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RESEARCH ARTICLE

A goal programming approach based on simulation and optimization to serve patients in an external orthopedic department

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ABSTRACT
This paper studies the problem of long waiting times for patients in the external department of orthopaedic surgery of Habib Bourguiba Hospital in Sfax, Tunisia. Three types of patients are treated and classified into two categories: those requiring only one treatment and those needing to consult doctors twice. In this paper, we aim to incorporate the priority-queue discipline for the first and second consultation, using simulation-optimisation and goal programming approach for the purpose of maximising patient satisfaction and reducing their waiting time. Our approach allows reducing average waiting time by 35% and increasing patient satisfaction by 30%.

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Simulation-optimisation; orthopaedic surgery; goal programming; priority-queue discipline; patient flow

1. Introduction

The study on the application of queuing theory is one of the substantial criteria for assessing the performance and efficiency of any service industry, including healthcare. Generally, queuing is a major challenge for healthcare systems. Hospitals, in particular, constitute a very important part of the service sector (Saadouli & Ltaif, 2020; Nor Aziati & Salsabilah, 2018).

In this paper, this research mainly aims at overcoming the most outstanding problem of the outpatient clinic of Habib-Bourguiba Hospital of Sfax, Tunisia. It consists in the long waiting time for different types of patients having to wait for too long during several stages of the process such as registration, consultation and payment.

The patient satisfaction and patient average waiting time are eminent factors in the field of healthcare service. This paper mainly aims at the performance of the optimal maximisation level for the three types of patient satisfaction towards the average waiting time, which is generally better compared to the current department.

In this article, the methodology is a coupling optimisation via simulation based on goal programming to determine the maximisation level of three types of patient satisfaction towards waiting time.

Specifically, the major contributions of this paper are as follows:

- Analysing the problem of managing the patient flow in the orthopaedic surgery in a framework of three types of patients, which is the stochastic environment where there are different key performance indicators.
- Defining a multi-objective and stochastic optimisation problem to obtain the optimal priority queue disciplines. It is solved by a simulation-based optimisation method.
- Determining which priority-queue discipline of patient assignment is when a doctor is available.
- Testing the performance of patient satisfaction and the patient average waiting time by using a simulation model reproducing the stochasticity in arrivals, service times, and pathways through the orthopaedic surgery.
- We will focus on the proposed multi-objective of maximising the level of three types of patient satisfaction with waiting time.

The remainder of this article is organised as follows. Section 2 reviews the literature on simulation and simulation optimisation in healthcare applications. Section 3 discusses the service problem. Section 4 presents the methodology of a coupling optimisation via simulation based on goal programming and describes the details of the simulation model and related parameters, including sensitivity analysis to validate the model. Experimental results are presented in Section 5. Eventually, Section 6 concludes the paper and suggests future directions for research.

2. Literature review

The Operations Research (OR) literature presents a brief review of outpatient dynamic scheduling. Truong (2015) considers a dynamic scheduling model with two patient classes: one which must be

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served immediately upon arrival and one which can be served at a future date. He introduces a non-committal scheduling policy where future commitments do not have to be honoured. Our work extends this literature through analysing a multi-stage outpatient healthcare program with no-shows but no same-day patients. Unlike previous work, patients in our setting may return for service, and the model we develop is the first to capture this phenomenon.

Beginning by the recent paper of Kou et al. (2021) that developed simulation budget allocation rules for the Motivated by the vector evaluation genetic algorithm (VEGA) in solving simulation optimisation problems, this research demonstrated the propose simulation budget allocation rules via comparing with some existing allocation rules. In addition, Yaping Fu et al. (2021) presented a hybrid approach integrating the grey wolf optimisation algorithm and the simulation optimisation framework. They used the grey wolf optimisation algorithm in order to search for candidate solutions from the solution space, while the simulation helps the algorithm to identify the desired solutions such that the search is guided to more promising regions.

Tang et al. (2014) use heuristic algorithms to solve the outpatient appointment scheduling problem for two types of patients (i.e., routine and urgent), considering no-show probability. They do not consider clinical paths of patients.

