose to assign the health care operation to the medical staff member who corresponds to the highest fuzzy value which reflects his availability rate. If two medical staff members have the same fuzzy value, we make the choice while balancing the workload between all health care providers.

This assignment procedure allows us to construct a set  $E$  of assignments ( $E = \{S^z / 1 \leq z \leq \text{cardinal}(E)\}$ ) and balance the medical staff members workload. Each assignment is represented in a table  $S^z$ ,  $S^z = \{S^z_{i,j,k} / 1 \leq j \leq N; 1 \leq i \leq n_j; 1 \leq k \leq M\}$ . For each  $i, j, k$ , the value of  $S^z_{i,j,k}$  can take 0 or 1. The value " $S^z_{i,j,k}=1$ " means that  $O_{i,j}$  is assigned to  $MS_k$ . The value " $S^z_{i,j,k}=0$ " means that  $O_{i,j}$  isn't assigned to  $MS_k$ .

#### • Scheduling Algorithm

For each assignment, it calculates starting times  $t_{i,j}$  by considering medical staff availabilities and precedence constraints. Conflicts are resolved by applying conventional priority rules (SPT, LPT, FIFO, LIFO, FIRO [Boucon, 1991], [Bel and Cavaille, 2001]), so we get a set of plans according to the applied priority rules. In emergency department priority is given at first to the most urgent cases, then to the patient who has arrived first. The scheduling procedure is as follows: according to the availability date of a medical staff members and the availability of the corresponding health care operation, the starting time of the operation is the minimum date among the two availabilities' dates.

#### 4.2 Second stage

The scheduling approach described in the previous paragraph can contribute to a multi-objective optimization by combining it with genetic algorithms and make develop an initial set of solutions to a final one while improving the performance of the whole system according to criteria we have fixed at the beginning [Michalewicz, 1992], [Yamada and Nakano, 1992]-[Ono, 1996].

Genetic algorithms are the most popular variant of evolutionary algorithms. Many specialists designate and continue to designate the evolutionary approaches as "genetic algorithms". As their name suggests, genetic algorithms are based on the genetic inheritance of an individual (genotype) represented by its chromosomes. The interaction of the genotype of an individual with its environment determines its phenotype which can be modified by mutation. Phenotype is evaluated by coding the genotype, which is often a binary symbol in order to provide a usable performance value by the selection of operators. The variation operators (crossover and mutation) presented above are related to the binary representation since they act on binary genotypes. In a simple genetic algorithm, the search is set by the successive application of the variation operators. The cross is the phase of cooperation between individuals while the mutation corresponds to the individual adaptation phase.

We consider the important characteristics of evolutionary algorithms and their relevance to solve NP-hard problems. We present some key points for solving approach:

- A genetic representation (coding) appropriate to the problem to determine possible solutions of the optimization problem;

- Genetic operators that transform the composition of children during reproduction. Because a task must be treated by a single medical staff member selected from the set of members who are able to provide the corresponding health care service, we choose to correct the solutions generated by another operator to meet this requirement;

- Parents are randomly selected from the current population for the crossover and mutation with a probability of crossover  $p_c$  ( $0 < p_c < 1$ ) and a mutation probability  $p_m$  ( $0 < p_m < 1$ );

- We take a non-elitist replacement technique to build the new population;

- Fitness functions evaluate solutions based on two criteria: medical staff workload and response time.

In this stage, we generate from the set  $E$  constructed in the first stage, an assignment scheme to control the genetic algorithm. This scheme is going therefore to represent a constraint that must be respected by the new created individuals. This method consists in considering the assignments  $S^z$  given by the earlier scheduling method and to determine (for each operation) the set of possible medical staff members using a genetic algorithm.

**Table 1. Medical Staff Skills**

$$\square C = \{C_{i,j,k} / 1 \leq j \leq N; 1 \leq i \leq n_j; 1 \leq k \leq M\}$$

		MS1	MS2	MS3	MS4
T 1	O 1,1	0.2	0.6	0.5	0.2
	O 2,1	0.4	0.9	0.3	0.2
	O 3,1	0.4	0.6	0.5	0.8
T 2	O 1,2	0.5	0.2	0.2	0.5
	O 2,2	0.3	0.4	1	0.4
	O 3,2	1	0.2	0.3	0.3
T 3	O 1,3	0.9	0.7	0.4	0.6
	O 2,3	0.5	0.6	0.9	0.2

A possible scheduling plan related to medical staff skills is given in Table 1. We consider that the assignment of a health care operation  $O_{i,j}$  to a medical staff member is possible when the competence  $C_{i,j,k} \geq 0.5$ .

