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Harmony Search Approach for Patient scheduling in Emergency Laboratories

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Abstract

This paper deals with the problem of scheduling prioritized patient in emergency department laboratories according to a triage factor. The problem is considered as a flexible open shop scheduling problem with the objective of minimizing the total completion time of prioritized patients. In this research, patient scheduling is addressed with a harmony search algorithm with wheel-roulette selection technique. Then, a comparative study is performed by considering results of genetic algorithm. Simulations on real data from emergency department show that the proposed approach improves significantly the total completion time of patients especially those with severe conditions.

1 Introduction

The aim of recent healthcare systems is to provide efficient and fast treatment of patients. In fact, one of the most significant indicators of social development in a country is accessibility to healthcare facilities when they are needed. In this context, an increasing interest was focused on optimizing this sector to enhance the availability and the quality of health services. The conducted researches in literature involve either patient scheduling or resource scheduling (e.g. staff and material resources). The objective of patient scheduling is to enhance patient satisfaction by reducing the waiting time and ensuring consecutive medical treatments without interruptions. In case of resource scheduling, many works have considered the nurse rostering, the operating room scheduling, the capacity planning as well as scheduling medical treatments for resident patients. Each type of scheduling has its own impact on the performance of healthcare systems especially at emergency departments. In fact, hospital emergency department is the crucial interface between medical services and society since they are increasingly chosen as the way of primary access to healthcare system. So, it plays a growing role in health care system, representing a rising proportion of patient admissions and serving as an advanced diagnostic center for primary care physicians. Such departments are faced with unpredicted volume of patient admissions and so the available resources may become overwhelmed with consequent risks for patient safety. Within these systems, the first phase on arrival at the emergency departments is assessment by the triage nurse who is an experienced nurse especially trained in assessment. This nurse performs a brief, focused evaluation of the patient's condition, and assigns him a triage acuity level which is a proxy measure of how long an individual patient can safely wait for a medical screening examination and treatment. For this purpose, emergency departments around the world employ different triage systems for assessing the severity of incoming patients' conditions and assigning treatment priorities. These systems are used in a structured and dependable fashion, in order to ensure high patient safety, especially when there is heavy pressure on resources. So, the role of modern triage in emergency department is very significant since it aims to ascertain the severity of illness of emergency patients in a structured way, grade patients who needed immediate care and assign the patients to the appropriate place for treatment.

According to Christ et al., (2010), five-level triage systems are the most common ones since they are judged valid and reliable methods for assessment of the severity of incoming patients' conditions by nursing staff in many emergency departments. This triage process provides clinically relevant stratification of patients into five groups from least to most urgent based on patient acuity and resource needs. Hence, the aim of the triage function is to guarantee that patients are treated in the order of their clinical urgency and to ensure that treatment is appropriately and timely. In our study, we focus on a real case based on a hospital emergency department in Tunis, where a five-level triage system is employed. The objective of our work is to enhance the service quality and the patient satisfaction by improving the efficiency of the emergency department. To do this, the total waiting time of patients have to be minimized with respect to their priority level of treatment in the emergency laboratories. The incoming patient may require some medical tests at laboratories (x-rays, observations, review by a specialist, etc.). So, an effective patient scheduling at these laboratories can significantly improve the service quality and will be saving time for the waiting patients. Given the similarity between the workshop scheduling field and the patients scheduling in emergency department, we have decided to address the problem of scheduling prioritized patients in emergency laboratories as a shop scheduling problem. Moreover, since there is no predefined route of tests for patient at most laboratories an open shop scheduling problem is more precisely formulated.

As it was already shown in literature, open shop scheduling problems are known as NP-hard optimization problems (Bai et al., (2016)). So, there is no exact method that can be employed for dealing with real-sized problems in a reasonable amount of time. In this paper, we chose to tackle the problem by using a stochastic population based method known as Harmony Search (HS) in which we integrated the wheel selection technique during the search process. We carried an experimental study of HS parameters in order to retain the best values that guarantee good solution quality. Then, the proposed algorithm is assessed on a set of real data collected from emergency department in Tunis. We notice that a comparative study is also performed on the base of results obtained by genetic algorithm. The obtained results show the outperformance of our HS algorithm. The rest of this paper is organized as follows. Section 2 presents a literature review on healthcare scheduling systems. Section 3 is devoted to open shop scheduling field in order to show the similarity with patient scheduling. In Section 4, we present the mathematical model of our problem the prioritized patient scheduling (PPS). The proposed solving approach based on harmony search (HS) is described in section 5. Then, computational results as well as a comparative study based on previous works are reported in section 6. Finally, section 7 provides conclusions and lines for future research.