Nor Aziati and Salsabilah (2018) determine the waiting for arrival time and service time of patients at the outpatient counter to model a suitable queuing system, using simulation, too. Arena student version is unable to develop more than 150 entities waiting, and to simulate the complex models. Only a simple flow can be developed.

Afrane & Appah (2014); Feldman et al., (2014); and Liu (2016) investigate applying the queuing theory and modelling to the queuing problem at the outpatient department at AngloGold Ashanti Hospital in Obuasi, Ghana. This study, however, does not consider costs, and it would be interesting to include the cost dimension in another research in the future.

Gocgun & Puterman (2014) and Saure et al. (2012) extend their work to include patients who can receive treatment across multiple time blocks and irregular treatment durations.

Barz and Rajaram (2015) formulate an average-cost MDP for determining whether patients requiring multiple resources should be admitted to a hospital.

More recently, Saremi et al. (2013) have proposed a novel simulation-based optimisation method by incorporating mathematical programming to schedule day surgeries.

Hossain et al. (2017) reduce the patient waiting time, and improve the overall throughput of the system. Increasing rerouting of patients to lab technicians may decrease the waiting time. Adelman (2007) and Tong & Topaloglu (2013) suggest an affine functional approximation to derive dynamic bid-price controls. Zhang and Adelman (2009) propose an approximate dynamic programming model where customers choose amongst several pre-specified flight options. Vossen and Zhang (2015) show that linear the value function approximations used in network revenue management studies can be reduced to more compact linear programs.

However, similar to several other articles tackling multi-objective scheduling of patients, Gul et al. (2011) and Saremi et al. (2013) do not offer a lot of solutions. They only provide a single solution for each scenario instead. In addition, their methodology only addresses the homogenous sequence of services and does not support multiple sequences.

Chen and Robinson (2014) present a multi-objective optimisation problem in order to make sequencing and scheduling decisions for same-day and advanced patients with the objective of minimising the patients' in-the-clinic wait time and practitioner idle/over time.

Lee and Yih (2014) imply a simulation-based optimisation method to schedule surgery cases in surgical suites. They develop a multi-objective method so as to minimise the patient waiting time, idleness of resources and completion time of the schedules. Their scheduling process includes two stages: sequencing of surgeries and determining the exact timing of each procedure. They use a genetic algorithm to fulfill the sequencing while the further scheduling is done by a "heuristic-decision". They evidence that the outcome of their method outperforms simple scheduling rules when used in regional hospitals.

Oddoye et al. (2007) use a goal programming methodology for calculating the number of beds in a medical assessment unit. Their work is one of the few papers dealing with multiple objective paradigms in healthcare.

Güler (2013) studies scheduling appointment for the assignment of the care providers to outpatient rehabilitation clinics. He suggests a hierarchical goal programming approach in order to develop schedules taking into account the care- provider preferences and reduction of schedule disruptions.

With reference to this literature analysis, we could underline several important points:

- Most researchers have used simulation models to understand the behaviour of a hospital system, and to assess the various strategies for the system operation.
- When the system is subjected to stochastics, different types of the simulation models-such as discrete, deterministic and stochastic events-have been developed and utilised.

- Optimisation is also taken into consideration in some research studies to determine the best option for minimising waiting time and the total cost, or maximising revenues.

3. Description of the service problem

In this work, the major problem is approached as a queuing system for the orthopaedic surgery at Habib-Bourguiba Hospital of Sfax. We have a set of N patients to be processed on a set D of Doctor, D = {D1, D2, D3}.

The external department of the orthopaedic surgery treats three types of patient appointments:

Patient First Appointment (FA) corresponds to the new patients arriving for the first consultation, and then leaving. Patient Second Appointment (SA) is about patients arriving at the system for the first consultation; then directing to the radiology; next returning to the second consultation; and finally leaving. Patient Third Appointment (THA) deals with patients returning there for a third time to the system for the first consultation; then directing towards the plaster room and radiology; afterwards going back to the second consultation; and eventually leaving (see Figure 1).