**Table 2. Assignment  $S^{ch}$**

$$\square S^{ch} = \{S^{ch}_{i,j,k} / 1 \leq j \leq N; 1 \leq i \leq n_j; 1 \leq k \leq M\}$$

		MS1	MS2	MS3	MS4
T 1	O 1,1	0	*	*	0
	O 2,1	0	1	0	0
	O 3,1	0	*	*	*
T 2	O 1,2	*	0	0	*
	O 2,2	0	0	1	0
	O 3,2	1	0	0	0
T 3	O 1,3	*	*	0	*
	O 2,3	*	*	*	0

The value " $S^{ch}_{i,j,k} = 0$ " indicates that the medical staff member  $MS_k$  is not enough qualified for this health care operation so we cannot assign it to him.

The value " $S^{ch}_{i,j,k} = 1$ " indicates that the assignment of the operation  $O_{i,j}$  to the medical staff member  $MS_k$  is *obligatory* because he is the only one whose  $C_{i,j,k} \geq 0.5$ , in this case, all values of the rest of the line (i, j) are equal to "0".

The symbol: "\*" indicates that the assignment is possible i.e. ( $C_{i,j,k} >= 0.5$ ).

We cannot have the value "1" and the symbol "\*" in the same line.

The application of the assignment procedure described in the first stage may give as result the following scheduling  $S$  (Table 3).

**Table 3. Assignment S**  
*S: possible scheduling*

		MS1	MS2	MS3	MS4
T1	O 1,1	0	0	1	0
	O 2,1	0	1	0	0
	O 3,1	0	1	0	0
T2	O 1,2	0	0	0	1
	O 2,2	0	0	1	0
	O 3,2	1	0	0	0
T3	O 1,3	0	0	0	1
	O 2,3	1	0	0	0

#### a. Coding

We represent the scheduling in the same assignment table  $S$ . Each  $S_{i,j,k}=1$  and  $S_{i,j,k} = *$  are replaced by the couple ( $t_{i,j}, tf_{i,j}$ ) where  $t_{i,j}$  is the starting time and  $tf_{i,j}$  is the completion time.  $S_{i,j,k} = 0$  remain the same.

#### b. Crossover

It consists in combining elements from two parent chromosomes into one or more child chromosomes. [Michalewicz, 1992]. It allows to create new combinations and enlarge our chance to find a better solution. Our operator uses a Crossover Mask. We apply an efficient coding inspired from [Kacem et al., 2001] which respects our problem constraints.

#### Crossover Algorithm

- Select 2 parents  $S^1$  et  $S^2$  randomly;
- Select randomly 2 integers  $j$  and  $j'$  such that  $j \leq j' \leq N$ ;
- Select randomly 2 integers  $i$  and  $i'$  such that  $i \leq n_j$  and  $i' \leq n_{j'}$  (in the case where  $j=j', i \leq i'$ );
- The assignment in  $f^1$  must match the same assignments in  $S^1$  for the set of operations between the line  $(i,j)$  and the  $(i',j')$ ;
- The rest of assignments in  $f^1$  must match the same assignments in  $S^2$ ;
- The assignment in  $f^2$  must match the same assignments in  $S^2$  for the set of operations between the line  $(i,j)$  and the  $(i',j')$ ;
- The rest of assignments in  $f^2$  must match the same assignments in  $S^1$ ;
- Call to "Scheduling\_Algorithm" to calculate the starting and completion times;

#### c. Mutation

The genetic operators should be therefore able to ensure this optimization according to the criteria presented in the previous section. Thus, we propose two artificial mutation operators: the first one is responsible for reducing the response time for patients' treatment.

