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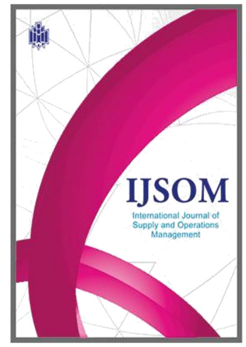

Genetic Algorithm for Patients Scheduling in Emergency Department: A Case Study

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Abstract

Emergency Departments (EDs) in hospitals typically aim to deliver accurate and rapid treatment to patients. The scheduling of patients in EDs is a challenging task that depends not only on the triage process but also on the availability of both human (staff) and material resources. In this paper, a real case study is conducted to tackle the issues coming from crowding and long waiting times for patients processing at the largest hospital in the region of Sfax (Tunisia). An integer programming formulation is proposed to minimize total patient waiting times (PWT) in EDs subject to procedural and staff availability constraints. Due to the large scale of the treated problem, a Genetic Algorithm (GA) is developed as a solution method. The efficiency of the presented approach is evaluated based on diverse sets of theoretically and randomly generated instances in a first way and on the actual data obtained from the real case study hospital in a second way. Results show significant improvements compared to the First Come First Served (FCFS) real case study's rule. The decrease in patient waiting time ranges between 18.84 % to 27.45%.

Keywords: Emergency Department; Patient Waiting Time; Patients Scheduling Problem; Genetic Algorithm; Case Study.

1. Introduction

1.1. Research motivation and literature review

Nowadays, the necessity for changes in healthcare is more than ever apparent in face to the variant challenges of healthcare systems and which are related to the increasing number of patients, the shrinking of budgets, and the lack of working staff (Holden, 2011).
With the complexity of healthcare and health services related to patient flow, various problems such as patient safety, cost containment and patient crowding appeared in various departments and especially in emergency department (ED). The most important objective of the emergency services (ED) consists on providing immediate care to patients who require urgent care. These departments have become more crowded in many countries (including Tunisia) for several reasons such as higher patient volumes and increasing complexity of both the patients' condition and the required treatments. Therefore, patients seeking emergency care may experience long waiting time.
The ED is the most accessible way in the hospital. It is the reception area for all patients whose admission has not been planned (Holden, 2011). The management of the ED of a given hospital is vital to eliminate patient crowding

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and to improve the healthcare services' quality. The effectiveness relies on how using the hospital (human and material) resources efficiently, particularly under limited medical resources (Zhang et al., 2019). One idea to eliminate such crowding is to apply patient demand forecasting techniques. In this case, Emergency Department demand prediction (showed as daily visits) is evaluated by the development of forecasts models employing diverse time-series based approaches.

It seems that most careful prediction of Emergency Department services' demands appears as an important tool for resource planning decisions (Yousefi et al., 2018; Duarte et al., 2021). However, these techniques are used on a long-term horizon and ignore the short-term planning. In EDs, it is important to take care of patients accurately and quickly. To improve the performance of the healthcare system, it is important to focus on patient scheduling, especially by seeking the social objective of minimizing patients waiting time. In fact, face to the lack of resources and the limited availability of healthcare professionals as well as the variability of patients' conditions, an efficient assignment process of patients to physician resources is needed (Erhard et al., 2018; Yeh and Lin, 2007).

In Tunisia, the Habib Bourghuiba's hospital suffers from a huge patients' waiting time, especially in Emergency Department (ED). This problem has caused a disturbance of all the flows and all the healthcare system in this department and influenced then the normal operation and the performance of this department. For this reason, and face to the complaints of most patients of this condition which can worsen their health, there is a need to search a solution to this major problem. The objective of this study consists on searching an effective and efficient Scheduling of incoming Patients in this department.

In recent years, researchers have paid great attention to the scheduling of the health care system. Research studies in this field can be classified into two principle families: resource scheduling problems (Bodaghi et al., 2020; Ben Othman et al., 2019) and patient scheduling problem (PSP). PSP plays a crucial part in the performance of all healthcare systems. It helps to reduce the total waiting time of incoming patients (Petrovic and Leite-Rocha, 2008). In this research study, we are concerned about the PSP related literature.

Elalouf and Wachtel (2015) presented an integrated patient scheduling approach in the emergency department. A patient flow simulation framework is developed and then coupled with two proposed methods (the 'floating patient' algorithm and the Physician-in-Triage algorithm) to reduce the patient's total length of stay in the ED.

Zhang et al. (2019) proposed an integrated ED capacity planning based-approach using a recurrent neural network and simulation technique.

Harzi et al. (20117) proposed a mixed integer linear programming (MILP) model in order to solve the patient scheduling problem in the ED to reduce the patients' total waiting time in the emergency department. In their model, they have taken into account four patient processes simultaneously: the registration and the triage step, the doctor's consultation step, the treatment step, and the hospitalization step. After that, Harzi et al. (2018) treated the same problem using a hybrid approach coupling the Iterated Local Search (ILS) metaheuristic and the Variable Neighborhood Descent method (VND).

Daldoul et al. (2017) proposed a MILP model (mixed integer linear programming) for patient scheduling in the EDs. They considered in their model four classes of patients. Moosavi and Ebrahimnejad (2018) treated the case of patient scheduling in the operating room. They proposed a multi-objective model combining three objectives: minimize the number of patients transferred to the following planning horizon, minimize the cost of both waiting patients and the extra beds obtained in the ward, and minimize the idleness as well as the overtime of operating rooms, the delays in children's operation, and the forwardness in operating of nonpriority patients.

Zachariasse et al. (2018) identified the most commonly used performance measures to evaluate ED triage systems.

Ben Othmen et al. (2019) developed a dynamic two-phases scheduling protocol in order to minimize the Patients Waiting Time (PWT) by reducing the interaction between scheduled and unscheduled patients who come to the emergency department. In the first phase, they developed a Genetic Algorithm (GA) to plan the scheduled patients. In a second phase, they integrate the dynamic and uncertain environment aspect related to ED (the arrival of new unscheduled patients) by continuously updating the patient schedule.