The current system treats three types of patients. Any patient arrives at this service must be registered. The patient arrival is random in the waiting room (Queue 1). When the small waiting room (Queue 2) is empty, the current system sets each time selection of patient waiting room (Queue 1) to short wait (Queue 2). The rule applies a single "first in first out" (FIFO) queue discipline rule. Several rules have been used in the literature for the queue discipline rules. The first problem consists in which priority-queue discipline rules to apply.

The second problem consists in assigning patients when a doctor is available. If the current system chooses the patients through a small waiting room (queue 2), the patients will wait there, and those of types Patient Second Appointment (SA) and Patient Third Appointment (THA) will wait for a 2nd consultation (queue 3) with the doctor on the same day.

The third problem consists in assigning return patients waiting for a 2nd consultation (queue 3).In fact, the current system selects the patients of types (SA) and (THA) waiting for a 2nd consultation (queue 3). If the doctor is available, the patients visiting them on the same day are selected on the return list. The rule FIFO is used as an instruction for the patients when entering the doctor's consultation room. The current system chooses the patients in the queue 2, and the other patients on the return list wait even longer.

The fourth problem consists in how patients returning on the same day at the second consultation are assigned.

We are interested in the allocation problems of patients with long wait times in the orthopaedic surgery at Habib-Bourguiba Hospital of Sfax, which we address here. They are characterised as depicted in Figure 1. Each Doctor has an upstream queue for awaiting patients to be processed. We consider systems where the operating hours and patient arrivals can be random.

4. Methodology

This paper focuses on the coupling of simulation and optimisation based on goal programming. First, the simulation techniques are used to evaluate the patient

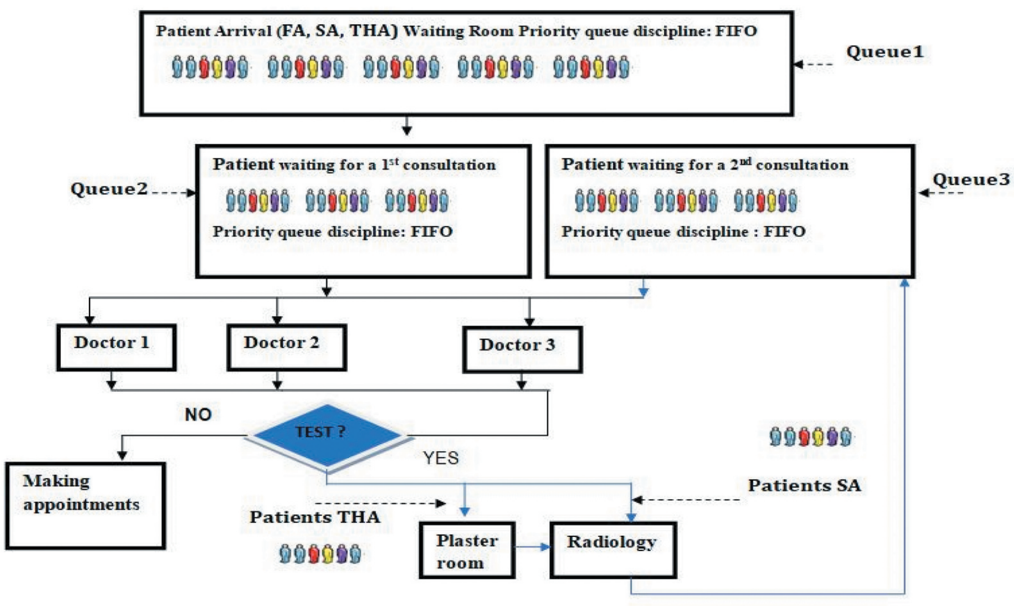


Figure 1. Queuing system of a doctor.