2 Healthcare Scheduling Systems : Literature Review

In this section, we provide a brief survey of existing approaches for healthcare scheduling. In this context, numerous research works have considered the scheduling of human and material resources compared with patient scheduling. For the first category, we mainly distinguish the following resource scheduling problems: nurse rostering, operating room allocation, medical treatment scheduling. Nurse rostering has aroused interest of many searchers in the community of Operation management and Artificial Intelligence. It aims to periodically schedule a number of shifts to nurses in rosters while satisfying a set of constraints and requirements (working/resting hours limit, skill levels, personal preferences, etc.). Among the existing approaches to deal with this problem we mention some Metaheuristics such as genetic algorithms that has been adapted by Aickelin, and Dowsland (2004), tabu search by Dowsland (1998), chemical reaction optimization by Arajy et al., (2015), simulated annealing by Ko et al., (2013). However, Hyper-heuristics have showed more flexibility and effectiveness in their applications to the rostering problem: Rule-Based Hyperheursitic by Aickelin et al., (2007), Memetic Algorithm hyperheuristics by Özcan (2005). Gutjahr and Rauner (2007) have developed an ant colony optimization approach for the problem of nurse scheduling by taking into account a number of constraints regarding working time, nurse qualifications and preferences, cost, etc. Another resource allocation problem in hospitals is the scheduling of operating room. This problem often presents logistical difficulties in terms of assigning doctors to specific operating rooms since a wide variety of challenging factors have to be considered such as room availability, working hours in a week, doctor preferences, and operating room capabilities, surgical scheduling. The main objective of this problem is to schedule as many surgical groups as possible while staying close to a target allocation time for each surgical group to increase the overall utilization of existing operating rooms. Early surveys on solution methods for operating room planning and scheduling can be found in Cardoen et al., (2010). Romanyuk and Silva (2012) have addressed the problem by implementing a mixed linear integer program to minimize the difference between a surgical group's target and allocated time within an operating room. Linear Programming techniques have been also used by Kuo et al. (2003) to optimize operating room allocation. Scheduling medical treatments for resident patient is another challenging problem in hospitals. Vlah et al., (2011) have addressed the problem by using a variable neighborhood search (VNS)-based method.