Alizadeh et al. (2020) developed an MILP model to handle scheduling appointments for non-emergency outpatient appointments in the case of a single device and a limited staff and while considering the priorities of the patients and the duration of the patient's appointments.

Aburayya et al. (2020) proposed a hybrid appointment system to schedule patients in Dubai primary healthcare centers. The suggested scheduling system integrates two methods: a walk-in system and an appointment system.

Hamed Samarghandi et al. (2021) presented the patient scheduling optimization problem of a cardiology clinic in Iran. In this study the patients were classified into six groups. The constraint programming gives the optimal solution.

Carlos Franco et al. (2017) studied the problem of patient scheduling and capacity planning for the vaccination process during the COVID-19 pandemic. The authors considered a non-linear mathematical modeling approach and they represented the dynamics of an open Jackson Network and a Generalized Network.
Table 1 presents a summary of the most related research on patient scheduling available in literature review.

Table 1: Summary of the related research on patient scheduling

Researches	Application	Approach
Elalouf and Wachtel (2015)	Emergency Department(ED)	Simulation
Zhang et al. (2019)	ED	recurrent neural network
Harzi et al. (2017)	ED	simulation technique
Harzi et al. (2018)	ED	mixed integer linear programming model
Daldoul et al. (2017)	ED	Metaheuristic mixed integer linear programming model (MILP)
Moosavi and Ebrahimnejad 2018)	Operating Room	multi-objective model
Zachariasse et al. (2018)	ED	performance measures
Ben Othmen et al. (2019)	ED	Genetic Algorithm (GA)
Alizadeh et al. 2020)	ED	MILP model
Aburayya et al. (2020)	primary healthcare centers	hybrid appointment system
Hamed Samarghandi et al. (2021)	Cardiology Clinic	Constraint Programming Model
Carlos Franco et al. (2017)	vaccination process	non-linear mathematical

As mentioned in Table 1, we notice that mathematical model is one of the methods to improve the efficiency of the Emergency Department and to optimize the waiting time. It's a practical method to manage patient scheduling.

1.2. Objectives of the study

Patient satisfaction has long been a challenge in the emergency department (ED). It consists on determining the order plan of patients in front of each treatment room in order to be served by a specific doctor. In fact, patients arriving at the ED suffer from increasingly long ED visit durations as well as average waiting times over the past decade (Wilper et al., 2008).
An emergency department (ED) is a complex system face to the limited medical resources, the health state of the interdependent patients and the unscheduled patients' visits. So, the need of medical resources cannot be pre-planned in advance. In front of such complex situations characterized by an uncertain environment and a high level of unpredictable events, wrong decisions can influence the total patient's waiting time and can also affect the health of the patient in case of errors made by decision makers.
Maximising the patient flows throughout the emergency care patient pathway is one of the most important objectives in the healthcare system. The Emergency Department (ED) is the critical point of this pathway in most hospitals, as the potential delays and the reduced the number of patients seen in the recommended time. One of the key delays in the ED is the patient's waiting time prior to treatment, which can be reduced by optimizing the patient treatment schedules. Face to the huge number of patients to be served each day and the lack of physician resources, it is required to optimize the time cycle of incoming patients by determining the most adequate passage of patients that minimizes their total waiting time.
To make improvements in ED, it is possible either to change layout or to add medical resources. However, this solution is very costly and requires financial investments. For this reason, face to the space and financial limitations, medical

decision-makers consider that the scheduling of patients can be the best alternative to improve the efficiency of a given ED.
In the literature, several research studies have addressed healthcare problems in hospitals and especially in emergency department. However, the essential concerns of the most of these certain studies are the allocation of healthcare resources and the scheduling of medical staff. There is a lack of the patients scheduling considerations. In addition, the existing models don't respect the specifications of the Habib Bourguiba Sfax hospital real case study. In other words, these studies suffer limits concerning the environment and the constraints and restrictions related to the case study such as the resources used in this hospital.
Patient scheduling plays a major role in the performance of the healthcare system. In this context, we offer emergency patient scheduling to reduce the patients' waiting time.
In this research study, we propose in a first way a mathematical model to ameliorate patient flow and to increase then patient satisfaction, at the Habib Bourguiba Sfax hospital, by minimizing the total patient's waiting time from its arrival in the ED until its achievement of treatment and exit. In a second way, we solve this problem using exact method for small scale instances and Genetic Algorithm based approximated method for large scale instances. This study presents two main contributions: the first contribution relates to suggest a mathematical model specific to the real case study. The second one consists in applying the Genetic Algorithm to solve this problem with a specific manner. In fact, in this algorithm, the representation of the chromosome (solution) plays an important role in the performance of the system. For this reason, we suggest a new presentation of the chromosome, and that is not adopted in the literature as far as we know. Figure 1 presents a conceptual framework describing the main contributions of the presented paper.

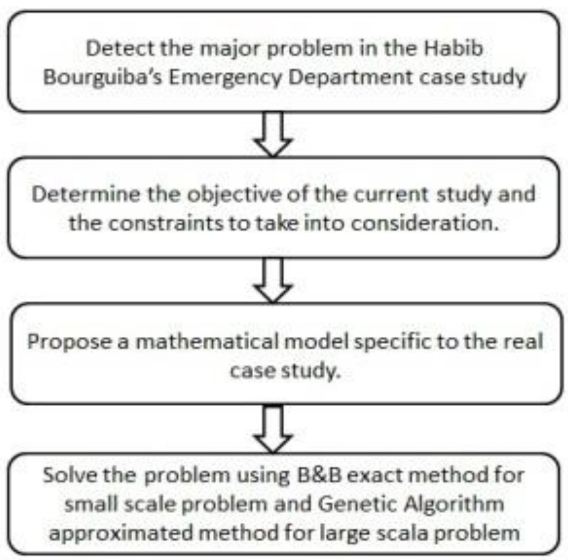

Figure 1: Conceptual framework of the main contribution of the study.