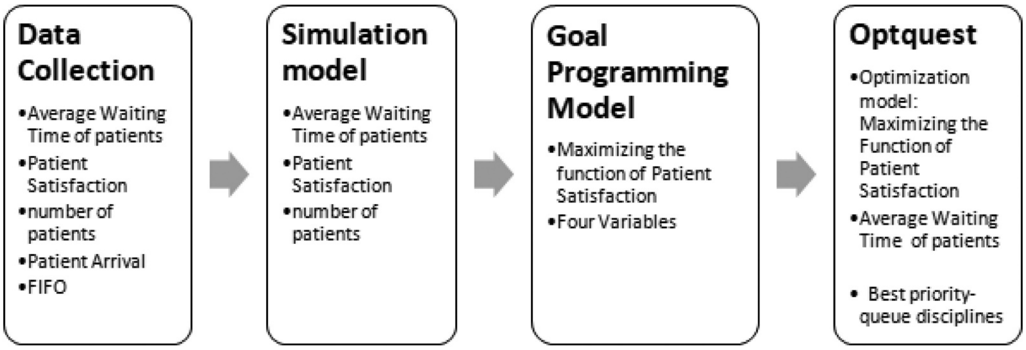


Figure 2. Framework for simulation-optimisation.

flow of the external orthopaedic surgery. Second, coupling optimisation via simulation is used to select priority queue 2 or queue 3 disciplines is the assignment of patients to the doctor. The process of the goal programming to determine multi-objective is the level maximisation of three types of patients satisfaction with average waiting time as given in Figure 2.

4.1. Data collection

In this study, this paper studies the problem of long waiting times for patients in the external department of orthopaedic surgery of Habib Bourguiba Hospital in Sfax, Tunisia. Indeed, from a structural point of view, the external orthopaedic surgery department has 6 functional sub-assemblies: admission, consultation of surgery (doctor), plasters room, meeting room, radiology and treatment room. The table below (Table 1) shows the distribution of human and medical resources associated with each available set.

Table 1. Breakdown Of Resources By Outpatient Department Of Orthopaedic Surgery (Ltaif et al. (2018))

The system state characterised by the vector S (t), which is defined at a current time t, is shown in Table 2.

4.2. Simulation

In this paper, we develop a discrete event simulation model of the described facility using the Arena™ 12 software. The simulation model proposed is based on the dynamic patient scheduling problem in an external orthopaedic service, taking into consideration the stochastic nature of task processing times. These distributions are released, using the "Input Analyzer" module of the ARENA simulation software.

Collected data about the patient arrivals and patient service times are used as input to the Input Analyser tool of evaluating statistical fit. The latter is an Arena tool, which is specifically designed to adjust the theoretical distributions with the observed data by estimating their parameters. Input analyser in the ARENA allows user to enter raw data and obtain the statistical distribution for the data as need.

The results are estimated according to exponential distribution inter-arrival time of each patient category as shown in Table 3.

Table 4 gives the distributions of the service times at each stage of the process. The overall process of the external orthopaedic surgery has been modelled by a discrete event simulation (DES) system.

The impact of the decision factors on performance measures is evaluated from the patients and the doctor's point of view. The patient waiting time in the orthopaedic surgery of the Habib-Bourguiba Hospital

Table 1. Breakdown of resources by outpatient department of orthopaedic surgery (Ltaif et al., 2018).

Rooms	Things to do	Medical staff
Reception	Registration and payment	2 Input operators 2 Payments
Medical consultation rooms	Medical consultation	3 doctors
Room service	Care	A nurse
Plaster room	Plaster removal	A nurse
Radiology	Radiology	A nurse
Meeting room	Making appointment	A nurse

Table 2. System state variables.

S1	Number of patients in the waiting room
S2	Number of patients returning "2nd consultation" in queue 3
S3	Number of patients in the queue 2
S4	The lower limits of the number of patients to the queue 2
S5	The upper limits of the number of patients to the queue 2
S6	Minimum, maximum and average process time on a doctor of patient first Appointment
S7	Minimum, maximum and average process time on a doctor of patient second Appointment
S8	Minimum, maximum and average process time on a doctor of patient third Appointment
S9	Minimum, maximum and average waiting time of patients in the waiting room
S10	Minimum, maximum and average waiting time of patients in the queue 2
S11	Minimum, maximum and average waiting time of patients returning "2nd consultation" in queue 3

Table 3. Statistical distributions patient arrival.