#### Operator of mutation reducing the response time for treatment for patient $j$ ( $RTL_j$ )

##### Mutation 1

- Select randomly an individual  $S$ ;
- Choose the treatment task  $j$  whose response time the most long : ( $\text{Max}_j \{ RTL_j \text{ such that } RTL_j = \sum_i \sum_k S_{i,j,k} \cdot d_{i,j,k} \}$ );
- $i=1$ ;  $r=0$ ;
- **WHILE** ( $i \leq n_j$  And  $r=0$ )
  - Find  $K_0$  such that  $S_{i,j,K_0}=1$ ;
  - **FOR** ( $k=1, k \leq M$ )
    - IF** ( $d_{i,j,k} < d_{i,j,K_0}$ ) **Then**  $\{S_{i,j,K_0}=0; S_{i,j,k}=1; r=1\}$ ;
    - End IF**
  - End FOR**
  - $i=i+1$ ;
- End WHILE**
- Call to "Scheduling\_Algorithm" to calculate the starting and completion times;

The second mutation is responsible for the workload balancing:

#### Operator of mutation balancing workloads of medical staff members

##### Mutation 2

- Select randomly an individual  $S$ ;
- Find the medical staff member who has the highest workload  $M_{k1}$  ( $\text{Max}_k \{ W_k / W_k = \sum_i \sum_j S_{i,j,k} \cdot d_{i,j,k} \}$ );
- Find the medical staff member who has the lowest workload  $M_{k2}$  ( $\text{Min}_k \{ W_k \}$ );
- Choose randomly an operation  $O_{i,j}$  such that  $S_{i,j,k1}=1$ ;
- Assign this operation to the medical staff member who has the lowest workload:  $S_{i,j,k1}=0$ ;  $S_{i,j,k2}=1$ ;
- Calculate the starting and completion times according to the algorithm "Scheduling\_Algorithm";

## 5. SIMULATION AND RESULTS

To better understand the proposed approach we present in this section a scenario of a clinical case in the PED.

We suppose the arrival of 3 patients at time  $t=0$  to the health care institution with 4 medical staff members mastering 3 types of skills, the degree is between 0 and 1.

**Table 4: Medical staff members**

Medical Staff	Description
MS <sub>1</sub>	Paediatrician
MS <sub>2</sub>	Nurse 1
MS <sub>3</sub>	Nurse 2
MS <sub>4</sub>	Care assistant

Patient 1 suffers from a mild concussion without loss of consciousness, patient 2 suffers from cardiopulmonary arrest and Patient 3 from an uncomplicated pneumonia.

The assignment table of medical staff members is given in the table below:

**Table 5: Assignment table with medical staff skills**

		MS1	MS2	MS3	MS4
T1	O 1,1	0.9	0	0	0.9
	O 2,1	0	0	0.8	1
	O 3,1	0.7	0	0.6	0
T2	O 1,2	0	1	1	0
	O 2,2	0.7	0.6	0	0
	O 3,2	0	1	0.8	0
T3	O 1,3	0	0	0.6	0
	O 2,3	0	0	0	1

**Table 6: Assignment using only the first step**

		MS1	MS2	MS3	MS4
T 1	O 1,1	0	0	0	0, 10
	O 2,1	0	0	30, 50	0
	O 3,1	50, 80	0	0	0
T 2	O 1,2	0	0, 10	0	0
	O 2,2	0	10, 40	0	0
	O 3,2	0	0	0	40, 60
T 3	O 1,3	0	0	0, 30	0
	O 2,3	0	0	0	30, 40

After applying the evolutionary approach, the final assignment table is as follows:

**Table 7: Final assignment**

		MS1	MS2	MS3	MS4
T 1	O 1,1	0, 10	0	0	0
	O 2,1	0	0	0	10, 20
	O 3,1	20, 50	0	0	0
T 2	O 1,2	0	0, 10	0	0
	O 2,2	0	10, 40	0	0
	O 3,2	0	0	0	40, 60
T 3	O 1,3	0	0	0, 30	0
	O 2,3	0	0	0	30, 40

We notice that in table 7, the treatment task T1 has the longest treatment time. We have therefore reduce it to 50. Besides, the highest workload was 50, by applying the evolutionary approach it became 40. The medical staff members have as a result balanced workload.