2. Problem definition

ED is one of the most important departments in hospitals, serving as a medical treatment center and as a portal receiving and operating continuously emergency situations for hospital admissions (Moosavi and Ebrahimnejad , 2018; Leksakul and Phetsawat, 2014). This department constitutes a complex system in a hospital that requires an important organization of both material and human resources. It corresponds to the access way of all unexpected patients (whose admission is not pre-planned) for a consultation or a hospitalization (Holden, 2011).
The principle issue of EDs is to take care of incoming patients not only accurately but also quickly. Patient scheduling is among the most important problems that have a major effect on the efficiency of the EDs and also on the performance of all the healthcare system (Schuur and Venkatesh, 2012). The literature review conducted in the previous section reveals limitations related to scheduling patients in hospitals and especially in the emergency department. Furthermore, existing studies that treat this problem do not well consider patient satisfaction, especially in terms of waiting time. In addition, the Habib Bourguiba Sfax Hospital ED does not use any strategy for scheduling patients. Therefore, arriving patients are

not satisfied due to the very long waiting time. All these reasons are behind our motivation to solve the patient scheduling problem in EDs with the objective of minimizing the waiting time of patients from their arrival until hospitalization.
Patients arriving at the emergency room can follow diverse pathways according to their health situations and their level of gravity.
The process begins when a patient enters the front door of the emergency department and finishes by the care of this patient.
The healthcare process in ED begins with the arrival of a patient, which can come either by himself or by the ambulance in dangerous situations. Then, a triage phase is performed for each incoming patient based on its emergency degree to determine its care process. Priority is given to serious situations. The care process is almost the same for patients with critical and non-critical conditions, whereas the administrative process is not. In fact, for non-critical condition patients, the administrative process starts at the beginning of the care process. In contrast, the administrative process begins after the care process for patients with critical conditions is completed.
After the selection (triage) process, each patient is referred for a normal consultation by a doctor who can request a supplementary analysis. Then, based on the analysis results, He decides either to care the patient by himself, or to ask for a specialist. In both situations, the patient can go home or be hospitalized (see Figure 2).

Figure 2: The healthcare ED process

This study was performed by scheduling of ED patients in order to minimize PWT while considering the queue of patient in front of each treatment room and the service times spent by patients in this department. By observing the ED for a period of one month and conducting interviews with some patients who are treated in the department, we determined the time of each activity that a patient goes through. The objective of this study is then to determine the order of these activities for each patient to minimize the total waiting time of the patients by solving mathematical models and using a metaheuristic approach.

3. Proposed solution methods

3. 1. Proposed mathematical model

In this section, a new integer linear programming formulation is proposed. The goal is to reduce the total expected patient's waiting time (PWT) in the ED healthcare system. In this study, we assume that the triage process is already performed in a first step and this model is concerned only by patient scheduling. In other words, the output of the triage process corresponds to the input of the proposed scheduling model, which determines the scheduling of patients in ED in a predefined planning horizon.
Hence, planners need a suitable model for generating helpful information (Mirzazadeh et al., 2014).
In the proposed model, the healthcare process in ED consists of a set of ordered services and which varies from one patient to another. A service here consists on a patient's treatment performed in a treatment room (it can be a simple consultation treated by a doctor, a well-defined analyze requested by a doctor, a detailed consultation treated by a specialist doctor…) and characterized by a duration varying from one patient to another (noted the treatment time period in the model). Each service is performed by a given physician resource (which can be a general doctor, a specialist doctor or an analyst) and which is affected to a well-defined treatment room.

In the ED, a varied number of patients should be examined each day. Our objective in this study is to determine if a given patient *i* is affected to service *j* and served by the physician resource *k* in time *t*. In other words, we search the schedule of patients in front of each service at each time *t* in order to minimize the PWT of each patient to be completely served and then the total waiting time of all patients in the ED.

3.2. 1. Indices

i: Index of patient,
j: Index of service,
t: Index of time period,
k: Index of physician resource

3.2. 2. Parameters

T: Time periods;
I: Number of patients at time period t
J: Set of services;
K: Set of physician resources
r_i : Ready time of patient i
P_{ij}: Treatment time period of patient i in service j
k_{ij}: Physician resource required for patient i for service j
w_{ij}: Waiting time for patient i go to service j
S_{ij}: Start time of service j go to patient i

3.2. 3. Decision variables

$X_{ijkt} = 1$, if patient i is affected to service j and served by the physician resource k in time t; and 0, otherwise.

3.2. 4. Model formulation

Equation (1) is the objective function that consists in minimizing the total patients' waiting time in the ED. Equation (2) ensures that the start time of the service 1 is equal to the sum of the ready time of patient i (we mean by the ready time here the time in which the patient i is accomplished the administrative and the triage process and is available to begin the treatment process) to be served and the waiting time of the patient i to be served by the first service. In Equation (3), the processes are accomplished in order: service $j+1$ begins after service j finishes. In other words, the treatment process of each patient is characterized by a set of ordered services. Equation (4) ensures that each patient is scheduled exactly once on each resource for each service and that each resource is used by only one patient at a time. Equation (5) guarantees that each resource k is assigned to at most one patient and service. Finally, Equations (6) and (7) represent the integrity and the non-negativity constraints respectively.