Patients category	Inter arrival time (min)
Patient first appointment (FA) arrival	EXPO(7)
Patient second-appointment (SA) arrival	EXPO(7)
Patient Third-appointment (THA) arrival	EXPO(10)

Table 4. List of statistical distributions used in the DES model.

Process	Time (min)
Doctor	UNIF(5,20)
consultation 1st time	UNIF(5,20)
consultation 2nd time	
Plaster removal	TRIA (5,10, 15)
Radiology	TRIA (5, 7,10)

of Sfax measures the effect of the average waiting time at the orthopaedic surgery (Table 5) the level of patient satisfaction.

The model validation ensures that the model correctly represents the real world. The simulation model is validated by comparing data generated by the model and data collected from the orthopaedic surgery of Habib-Bourguiba Hospital of Sfax. Tables 6 and 7 show confidence intervals of the simulation outputs at the 95% (α = 0.05) confidence level and the actual values obtained from the collected data. The comparison verifies that, for total average waiting time and total patient satisfaction, there are no significant differences between the results obtained, using the simulation and those that have occurred in the real system. We conclude that the model is truly representative of the existing environment. Therefore, the validated model can be used for a subsequent analysis (Tables 6 and 7).

Table 5. Key performance indicators.

Key performance indicators
Total Average Waiting Time
Total Patients Satisfaction

In the next step, by using a comparison test, the final results of the simulation model and real data are compared, and no significant difference has been observed. Differences between the final results of the simulation model and real data are also assessed by Student's t-tests, with a α = 0.05 in SPSS software.

Since Sig is less than 0.05, the null hypothesis (H0: $\mu_1 = \mu_2$, H1: $\mu_1 \neq \mu_2$) is accepted, and the simulation model is considered to be valid.

4.3. Priority queuing discipline

In this research, different priority rules will be compared. These are:

- Priority queue disciplines are assigned to queue 2:
- First in First out (FIFO),
- Shortest Processing Time (SPT),
- Longest Processing Time first (LPT),
- Alternative Method (P1, P2, P3, P1, P2, P3 . . .).
- Priority queue 2 or queue 3 disciplines are patient assignment to the doctor

Table 6.. Validation of simulation model by a comparison simulated and collected data.

	Performance measures average waiting time of patients					
	Collected data	Simulation model	Confidence interval 95%	P-value	T- test	Difference (%)
Test case 1 N = 80 patients	114	115	[100,130]	0.00	6.991	0.86%
Test case 2 N = 90 patients	136.5	137	[110,150]	0.00	11.625	0.36%
Test case 3 N = 100 patients	141.5	142	[120,160]	0.00	18.437	0.35%
Test case 4 N = 120 patients	334.5	335	[310,360]	0.00	10.597	0.14%
Test case 5 N = 130 patients	398.5	399	[350,450]	0.00	5.217	0.12%
Test case 6 N = 150 patients	449.5	450	[400,500]	0.05	2.843	0.11%

Table 7. Validation of simulation model by a comparison simulated and collected data.

	Performance measurestotal patients Satisfaction					
	Collected data		Simulation model		Confidence interval 95%	Difference (%)
	Satisfied	Dissatisfied	Satisfied	Dissatisfied		
Test case 1 N = 80 patients	47	33	48	32	[20,80]	0%
Test case 2 N = 90 patients	34	56	35	55	[20,90]	0 %
Test case 3 N = 100 patients	54	46	54	46	[20,100]	0%
Test case 4 N = 120 patients	77	43	78	42	[20,95]	0.2%
Test case 5 N = 130 patients	75	55	76	54	[20,95]	0.2%
Test case 6 N = 150 patients	86	64	86	64	[20,95]	0%

- First In First Out (FIFO),
- Shortest Processing Time (SPT),
- Longest waiting time (LWT).

4.4. Goal programming model

In this subsection, we formulate a mathematical model that is based on goal programming.