Furthermore, a multi-objective formulation of this problem was proposed by Figueira et al., (2012) and three types of metaheuristics were implemented: variable neighborhood search (VNS)-based method (Khmelev and Kochetov (2015)), scatter search (SS) based methods and a non-dominated sorting genetic algorithm (NSGA-II). The second category of healthcare scheduling problems concerns patient scheduling. In fact, many research works focused on patient scheduling with the objective of reducing waiting time and enhancing the satisfaction level. These works varies according to the point of care which is characterized by different conditions and settings (surgery room, pathology laboratories, emergency room). Azadeh et al., (2015) have addressed a semi-online patient scheduling in pathology laboratories. The problem was formulated as a semi-online hybrid shop scheduling problem for which the authors have proposed a mixed linear programming model and a genetic algorithm for its optimizing. Demeester et al., (2010) have developed a hybridized tabu search algorithm to tackle patient admission scheduling. The objective is to ensure an efficient assignment of patients to beds in the appropriate departments, taking into account the medical needs of the patients as well as their preferences, while keeping the number of patients in the different departments balanced. Marinagi et al., (2012) have considered the planning and scheduling of patient requests for examination tests in hospital laboratories. Therefore, the authors proposed an integrated patient-wise planning and scheduling system which supports the dynamic and continual nature of the problem. The developed system is based on a combination of multiagent and blackboard architecture to allow the dynamic creation of agents that share a set of knowledge sources and a knowledge base to service patient test requests. Min and Yih (2010) have developed a stochastic dynamic programming model for surgery scheduling with limited capacity. The proposed model show the effect of patient priority as well as the inherent uncertainty in surgeries (arrival of new requests, emergent surgery patients and the duration of each surgery) on the surgery scheduling policy. In order to ensure an efficient scheduling of patient appointments on expensive resources, Vermeulen et al., (2009) have proposed an adaptive approach to automatic optimization of resource calendars. The proposed approach allocates the resource capacity to patient groups and finds the optimal resource openings hours. Pérez et al., (2013) have presented a stochastic online scheduling algorithm for patient and resource scheduling in nuclear medicine departments which take into account the time constraints imposed by the decay of the radiopharmaceuticals and the stochastic nature of the system when scheduling patients. Ceschia and Schaerf (2011) have firstly developed a multi-neighborhood local search procedure to solve the patient admission scheduling problem. Afterwards, the authors have considered a dynamic scheduling of patient admission under uncertainty in Ceschia and Schaerf (2012). Then, a more elaborate model was also proposed by Ceschia and Schaerf (2014) through the integration of a flexible planning horizon, a complex notion of patient delay, and new components of the objective function. The authors have also designed a solution approach based on local search, which explores the search space using a composite neighbourhood. Chern et al., (2008) have designed a health examination scheduling algorithm which is based on heuristics to solve efficiently and effectively the underlying scheduling problem. The proposed algorithm has two primary objectives: minimizing examinee waiting time and minimizing doctor waiting time. Turkcan et al., (2011) have developed a sequential appointment scheduling approach by considering some service criteria such as expectation and variance of patient waiting time, queue length, and overtime. The main contribution of the study was using unfairness and congestion measures as primary objectives. Therefore, the authors have proposed new unfairness measures in order to find uniform schedules for the patients assigned to different slots. The proposed measures are the minimization of the difference between maximum and minimum expected waiting times at each slot and the number of patients in the system at the beginning of each slot. By focusing on patients scheduling in emergency department, very few works have been conducted in literature. To our knowledge only the following research works have considered this problem. Azadeh et al., (2014) has proposed a genetic approach to deal with the patient scheduling at emergency as an open shop problem. Let us notice that in their research, the authors have considered a triage of the incoming patient. Kırıs et al., (2010) has conceived a knowledge-based reactive scheduling system for emergency department by considering patients priorities, their arrival times, flow times, doctors work load. The objective of this system is determining the patient with higher priorities and then minimizing their waiting times while considering doctors work load. Vermeulen et al., (2009) have considered the online problem of scheduling patients with urgencies and preferences on hospital resources with limited capacity. The proposed scheduling solution consists of four main parts that were optimized simultaneously: determining the allocation of capacity to patient groups, setting dynamic rules for exceptions to the allocation, ordering timeslots based on scheduling efficiency, and incorporating patient preferences over appointment times in the scheduling process. Yeh and Lin (2007) have used a simulation technique and a genetic algorithm to improve the quality care of a hospital emergency department. The simulation model was proposed to cover the complete flow for the patient, while the genetic algorithm was applied to optimize the nurse scheduling with consideration of minimizing queue time for patient.

Following this literature review, we noticed that patient scheduling in emergency departments remains a poorly studied field and several artificial intelligence techniques are still unexplored to improve the quality of service. Therefore, we propose in our work to deal with this problem by using a harmony search algorithm given its successful application in several optimization problems. Our problem is considered as a particular Open Shop Scheduling Problem (OSSP) given the similarities between production scheduling field and patient scheduling in emergency department. In the next section, we will introduce the open shop scheduling problem and emphasize on its complexity and its mathematical formulation in order to deduce the similarity between the generalized problem and the patient scheduling in emergency department and to justify our choice for the metaheuristic of Harmony Search.

3 Open Shop scheduling

The open shop scheduling problem (OSSP) is defined in Bai et al., (2016) as follows: given a set of n jobs that have to be processed once for given amounts of time at each of a given set of c workstations, in an arbitrary order without interruption, the goal is to determine the time at which each job is to be processed at each workstation. When considering a number of parallel machines for each stage, a flexible open shop scheduling (FOSS) is identified (Naderi et al., (2011)). The objective is to find a schedule that simultaneously determines machine processing orders and job visiting routes to optimize some criteria, such as makespan or total completion time. The open-shop scheduling problems can be solved in polynomial time for instances that have only two workstations or only two jobs. For three or more workstations, or three or more jobs, with varying processing times, open-shop scheduling becomes NP-hard. Given the complexity of this kind of problem, no exact method could be used for real-sized problems within a reasonable computational time. In literature, the flexible Open Shop have been addressed by using some heuristics such as in Naderi et al., (2010) and mainly metaheuristics such as genetic algorithms by Naderi et al., (2014), simulated annealing by Roshanaei et al. (2010), tabu search by Seraj et al., (2009), ant colony optimization by Panahi et al. (2011), particle swarm optimization by Noori-Darvish et al., (2012). These methods have been used separately or with some hybridization such as the works of Anand and Panneerselvam (2015). The Flexible open shop problem is defined mathematically by the following Mixed Integer Linear Programming (MILP) model as reported by Naderi et al., (2011). We denote by:

n : number of jobs
m: the number of stages
mi: the number of identical machine at each stage i
Oji: operation of job j at stage i
Pji: processing time at stage i
M : an arbitrary large number
j, k : jobs index ∈ {1, 2, …, n}
i, l : stages index ∈ {1, 2, …, m}
r : index for machine in stage i, r ∈ {1, 2, …, mi}
Cj,i : Completion time of job j in stage i with Cj,i ≥ 0
Fj : Completion time of job j

Let the following decision variables:

$$Zj,i,r \begin{cases} 1 & \textit{if Oji is processed on the machine r at stage i} \\ 0 & \textit{otherwise} \end{cases}$$

with *r* ∈ *{1, 2, . . ., mi}.*

$$Xj,i,l = \begin{cases} 1 & \textit{if Oji is processed after Ojl} \\ 0 & \textit{otherwise} \end{cases}$$

with *i* ∈ *{1, 2, . . ., m-1}, l > i.*

$$Yj,i,k = \begin{cases} 1 & \textit{if Oji is processed after Oki} \\ 0 & \textit{otherwise} \end{cases}$$

with *j* ∈ *{1, 2, . . . , n - 1}, k > j.*

The MILP model is defined by the following objective function Minimize $\sum_{j=1}^{n} Fj$ (1)

Subject to:

$$\sum_{r=1}^{mi} Zj,i,r = 1 \qquad \forall\, j,i \qquad (2)$$

$$Cj,i \geq Pj,i \qquad \forall\, j,i \qquad (3)$$

$$Cj,i \geq Cj,l + Pj,i - M * (1 - Xj,i,l) \quad \forall\, j,i \in \{1,2,\ldots,m-1\},\ l > i \quad (4)$$

$$Cj,l \geq Cj,i + Pj,i - M * Xj,i,l \qquad \forall\, j,i \in \{1,2,\ldots,m-1\},\ l > i \quad (5)$$

$$Cj,i \geq Ck,i + Pj,i - M * (1 - Yj,i,k) - M(2 - Zj,i,r + Zk,i,r) \qquad \forall\, i,r,j \in \{1,2,\ldots,m-1\},\ k > j \quad (6)$$

$$Ck,i \geq Cj,i + Pj,i - M * Yj,i,k - M(2 - Zj,i,r + Zk,i,r) \qquad \forall\, i,r,j \in \{1,2,\ldots,m-1\},\ k > j \quad (7)$$

$$Fj \geq Cj,i \qquad \forall\, j,i \qquad (8)$$

The objective function (1) minimizes the total completion time of all the jobs. Equation (2) guarantees that each job is processed by only one machine at each stage. Constraint (3) ensures that the completion time of each operation is greater than or equal to its processing time. Constraint (4) and (5) specify the precedence relation between two successive stages i and l for a job j. Constraints (6) and (7) are relatives to the completion time of two jobs at the same stage i to ensure the respect of their arrival time especially when they are processed by the same machine. Constraint (8) is relative to the total completion time of a job j that must be greater than its completion time at any stage.

4 Prioritized Patient Scheduling (PPS)

After a brief introduction of the OSSP, we can deduce the similarity between scheduling patients in emergency department laboratories and the case of open shop scheduling. In fact, each incoming patient may need several tests in the different department laboratories without a predetermined order for tests (scan, radiology, hematology, urinalysis, etc.). So, we can consider each patient j as a job Oji that have to be assigned to a laboratory i without any predefined sequence of test. In real world cases, each laboratory may have parallel places or multiple staff for performing the same test to avoid the bottleneck in laboratories. Therefore, our patient scheduling problem can be considered as a flexible open shop scheduling. In table 1, we illustrate the analogy between the two domains.