$$Min\ Z = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=1}^{T} w_{ij}X_{ijkt} \tag{1}$$

$$S_{i1} = r_i + w_{i1}, \forall\, i \in \{1, .., I\} \tag{2}$$

$$S_{ij} + P_{ij} + w_{ij+1} = S_{ij+1}, \forall\, i \in \{1, \dots, I\}, j \in \{1, \dots, J-1\} \tag{3}$$

$$\sum_{k=1}^{K}\sum_{t=S_{ij}}^{S_{ij}+P_{ij}} X_{ijkt} \le P_{ij}, \forall\, i \in \{1, \dots, I\}, j \in \{1, \dots, J\} \tag{4}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J} X_{ijkt} \le 1, \forall\, k \in \{1, \dots, K\}, t \in \{1, .., T\} \tag{5}$$

$$X_{ijkt} \in \{0,1\}, \qquad \forall\, i \in \{1, \dots, I\}, j \in \{1, \dots, J\}, k \in \{1, \dots, K\}, t \in \{1, \dots, T\} \tag{6}$$

$$w_{ij}, S_{ij} \ge 0, \forall\, i \in \{1, \dots, I\}, j \in \{1, \dots, J\} \tag{7}$$

For more understanding the proposed mathematical model, we take the example explained in Figure 3. In this example, we take the schedule of one patient (patient $\boldsymbol{i}$). The objective here is to select the pathway of this patient while taking into consideration that there is three treatment rooms (service 1, service 2 and service 3) for doctor consultation, two rooms for analyzes (services 4 and 5), two rooms for radiology (services 6 and 7) and three treatment rooms for specialists (services 8, 9 and 10). Each treatment room is served by a specific physician resource (noted PR in Figure 3). We consider here that the pathway of this patient consists of: triage-doctor consultation-analyze- radiology-back to doctor-specialist. We note also that each specialty can have different service rooms. The physician resource is then an indicator for both the specialty and the service room. For example, in Figure 3, analyzes services contains two service rooms. Our issue in this study is to determine the set of patients assigned to each service and then scheduling them.

If the selected pathway is triage-service1-service 4- service 6 –service 1 and service 9, then the total waiting time of this patient (which corresponds to the sum of the total times in front of each service) is equal to 240 min. Now, if the selected pathway is triage-service 2-service 5- service 7-service 2 and service 8, then the total waiting time of this patient (the waiting time in front of each service is noted in Figure 3 WT) is equal to 250 min. Therefore, the most appropriate pathway for this patient about these two alternatives is the first one because it has the smallest waiting time.

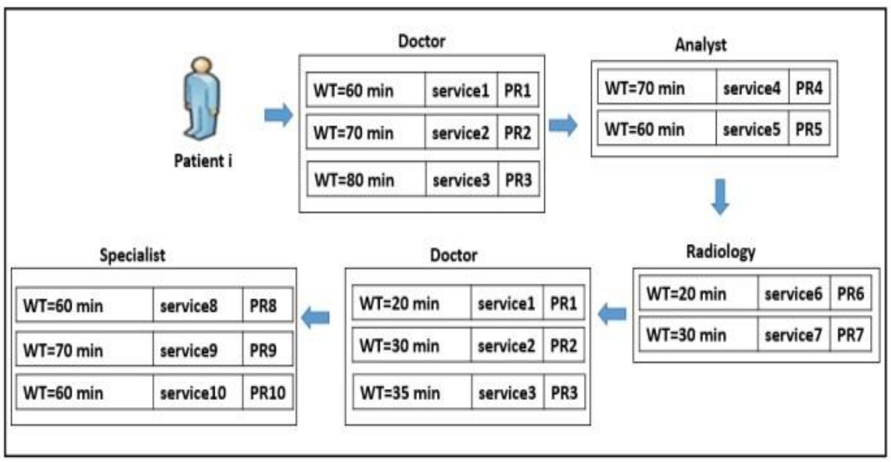

Figure 3: Example of a patient schedule

3. 2. The proposed Genetic Algorithm

The research on patients Scheduling Problem is known to be of complexity NP-Hard (Rezaeiahari and Khasawneh, 2017; Abdalkareem et al. 2021). Face to the complexity of this problem, large-sized instances cannot be solved using exact methods within a reasonable time. Hence, the approximated methods seem to be effective in such cases.

These algorithms are used to achieve near-optimal (approximated) solutions in a reasonable execution time. The GA is one of the most efficient and well-known of these methods. It is an approximated method inspired from the natural evolution of living beings. We opt to apply it to solve the studied patient scheduling problem because, on the first hand, GA has demonstrated its efficiency in different complex problems in the literature (Alizadeh et al., 2020; Yin et al., 2021) and has been heavily applied in scheduling problems; on the second hand, it is a population-based metaheuristic which allows a large exploration of the feasible solution space.

GA is a bio inspired natural algorithm that simulates the Darwin's evolution theory to enhance the performance of computational optimization systems (Yin et al., 2021). The procedure of such algorithms is about the evolution of a set of initial solutions which are updated iteratively. In each iteration, the less effective solutions (which is known according to the fitness values), will be removed and new other solutions will be appeared face to the generation of the crossover and mutation operations (Chui et al., 2017).

GA has improved its effectiveness in various areas, including industrial and logistics optimization, operational management, and healthcare management. In recent years, GAs marks its popularity for solving complex optimization problems in healthcare management especially in the scheduling and timetabling areas (Aickelin an Kathryn, 2004).

Similarly to the biological context, in genetic algorithms, individuals represent feasible solutions. At each iteration step, a number of new solutions appear, some existing solutions give birth to other new solutions facing a slight change in their structure, and some others disappear.
The different steps of the proposed algorithm are illustrated in Figure 4.