Goal Programming model with satisfaction function introduced by Aouni et al. (2005) is formally represented as:

$$MaxZ = \sum_{i=1}^{p} (w_i^+ F_i^+(\delta_i^+) + w_i^- F_i^-(\delta_i^-))$$

S/C

$f_i(x) + \delta_i^- - \delta_i^+ = g_i \quad i = 1 \ldots p$

$\delta_i^-, \cdot \delta_i^+ \geq 0 \quad i = 1 \ldots p$

$0 \leq \delta_i^- \leq \cdot \alpha_{ij}{}^- \cdot; 0 \leq \delta_i^+ \leq \alpha_{ij}{}^+ \cdot \quad i = 1 \ldots p$

The coefficients w_i^+, w_i^- express the relative importance of the different objectives. Where δ_i^- and δ_i^+ indicate, in order, positive and negative deviations on the gap between the level of achievement of objective i ($f_i(x)$) and the level of the target (goal g_i) set by the decision maker.

$$F(\delta_i = \begin{cases} 1 if \delta_i \leq \alpha_1 \\ \frac{\alpha_2 - \delta_i}{\alpha_2 - \alpha_1} if \alpha_1 \leq \delta_i \leq \alpha_2 \\ 0 if \alpha_2 \leq \delta_i \end{cases}$$

The general form of satisfaction functions as:

F (δ_i): Satisfaction level

α_{i1}: Indifference threshold.

α_{i2}: Nil satisfaction threshold.

α_{i3}: Veto threshold.

The indifference threshold (α_{i1}): the decision-maker's is totally satisfied when the ith goals' deviations are within the interval [0, α_{i1}]. The nil satisfaction threshold (α_{i2}): the decision-maker's draws no satisfaction when the ith goal's deviation reaches this threshold but the solution is not rejected. The veto threshold (α_{i3}): the decision-maker's rejects any solution that lead to deviations from his fixed goals larger than this threshold.

The aim of this model is to maximise the level of three types of patient satisfaction with waiting time. The model proposed is characterised by a set of parameters and a set of decision variables as follows:

Indices:

i = index of patient,

j = types of patients j = 1, 2, 3 (j = 1: FA, j = 2: SA, j = 3: THA).

Set and Parameters used in this model are as follows:

N: Number ofpatient

$Nbmin_i$ = Lower limits of the number of patients i to the queue 2.

$Nbmax_i$= Upper limits of the number of patients i to the queue 2.

WT_{ij}= Average waiting times ofpatient i types j,

α_1 = Lower limits of the waiting times of patient First Appointment

α_2= Upper limits of the waiting times of patient First Appointment

$\alpha\prime 1$ = Lower limits of the waiting times of patient second Appointment

α'_2 = Upper limits of the waiting times of patient-second Appointment

α'_1 = Lower limits of the waiting times of patient third Appointment.

α'_2 = Upper limits of the waiting times of patient third Appointment.

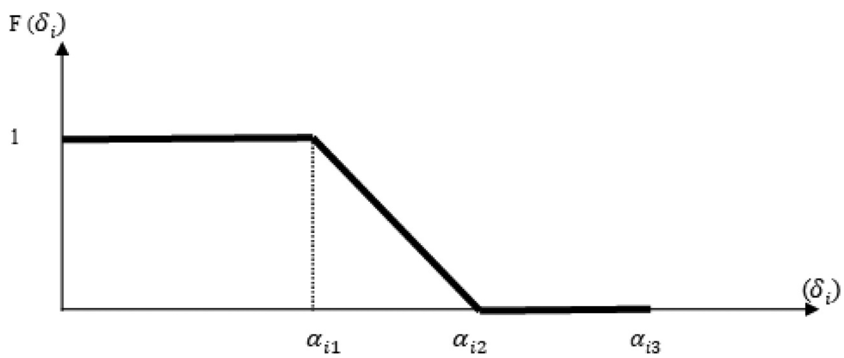
p_j= weighted weight.

Decision Variables:

V1 : is vector the size of the queue 2.

V2 : is vector of decision variable values priority-queue 1 disciplines in the assignment of patients to queue 2 (1: FIFO, 2: SPT, 3: LPT, 4: ALTERNATIVE).