Flexible Open Shop Scheduling	**Patient scheduling**
Job	Operation / Patient
Stage	Laboratory
Machine	Place / staff

Table 1. Analogy between the FOSS and patient scheduling

Consequently, the previous mathematical formulation of the FOSS problem could be adapted for the case of patient scheduling by considering this analogy. As we mentioned before, the studied department is a special hospital department since it deals with life and death situations permanently. Therefore, a triage factor is considered in order to define a priority of treatments. Hence, the objective function concerns the total completion time of all the patients j by considering their priorities pj as follows: Minimize $\sum_{j=1}^{n} pj\ Fj$ with $pj \in \{1, 2, 3, 4, 5\}$ (1)

Our emergency department employs a five level triage system that provides clinically relevant stratification of patients into five groups from most to least urgent based on acuity. Hence, the five levels are defined as follows: 5- resuscitation, 4- emergent, 3- urgent, 2- less urgent, 1- nonurgent.

The completion time for patient j is defined in Fj. The decision variable $X_{j,i,l}$ is relative to the order of patient visits in laboratories i and l. $Y_{j,i,k}$ indicates if patient j precedes patient k at laboratory i. $Z_{j,i,r}$ verifies whether patient j undergoes a medical test on machine r at laboratory i. The various constraints presented earlier are still valid in our case. Constraint (3) ensures that the completion time of each patient at a given stage must be less than or equal to the total completion time. Constraints (4-5) guarantee that each patient undergoes only one test at the same time. Constraints (6-7) indicate that each machine can be assigned to only one patient at a time. According to the problem modeling as a Flexible Open Shop Scheduling (FOSS), we can deduce its complexity as NP-hard problem. So, in order to deal with our patient scheduling problem, it is necessary to opt for an approximate method that guarantees good solution in a reasonable time.

5 The proposed HS Approach

In order to deal with our optimization problem, we propose here to use a stochastic algorithm known as harmony search (HS). In this section, we will provide a brief introduction of the standard HS algorithm. Then, we will present the proposed algorithm as adapted to our problem: prioritized patient scheduling.

5.1 Standard HS algorithm

This metaheuristic was successfully applied to various optimization problems such vehicle routing, job shop scheduling, nurse rostering in Hadwan et al., (2013). However, we noticed that in literature, the flexible open shop problem as our case has not been addressed with this metaheuristic. This further justifies our choice of the method for solving our problem. As reported by Kim et al., (2001), the method is a population based method since a set of solutions is collected in a harmony memory which is updated iteratively after the generation of a new harmony vector. The improvisation of a new solution at each iteration is performed according to three operators: Memory consideration, pitch adjustment and random selection. The basic scheme of our metaheuristic is illustrated in Figure 1. As we can see in this figure, five steps are defined in the HS algorithm: parameters initialization, memory initialization, improvisation of new harmony vector, memory update, checking stopping criteria:

– *Parameters Initialization*: in this step, a parameters configuration is performed: size of harmony memory (HMS), harmony memory consideration rate (HMCR), pitch adjustment rate (PAR), number of improvisation (NI).
– *Memory Initialization*: the harmony memory (HM) is initialized with HMS solutions before the improvisation process of new solutions. This memory is always sorted according to solutions performances.
– *Improvisation of new Harmony Vector*: this step is performed iteratively in order to generate new solutions (or harmony vectors) through three possible operators: random selection, Harmony Memory Consideration, pitch adjustment. During each improvisation, the new vector is constructed progressively by using the mentioned operators probabilistically on the base of HMCR and PAR (see figure 2).
– *Memory update*: after evaluating the performance of the new generated solution, an update of the harmony memory is performed. Whenever the new solution improves the function cost, it replaces the worst solution and a HM sorting is performed according to solutions performances.

– *Checking stopping criteria*: after HM update, the stopping criteria of the improvisation process is checked. This criterion is generally defined by the number of improvisation (NI), or by the number of improvisation without solution improvement.