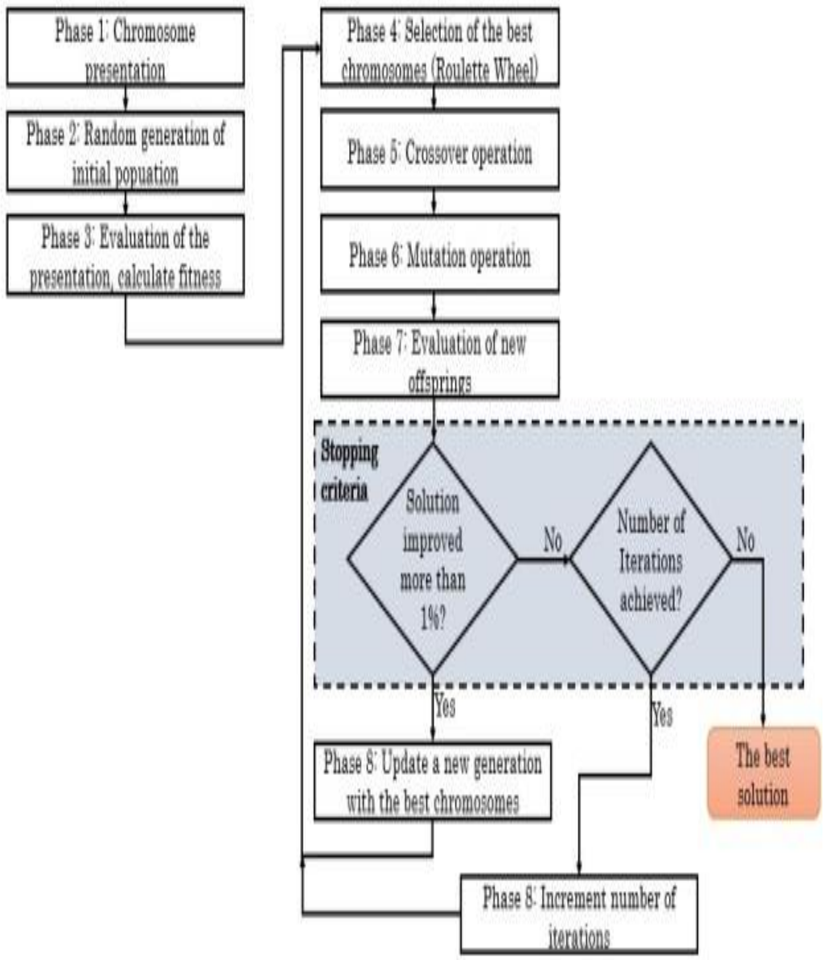

Figure 4: Flow chart of the proposed Genetic Algorithm

In this study, for obtaining the patient scheduling, we propose to apply the GA for each treatment room to obtain the schedule of patients in this room. The total waiting time of each patient will then be calculated by the sum of the waiting times in front of each treatment room (if a patient was not assigned to a given treatment room, then the waiting time in front of this room will be equal to 0). In other words, the GA is applied as many times as the number of the available treatment rooms in the time t.
The implementation of each GA step applied in each treatment room to solve the PSP is detailed in the following subsections.

3.2. 1. Chromosome encoding (Phase 1)

The solution coding of patient scheduling problem plays an important role in the efficiency of the GA. In our proposed algorithm, the solution (denoted a chromosome in GA) is represented by the patients schedule in the different treatment rooms. As far as the authors' knowledge, this paper is the first adopting the representation of the chromosome in this way.

To illustrate the structure of the solution, we take the example of 3 patients to be scheduled in 10 treatment rooms (we take the same example of Figure 3). The pathway process of each of these patients is determined in a first step (as summarized in Figure 5). As shown in Figure 5, the first case is related to the patient number and the remaining cases are related to the patient pathway (the pathway is the set of services that a given patient goes through). For example, the pathway of patient 1 is: service 1- service 4- service 6- service 1 and service 9.

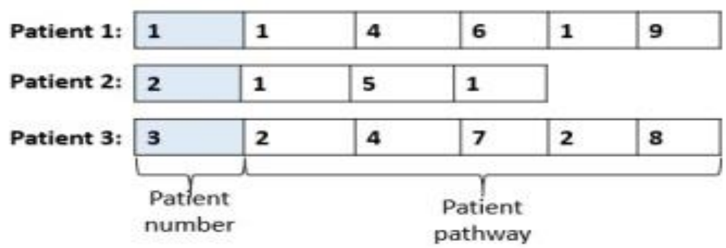

Figure 5: Example of patients' pathway

In this example, 2 patients (patient number 1 and patient number 2) are assigned to the first treatment room at time t. After the determination of the set of patients in front of each service, the patients scheduling solution is then determined in the chromosome construction phase. This study is based on an integer presentation of the chromosomes in which the components of a chromosome are represented by integer values describing the schedule of patients. The length of the chromosome here represents the sum of the number of patients waiting to be served in front of each service (see Equation 8).

$$chromosome\ length = \sum_{j=1}^{J} nb\ of\ patients\ in\ front\ of\ j \tag{8}$$

If we return to our example, the number of patients in front of each service is summarized in Table 2. So, the length of the chromosome in this example is equal to 10.

Table 2: Number of patients in front of each service

Service	Number of patients
1	2
2	1
3	0
4	2
5	1
6	1
7	1
8	1
9	1
10	0

The chromosome representation of the treated example is depicted in Figure 6. As shown in this figure, a chromosome contains the schedule of patients in front of active services (an active service related to a service visited by at least one patient in time t). For example, service 1 contains patients 1 and 2. The chromosome represents the schedule of these two patients and the schedule of patients of all the active services at time t.

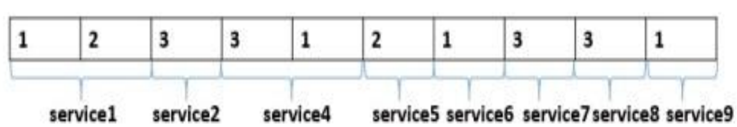

Figure 6: A chromosome representation

The solution construction step is based on the generation of a population of solutions (a set of solutions depending on the size of the population) containing a set of scheduled patients in each of the given treatment rooms for a time period t. In this study, the order of patients on each chromosome of the population is randomly initialized.

3.2. 2. Generation of initial solutions' population (Phase 2)

The initialization phase consists in generating a set of initial solutions randomly (note as population of solutions). It consists on generating a set of chromosomes randomly by determining, in a random way, the assignment of patients to services (of the same specialty) and the schedule of the different patients in front of each service.