V3: is decision variable values assignment of patient to the doctor (1: selection of patients through queue 2, 2: selection of patients in the queue 3, 3: if the doctor is available, select the patients in the return list who visits this doctor in the queue 3).



V4: is vector of decision variable values priority-queue 2 or queue 3 disciplines in the assignment of patients to the doctor (1: FIFO, 2: SPT, 3: LWT).

4.4.1. Optimisation model: Maximising the function of patient satisfaction.

$$\boldsymbol{MaxZ} = \boldsymbol{E}(\sum_{i=1}^{N}\sum_{j=1}^{3} p_j^{+}\boldsymbol{F}(\mathrm{WT_{ij}})) \tag{1}$$

S/C:

$$\leq Nbmax_i \forall i = 1\ldots N \tag{2}$$

$$1 \leq V2 \leq 4 \tag{3}$$

$$1 \leq V3 \leq 3 \tag{4}$$

$$1 \leq V4 \leq 3 \tag{5}$$

$$WT_{ij} \in \Re \forall i = 1\ldots N \tag{6}$$

The objective function can be divided into multiple objectives: the primary objective is to maximise Patients First Appointment Satisfaction Function F $(\mathrm{WT_{i1}})$ must take the value 1 when the deviations $\mathrm{WT_{i1}}$ belong to a specific interval defined by the threshold α_{i1} .

According to this model, when the deviations WT_{i1} is within [0, α_{i1}], the decision maker is fully satisfied and the satisfaction level is 1. As the deviation exceeds α_{i1} , the satisfaction level falls until reaches zero at α_{i2} . If the deviation exceeds this level, the decision maker may still consider the solution. But the solution is rejected if it exceeds veto threshold α_{i3} .

$$F\ (\mathrm{WT_{ij}}) \ = \begin{cases} 1 if \mathrm{WT_{ij}} \leq \alpha_1 \\ \frac{\alpha_2 - \mathrm{WT_{ij}}}{\alpha_2 - \alpha_1} if \alpha_1 \leq \mathrm{WT_{ij}} \leq \alpha_2 \\ 0 if \alpha_2 \leq \mathrm{WT_{ij}} \end{cases}$$

The second objective is to maximise Patient SecondAppointment Satisfaction Function

F $(\mathrm{WT_{i2}})$ must take the value 1 when the deviations $\mathrm{WT_{i2}}$ belong to a specific interval defined by the threshold α'_1 . According to this model, when the deviations WT_{i2} is within [0, α'_{i1}], the decision maker is fully satisfied and the satisfaction level is 1. As the deviation exceeds α'_{i1} , the satisfaction level falls until reaches zero at α'_{i2} . If the deviation exceeds this level, the decision maker may still consider the solution. But the solution is rejected if it exceeds veto threshold α'_{i3} .

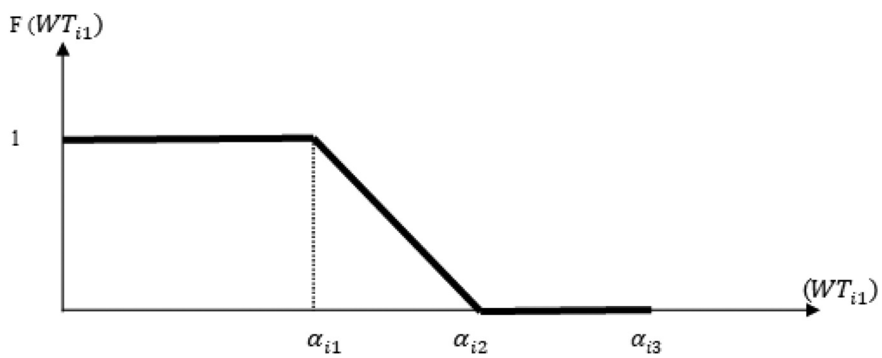
The third objective is to maximise Patients Third Appointment Satisfaction Function $\mathrm{F(WT_{i3})}$ must take the value 1 when the deviations $\mathrm{WT_{i3}}$ belong to a specific interval defined by the threshold α''_1. According to this model, when the deviations WT_{i3} is within [0, α''_{i1}], the decision maker is fully satisfied and the satisfaction level is 1. As the deviation exceeds α''_{i1}, the satisfaction level falls until reaches zero at α''_{i2}. If the deviation exceeds this level, the decision maker may still consider the solution. But the solution is rejected if it exceeds veto threshold α''_{i3}.