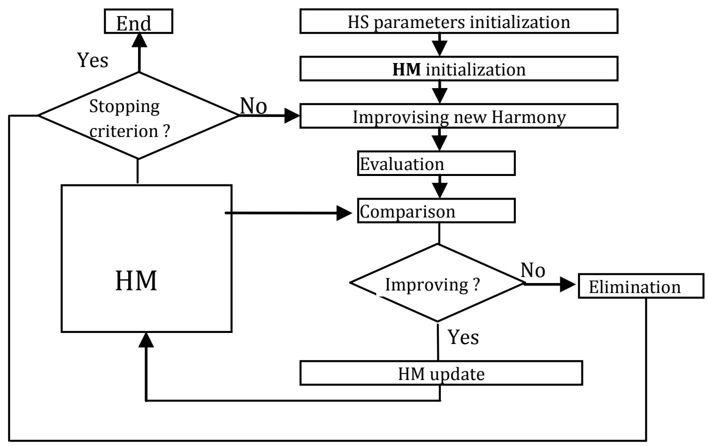

Figure 1: Harmony Search Algorithm Flowchart

5.2 Harmony Search for the Prioritized Patient Scheduling

The HS is based on random and stochastic research which enhances the diversification process. Furthermore, it does not require decision variable initialization since a new vector is progressively generated during the improvisation process. The generation of the new vector is performed by considering all the harmony memory unlike the genetic algorithm where only two parent vectors are considered. These features enhance the flexibility of the algorithm and may guarantee a good solution quality. In our problem solving we proposed to integrate the proportional solution selection instead of random selection in the improvisation process as we will further explain in this section.

5.2.1. Solution Representation

A problem solution (or harmony vector) is a feasible patient scheduling which is defined by an ordered sequence of operations O_{ij} where i is the patient identifier and j the laboratory index. In order to illustrate our solution representation, we consider the following problem defined by three patients that have to undergo tests in one or more laboratories among three (analysis, scanner, radiology). We assume that patient 1 and 2 both have tests in the 1st and the 3rd laboratories, while patient 3 has tests at the 2nd the 3rd laboratory. Hence, the set of operations *Xi* to be performed is defined as the range of possible notes in a harmony vector. In our example it corresponds to the following set: $Xi = \{O_{11}, O_{13}, O_{21}, O_{23}, O_{32}, O_{33}\}$.

As in real cases, laboratories offer the possibility of treating more than one patient in parallel; we consider then the following configuration: the two first laboratories have two parallel places whereas the last laboratory has only one place. We also assume that the test duration at laboratory 1 is one time unit, while the term is doubled for the 2nd laboratory and tripled in the 3rd one. The flexible Open Shop scheduling problem here can be defined as finding the optimal assignment of patients to laboratories by considering their capacity constraint so that the total completion time for patients is minimized with respect of their priorities. The optimal solution is then defined as the optimal sequence of operations to be performed.

In Figure 2, we illustrate a feasible solution x for the considered problem. As we can see operations O_{21} and O_{11} are performed simultaneously given the allowed places in laboratory 1

(Analysis). O_{32} cannot be performed in parallel with operation O_{33} since each patient must undergo only one test at the same time. We also notice that operations O_{23} and O_{13} cannot be ensured simultaneously since laboratory 3 has only one place.

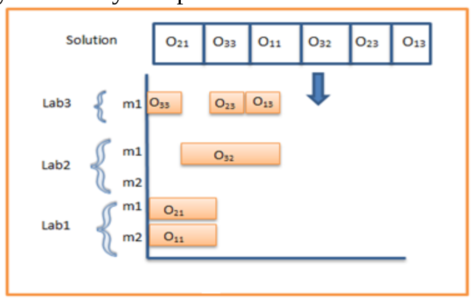

Figure 2: Solution representation

Hence, a solution for the problem is a sequence of operations that define the order of performing tests at laboratories with respect of place/staff availabilities and test duration.

In Figure 3, we present an example of harmony memory which is sorted according to solutions performances.