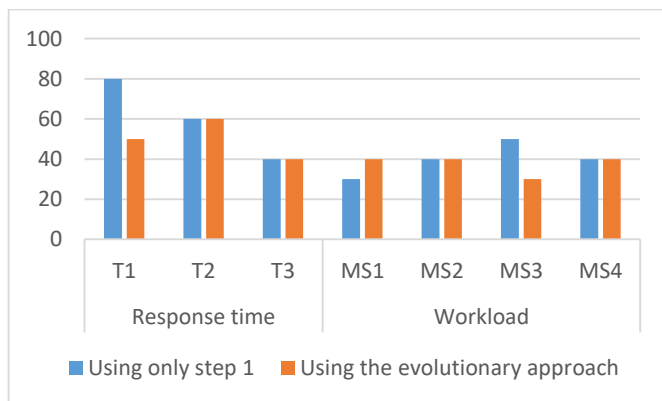
**Figure 1: Comparison between results of the first step and results given by the evolutionary approach**

Figure 1 shows that the evolutionary approach contributes to the improvement of our system performance. Balancing the workload between the health care providers leads to a less stressed medical staff and then to a higher performance and minimizing response time reassures patients.

## 6. CONCLUSION

In this paper, we have presented an efficient approach for multi-skill health care tasks scheduling problems.

This method evolves two steps: the first one is to apply the assignment procedure to solve the resource allocation problem and generate the assignment plans and the second one is to apply a controlled evolutionary algorithm. The initial

population is constructed starting from the results of the first phase. This approach helps us to improve the performance of the proposed medical staff scheduling system.

In our future works we will consider the rest of the performance indicators and we will integrate our approach in an intelligent agent-based system.

## REFERENCES

- Abbod, M. F., Von Keyserlingk, D. G., Linkens, D. A. and Mahfouf, M. (2001). Survey of utilization of fuzzy technology in Medicine and Healthcare. *Fuzzy Sets Syst.*, volume (120), N° 2, pp. 331-349.
- Bel, G. and Cavaille, J-B. (2001). *Production Scheduling*, Chp 6: Simulating Approach, under the supervision of Lopez, P. and Roubellat Hermes, F. France.
- Bertrand, X. (2006). Press Kit, "Emergencies", Ministry of Health and Solidarity.
- Boucon, D. (1991). Scheduling Workshop: assistance to the choice of priority rules. Ph.D. ENSAE, Toulouse, France.
- Canelon, M.A, Davilas, J. and Morles, E.C (2009). Intelligent supervision of petroleum processes based on multi-agent systems. *WSEAS TRANSACTIONS on SYSTEMS and CONTROL*, ISSN: 1991-8763, Issue 9, volume (4), pp 435-444.
- Ghoutha. (1993). Scheduling problems. *Operational Research*, volume (27), N° 1. pp 77-150. France.
- Isaai, M. T and Singh, M. G. (2000). An Objectif-oriented Constraint-based Heuristic for a class of Passengers Train Scheduling Problems, *Journal of IEEE/SMC Part C: Applications and Reviews*, volume (30), n. 1, pp 12-21.
- Kacem, I. Hammadi, S. and Borne, P. (2001). Direct Chromosome Representation and Advanced Genetic Operators for Job-shop Problems. Proceedings of the International Conference on Computational Intelligence for Modelling, Control and Automation (CIMCA'01), the special session on 'Multiobjective Evolutionary Optimization', Las Vegas, USA.
- Michalewicz, Z. (1992). Genetic Algorithms + Data Structures = Evolution Programs. *Springer Verlag*.
- Ono. (1996). A genetic algorithms for job-shop scheduling problems using job-based order crossover. In ICEC'96, Proceedings of the 1996 IEEE In conference on Evolutionary Computation, pp 574-552.
- Pham, M.C. (2002) Care of the patient in the hospital to better manage the complexity of the coordination of actors, Dissertation of the National School of Public Health, Renne.
- Yamada, T. and Nakano, R. (1992). A genetic algorithm application to large scale job shop problems, In Manner, R. and Manderick, B. editors. *Parallel Problem Solving from nature II*, pp 281-290, Elsevier Science Publisher B. V.