3.2. 3. Evaluation of each individual (Phase 3)

In general, the GA method aims to provide the most fitted solution (chromosome) over a set of generated chromosomes. The fitness function consists on measuring the performance (fitness) of each individual (or chromosome) of the population. In the proposed GA, the fitness of an individual, noted T, minus the patient's total waiting time in front of each treatment room.

3.2. 4. Stopping criteria (Phase 4)

The stopping criterion of the proposed GA procedure consists on the non-amelioration of the best obtained solution' fitness more than 1% after a certain number of iterations (the number of iterations is fixed to 50 in this study). Authors can note that this number of instances is generated randomly. Figure 4 explains the convergence behavior.

3.2. 5. Recombination: selection and crossover (Phase 5)

After initializing the population with a set of randomly generated chromosomes, the algorithm will select two parents from the population to apply the crossover and mutation operations. We distinguish different strategies for selection, such as the Roulette Wheel strategy, which represents the most common method (Bazzazi et al., 2019), the range strategy, the tournament strategy, the elitism strategy, etc.

In this study, we choose the Roulette Wheel method, in which the set of parents' solutions is selected according to the chromosome performance. In other terms, each chromosome of the population is placed in a circular roulette wheel and the place given to each chromosome is proportional to its fitness value. Then, the best fitness value is likely the solution to be selected.

The crossover operation consists in generating new children by the combination of pairs of parents' chromosomes that have been selected in the selection phase. Children are new solutions resulting from combining two parent solutions. There exist different types of crossovers including single point crossover, two-point crossover, ordered crossover, crossover with reduced surrogate, Shuffle crossover, etc.

In this study, we propose a new three steps strategy for applying the crossover. In the first step, we choose randomly the specialty in which we will apply the crossover. As explained in Figure 3, each specialty can have different service rooms and, in front of each one we can find a set of patients waiting to be served. The second step consists in selecting from each parent the related sub-chromosome that is a part of the chromosome containing services (treatment rooms) treating the selected specialty (the output of step1). If we return to the example of Figure 3, if the selected specialty is that of analyzes, the crossover operation will be done only by services 4 and 5. In other words, each sub-chromosome of a parent contains the schedule of patients in front of these two services. Finally, the last step consists on applying the crossover operation in the selected sub-chromosomes.

To preserve the feasibility of the offspring (the newly generated solution), each gene of the sub-chromosome (which represents a patient) must appear only once on the chromosome. In this paper, we adopted the 1X crossover named also the single point crossover. It concerns the random selection of a cutoff point, copying the fragments of the first parent situated before this point, and completing the end of the offspring situated after the cutoff point by missing numeric values in the order of the second parent. In other words, the permutation is copied from the left part of the first parent as it. Next, the second parent is scanned and genes which don't exist in the child will be added in the same order.

Figure 7 presents an example of a 1X crossing operation. In this example, the cutoff is at the second position. The offspring 1 took the first two genes from parent 1. The other genes are then taken in the order of their appearance on the parent chromosome 2. In fact, in the first position there is Patient 1. The latter has been already scheduled in Offspring 1, so this patient should be skipped, and the next gene is explored. In this position, there is patient 5. The latter is not yet scheduled, so it takes the third position in Offspring 1. The procedure continues until the whole offspring chromosome is filled. The similar procedure applies for Offspring 2 while replacing parent 1 by 2 and vice versa (see Figure 7).

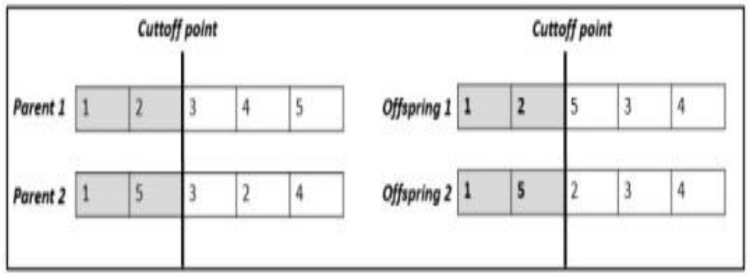

Figure 7: Example of 1X crossing operation

In Figure 8, we present an example with the proposed three steps crossover. In this example, the analyzes specialty is selected for the chromosome and then the sub-chromosomes containing the patients scheduled in front of each of the services 4 and 5 are selected. We have two parents ‘Parent1’ and ‘Parent2’ in which only the sub-chromosome part will be considered for crossing operation. A crossover point is fixed in the sub-chromosomes’ first node. Two offspring are generated considering this crossover point. In a first way, the left part of the first child is obtained by taking the left part of the ‘Parent1’ crossover point. In a second way, the right part of the obtained first child is accomplished by browsing ‘Parent2’ and taking not existing nodes in the same order. The rest nodes of child 1 (nodes corresponding to non-selected services) other than those created by recombination are copied from ‘Parent1’. The second child is created with the same manner as the first child.

In the example of Figure 8, we have two parents. We have selected randomly the analyzes specialty. This specialty contains two rooms numbered as room 4 and room 5. In parent 1, the schedule of patients in front of room 4 is patients 3-1 and that in front of room 5 is patient 2. After the crossing operation, the schedule of patients in front of room 4 becomes patients 3-2 and that in front of room 5 becomes patient 1.