HM						Costs	
O_{21}	O_{32}	O_{11}	O_{33}	O_{23}	O_{13}	150	Best solution
O_{13}	O_{23}	O_{21}	O_{11}	O_{32}	O_{33}	155	
O_{21}	O_{33}	O_{11}	O_{32}	O_{23}	O_{13}	160	
O_{33}	O_{13}	O_{23}	O_{21}	O_{32}	O_{11}	165	

Figure 3: Structure of Harmony Memory

5.2.2. Improvisation process

After initializing the parameters and generating the initial harmony memory, an improvisation process is performed according to an iterative scheme. At each iteration, a solution vector $x = \{x_1, x_2,.., x_n \mid n\text{: number of jobs}\}$ is constructed progressively by using three operators: Memory consideration, random selection, pitch adjustment. Therefore for each variable initialization, a random rate $t \in [0, 1]$ is generated. Then, it is compared to HMCR to decide whether a memory consideration or a random selection must be performed.

$$xi' \leftarrow \begin{cases} xi' \in xi_1, xi_2, \ldots xi_{HMS}, & \text{with probability of HMCR} \\ xi' \in Xi & \text{with probability of 1-HMCR} \end{cases}$$

In case of memory consideration, the value (or the note) to be assigned to the current variable xi' is selected from the harmony memory. In our case and contrary to the standard algorithm, the selection is not performed randomly. In fact, we consider a proportional selection from our population as in genetic algorithm in order to improve the improvisation process. Hence, the selection probability of a value from a harmony vector is proportional to its harmony performance. So, for each harmony vector h, we denote $cost_h$ its performance, ph the selection probability and $Cumul_h$ the cumulative probability. Theses probabilities are defined as follows:

$$p_h = (1/cost_h)/\sum_{i \in h} pi$$

$$Cumul_h = \sum_{i \in h} pi$$

The selection process of a value starts by generating a random number $r \in [0, 1]$. If $r \leq Cumul_1$, the value of the first vector is chosen in the current column i. Otherwise, the selection will be performed on harmony vector h with $2 \leq h \leq HMS\text{-}1$ (see figure 4).

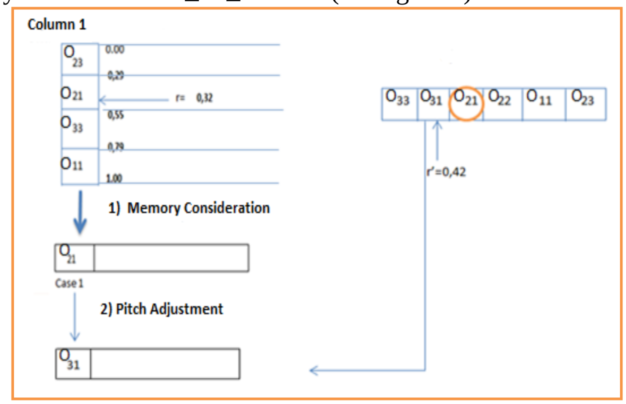

Figure 4: HM Consideration with proportional selection and Pitch Adjustment

In Figure 4, we illustrate an example of roulette selection by considering cumulative probabilities. After selecting an operation from the memory, a pitch adjustment may happen with a probability PAR. This adjustment consists in altering the selected operation by a neighboring value (preceding or succeeding) from the range of operations. Therefore, a random rate r' in [0, 1] is generated and assessed.

$$xi' \leftarrow \begin{cases} xi\,(k+m) & \text{with probability of PAR} \\ xi' & \text{with probability of 1-PAR} \end{cases}$$

Where xi': the value obtained from HM consideration;
$xi(k)$: the k^{th} element in the range of notes Xi ;
m: the neighboring index such that $m \in \{\ldots., -2, -1, 0, 1, 2, \ldots.\}$.

Random selection is performed when the generated probability is inferior to $1\text{-}HMCR$. In this case, a value within the defined set Xi is randomly chosen and then assigned to the decision variable xi'. When the new harmony vector is completely constructed and the problem constraints are checked, its performance (or cost) is computed in order to compare it to the worst solution in the Harmony Memory. If the new vector improves the function cost, a memory update is performed by replacing the worst solution in sorted order. At the end of each iteration, the stopping criterion is checked to decide whether a new improvisation cycle has to be launched by considering a new empty vector. In our case, this criterion corresponds to the limited number of improvisation NI.