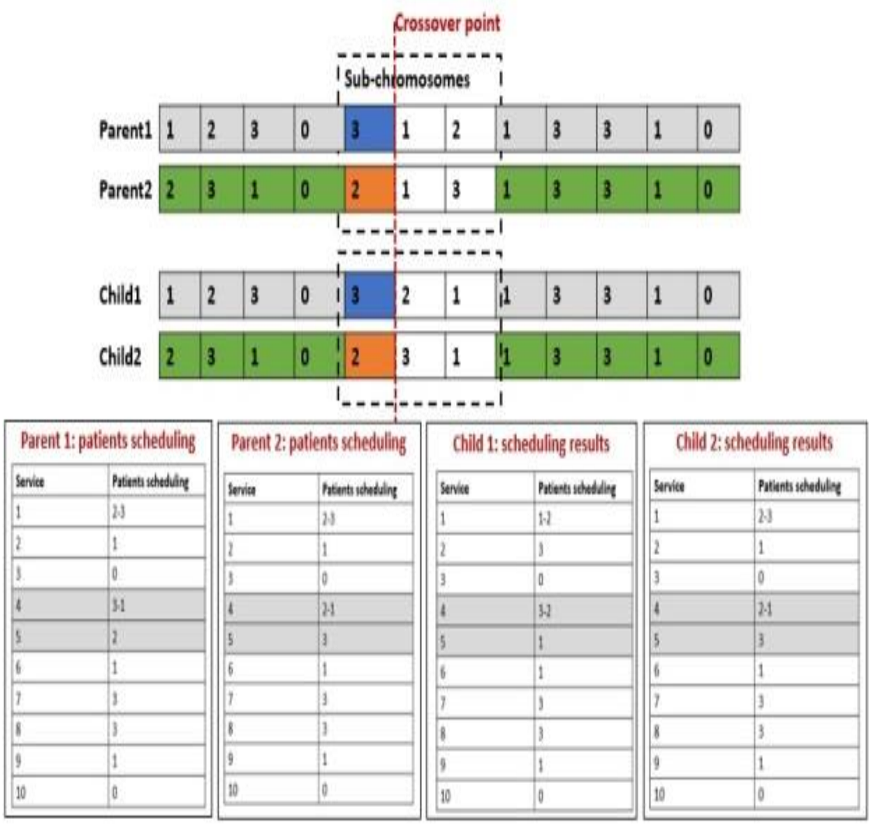

Figure 8: Example of the proposed three steps crossover

3.2. 6. Mutation operation (Phase 6)

In addition to the reproduction operation (crossover operation), the mutation operator is adopted to guarantee the diversity of the population and to maximize the use of the solution space. In this step, we applied the swap mutation which consists in selecting two genes of a parent at random and swapping them to obtain a new offspring. An example of mutation is provided in Figure 9. To achieve this operation, a mutation probability P_m is fixed. It represents how often the genes on a chromosome are mutated.

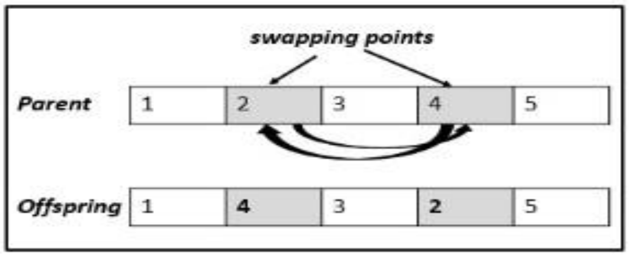

Figure 9: Example of swapping mutation

3.2. 7. Evaluation of each offspring (Phase 7)

As in phase 3, each offspring obtained by the application of crossover and mutation operations is evaluated. The new obtained solutions may be either better or worse to solutions of the population. In this research, the elitist strategy is used as a replacement strategy.

3.2. 8. Updating the new generation (Phase 8)

In this phase, the current population is updated by keeping the individuals having the best fitness value, and which are selected from the current population and the offsprings obtained from both the crossover and the mutation operations. At the end of this step, a new generation is obtained.

3. 3. GA Parameters selection

To authenticate the quality of the developed GA, a number of tests are set up to adjust the parameters of this algorithm. Table 3 presents the final used parameters to solve the patient scheduling problem.

Table 3: Calibrated parameters of the proposed Genetic Algorithm

Parameter type	Description	Value
P	Population size	50
P_c	Crossing rate	0.85
P_m	Mutation rate	0.2
Iter	Number of iterations	50

3. 4. Performance criteria

To analyze the efficiency of the developed GA with regards to the optimality, three performance criteria are used including the following.

The first performance criterion is $Gab_{B\&B}$ percentage which consists on the deviation percentage of the obtained proposed solution from the optimal solution (required from B&B algorithm). It is measured by Equation (9):

$$Gab_{B\&B} = \frac{GA\ result\ -\ B\&B\ result}{B\&B\ result} \times 100 \tag{9}$$

The second performance criterion is the Average Percentage Gap (APG) calculated according to Equation (10):

$$APG = \frac{\sum Gab_{B\&B}}{number\ of\ instances} \tag{10}$$

The third performance criterion is Gab_{FCFS} percentage which compare obtained results from the proposed GA approach and the results of the priority rule Fist Coming First Served (FCFS). Contrary to $Gab_{B\&B}$, this criterion is used for large scale problem instance. The criterion Gab_{FCFS} is calculated according to Equation (11).

$$Gab_{FCFS} = \frac{GA\ result - FCFS\ result}{FCFS\ result} \times 100 \tag{11}$$

4. Results and discussion

4. 1. Computation results

To evaluate the performance of the proposed approach, computational tests are conducted based on the basis of two main parts. In a first part, testing of the proposed near-optimal algorithm is elaborated with comparison to the mathematical modelling results using CPLEX package and this for small and medium problems size. Then, in a second part, the suggested approximated Genetic Algorithm is tested relying on a real case study. Both parts are implemented with Microsoft Visual Studio 2010 programming language and using a PC with an Intel(R) Pentium (R), a 1.8 GHz processor running, and a 4Gb of RAM.
First, we considered 15 randomly generated small and large-sized instances and compared the obtained results with those of the proposed mathematical model using IBM ILOG CPLEX 12.4. The objective of this comparison is to evaluate the performance of the GA by showing its ability to provide solutions near the optimal B&B solution. Instances are built based on the behavior of the Habib Bourguiba real case. We kept the same number of services and physician resources as the ED case study.
Table 5 presents the computational results in terms of objective values, the total Patient Waiting Time (PWT) obtained by the application of both B&B and proposed GA methods; and computational time.
Based on the results of Table 4, the Average Percentage Gap (APG) for the ten replications generated is equal to 0.80%. We show that the proposed approach can present effective solutions (near-optimal) in a reasonable time. We notice also that over 26 patients, the B&B method becomes unable to give the optimal solution in a reasonable time (more than 2 hours). The best solutions are then produced by our proposed algorithm after 26 patients.
As described in Table 5, the proposed algorithm presents a great improvement with respect to the computational time (CPU time) compared to the exact method B&B.

4. 2. Real case study

The proposed approach has been implemented based on data collected from the Emergency Department of Habib Bourguiba Tunisian Hospital. This department is located in Sfax city (Tunisia) and represents the entrance door. In fact, the geographical location of this city makes the department studied polarizing a large number of patients on the public highway. As the second industrial and economic pole that shelters various companies, the number of job casualties in this city is continuously growing.
The Habib Bourguiba emergency department has a major problem concerning the essential patients waiting times which affect not only the performance but also the quality of service of this department as well as the non-satisfaction of patients. It uses a first-come-first-served (FCFS) method to schedule new patients and does not integrate diverse criteria such as the emergency state of each patient and the availability of staff and material resources. The principle of the FCFS method is to schedule and then serve patients according to their order of arrival.
The Habib Bourguiba emergency department is composed of two care rooms, two post offices, one plaster room, one general surgery room, one orthopedy room and one visiting medical room. The average number of incoming patients to this department is about 300 patients/day and the total number of personnel in this department is 13.
Table 4 indicates a sample of the whole process by which patients are admitted to the ED of the Habib Bourguiba Hospital and the time taken to complete all activities. Data are collected by observations and interviews of 25 patients.

Table 4: Emergency department historical time data (in MINUTES)

Patient Number	Standard	Physician	Analyze	Radiology	Physician	Specialist
1	15	60	70	20	30	60
2	5	30	60	-	20	-
3	60	45	180	30	30	180
4	5	5	120	-	30	-
5	45	45	-	60	60	120
6	30	30	-	30	45	-
7	10	-	-	60	-	180
8	15	15	-	30	60	-
9	15	30	120	20	30	120
10	30	30	90	-	120	-
11	20	15	-	20	90	180
12	5	20	-	45	75	
13	15	15	120	-	60	120
14	10	5	150	15	45	-
15	30	30		20	90	120
16	5	15	180	-	120	180
17	15	30	150	-	45	-
18	5	15	210	-	50	240
19	15	50		25	60	-
20	5	15	180 (3h)	30	50	-
21	10	30	-	30	75	180
22	90	90	150	-	45	2880
23	30	5	-	10	15	-
24	15	15	180	-	50	-
25	90	10	15	90	150	-

To show the performance and the applicability of the proposed algorithm, we compared the results obtained with the current actual system used in the Habib Bourguiba emergency department. A shown in Table 5, we have tested the B&B method for 300 patients and have concluded that the CPU time exceeds 24 hours, which is not convenient. In addition, for 26 patients, the system becomes unable to provide a solution face to the complexity of the problem. For this reason, we have made a comparison between the actual real case scheduling (based on the FCFS method) and the obtained scheduling results of the GA (see Table 6).

Table 5: Comparison results between the proposed GA and B&B method

Number of patients	Proposed approach solution		B&B Solution		Gab (%)
	PWT (min)	CPU time(s)	PWT (min)	CPU time (s)	
8	31.620	10	31.620	10	0.00%
10	34.500	15	34.300	19	0.58%
12	37.230	17	37.220	540	0.03%
14	41.300	17	40.500	690	1.97%
16	43.720	19	43.630	940	0.21%
18	46.460	36	45.650	1300	1.77%
20	48.390	40	47.850	2350	1.13%
22	50.820	46	50.721	3510	0.19%
24	52.500	54	51.800	3720	1.35%
26	55.960	54	N.P.	N.P	N.P.
				APG	**0.80%**

NP: not possible to compute

Table 6 illustrates the total PWT obtained by the actual used FCFS method and the proposed algorithm for 6 days. The obtained results correspond to the average results of 50 executions for each number of patients.

Table 6: Comparison between actual system and proposed GA algorithm

Day	Number of patients	PWT for actual FCFS scheduling (min)	PWT for proposed algorithm (min)	Gab (%)
1	10	292	237	-18.84%
2	20	389	293	-24.68%
3	25	425	336	-20.94%
4	27	467	354	-24.20%
5	30	516	398	-22.87%
6	35	572	415	-27.45%

As shown in Table 6, for all six days, the proposed GA provides better solution compared to the FCFS rule. The gain raise from 18.84 % to 27.45%. We can conclude then that our research is relevant because the proposed model has helped Department managers to decrease the waiting time.

However, despite the efficiency of the method to improve the waiting system in the hospital, it is noteworthy that the current model should be improved by integrating the triage process as new constraints. In addition, the patient scheduling in this work has been studied under static environments. In our research we haven't consider the dynamic patient scheduling problem.

5. Conclusion

In this research study, a mathematical model has been presented for scheduling of patients at Emergency Department. Patient satisfaction is considered the most significant factor in emergency departments. Therefore, the primary goal is to minimize the patient waiting times. For large-scale instances, a genetic algorithm-based approach has been proposed to solve this problem. The computational results obtained are promising and show that the application of GA for the resolution of the patient scheduling problem can be efficient. The proposed approach improves the current traditional procedure for scheduling patients in the emergency department and makes efficient of the available resources. Integration of the triage process in the proposed mathematical model and the calibration of the parameters of the proposed GA will be treated as a future study. Face to the time consuming of the proposed GA, another prospect also concerns the evaluation of the performance of the GA approach by its comparison with other artificial intelligence-based methods such as the the case-based reasoning heuristic or machine learning methods.

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