6 Experiments and Results

In order to test the performance of our approach, we considered a case study of an emergency department in Tunis. This department is defined by six laboratories: blood analysis (BA), scanner, radiology, Magnetic Resonance Imaging (MRI), electrocardiography (ECG), urinalysis (UA). Each laboratory is defined by a number of parallel places (or multiple staff) and a processing time as shown in table 2. Let us notice that our real emergency department employs a five-level triage system in order to assess the severity of incoming patients' conditions and assign treatment priorities. After implementing our Harmony Search approach with JAVA language, we studied the configuration of the algorithm parameters in order to choose the best values that guarantee good solution quality. In table 3 we illustrate the results we obtained for different values of parameters HMS, HMCR and PAR respectively on the base of some problem instances with different sizes (5, 10, 15 and 20 patients). We notice that the considered parameters values are inspired from literature of different optimization problems that were addressed by Harmony Search algorithm (Hadwan et al., (2013)). For each parameter in each instance we consider the best cost that we obtained after a number of tests. Then, we retained the values that gave the lower cost. So, the obtained parameters values are: HMS = 10, HMCR = 0.9, PAR = 10-4.

Laboratory	**Processing time(s)**	**Number of places**
Blood Analysis (BA)	360	4
Scanner	480	3
Radiology	600	2
Magnetic Resonance Imaging (MRI)	1800	1
Electrocardiography (ECG)	240	2
Urinalysis (UA)	300	3

Table 2. Characteristics of laboratories in real emergency department

N°Instance	**Number of patients**	**Total Completion Time (s)**								
		HMS			**HMCR**			**PAR**		
		5	10	15	0.7	0.8	0.9	10^{-2}	10^{-3}	10^{-4}
1	5	7200	4920	7080	6780	6720	7800	6000	7920	8880
2	10	18300	23460	27360	31560	18660	19980	16800	20760	21060
3	15	54780	61440	60420	57900	54300	49080	58920	42180	53040
4	20	83160	68340	74400	82680	87360	65460	89760	84780	66660
Average value		40860	**39540**	42315	44730	41760	**35580**	42870	38910	**37410**

Table 3. . Experimental study of parameters values (HMS, HMCR, PAR)

Afterwards, a comparative study is performed by considering 16 problem instances that we randomly generated with different sizes. Since our problem has been studied in literature with the standard genetic algorithm by Azadeh et al., (2014), we decided to undergo a comparative study of our approach. Therefore, we implemented the genetic algorithm and we performed a parameter tuning to retain the best parameters values in the same way as Azadeh et al., (2014). For each problem instance, we run the two algorithms in parallel to study their performances for our problem. The obtained results are shown in table 4. The illustrated costs represent the total completion time of all patients by considering their priorities and the processing time of laboratories. We noticed in this table that the obtained results by the two algorithms are the same for a small number of patients (or jobs).

When the number of patients grows, the Harmony Search algorithm provides better results than those of genetic algorithm for the same instances. Consequently, for small instances the two approaches are generally equivalent in terms of performances. However, for an average or great instances, our approach is more convenient to get good solutions quality.

N° Instance	Number of patients	Best solution RH(s)	Best solution with GA(s)
1	5	6900	6900
2	10	18720	18720
3	15	**37560**	38940
4	20	**83400**	87480
5	25	**115500**	126900
6	30	**213060**	244380
7	35	**308460**	334260
8	40	**308820**	348300
9	45	**596100**	663660
10	50	**708720**	808140
11	55	**751260**	851400
12	60	**1018500**	1139760
13	70	**2160600**	2407080
14	80	**2309160**	2663280
15	90	**3171660**	3606420
16	100	**4221540**	4628820

Table 4. Simulation Results with HS approach and Genetic algorithm

7 Conclusion

In In this paper, we focused on patients scheduling in emergency department according to treatment priorities. The problem has been formulated as a particular open shop scheduling problem aiming at optimizing the total completion time with respect of their priorities and some operational constraints. After a literature review on healthcare management systems and theoretical open shop scheduling, we proposed to address our problem with a stochastic method that have not yet been adapted for this kind of problem. Our approach is based on harmony search algorithm with the integration of proportional selection in the improvisation process. In order to illustrate the high performance of our approach, we implemented it by using real data from an emergency department in Tunis. Then, we performed a comparative study with a genetic algorithm from literature. Simulation results show that the proposed approach considerably enhances the performance of patients scheduling and optimizes the service quality for patient as well as the use of available resources. We notice that as current works, we are considering parameters tuning in order to analyze possible interactions between parameters by using response surface methodology (RSM). This powerful experimental approach explores the relationships between several explanatory variables and one or more response variables. Moreover, we intend to integrate a local search procedure in the algorithm design in order to enhance the results.

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