The Constraint (2) determines the size of the queue 2. The Constraint (3) determines a vector of decision variable values priority-queue 1 disciplines in the assignment of patients to queue 2. The Constraint (4) determines a decision variable values assignment of patient to the doctor. The Constraint (5) determines a vector of decision variable values priority-queue 2 or queue 3 disciplines in the assignment of patients to the doctor. Equations (6) define the decision variables.

4.5. Optquest

In this subsection, Simulation optimisation is a stochastic optimisation method enabling a search for solutions to problems where some or all of the system parameters are stochastic. The metaheuristic also includes secondary heuristics based on tabu search, integer programming, and neural networks.

The detailed simulation optimisation procedures are described as follows



Algorithm: 4 OptQuest for ARENA

Step 1. *For each iteration, generate initial random values, which are between the lower bound and the upper bound, for four decision variables: the size of the queue 2, vector of priority queue discipline is assigned to queue 2, variable values selection of patients to the doctor, vector of priority queue 2 or queue 3 disciplines is a patient assignment to the doctor. Go to* ***Step 2.***
Step 2. *Perform 100 replications simulation of the current configurations and record a summary of the simulation results.*
Step 3. *Check the feasibility of the solution. If the results of the solution satisfy all constraints, the solution will be a feasible solution then go to* ***Step 4.*** *Otherwise, go to* ***Step 6.***
Step 4. *If a feasible solution is better than the current best solution, go to* ***Step 5.*** *Otherwise, go to* ***Step 6.***
Step 5. *Update the current best solution and go to* ***Step 6.***
Step 6. *The two common stopping rules of the simulation optimisation procedures are maximum iterations and maximal programming running time. In order to ensure convergence of the simulation optimisation procedures, the maximum iterations are used as the stopping rule. If the maximum of iterations is reached, go to* ***Step 7.*** *Otherwise, go to* ***Step 8.***
Step 7. *Obtain the optimal or near-optimal solution. The proposed procedures then stop.*
Step 8. *Update the values of the decision variables for the next iteration. The procedures for generating a new solution are based on the scatter search and tabu search. The scatter search uses a weighted linear combination of reference points to generate new values for the decision variables. The tabu search is used to avoid revisiting the previous solutions in order to reduce the search time. Go to* ***Step 2.***

5. Results and discussion

In this section, we are interested in evaluating our approach. In fact, we consider an experimental analysis which results in the computational performance of the goal programming proposed. The platform for conducting the experiments is a LENOVO with 4 Go RAM. Typically, a simulation optimisation runs based on 100 replications.

- The weighted weight: p_1 =0.3; p_2 =0.3; p_3 =0.4.

We have used the Optquest engine to optimise the model. The design variables considered as shown in Table 8.

Table 8. Defined design variables for optimisation.

Variable	Lower bound	Suggested value	Upper bound
Variable 1	2	10	20
Variable 2	1	1	4
Variable 3	1	1	3
Variable 4	1	1	3

Improvement percentage of the patients satisfaction function % = $\frac{Total\,optquest - Totalsimulation}{Totaloptquest}$ ***100%**

Improvement percentage of the Average waiting time % = $\frac{\mathbf{Totalsimulation - Totaloptquest}}{\mathbf{Totalsimulation}}$ ***100%**

Using the Optquest tool, the objective function and constraints for 6 test cases are suggested in this article. Each case describes are follows:

The results by Table 9 in test case 1 show the variable 1 determining the size of the queue 2 equal 2 patients. Variable 2 determines a vector of decision variable values priority-queue 1 disciplines in the assignment of patients to queue 2, which is equal to Alternative Method (P1, P2, P3, P1, P2, P3 . . .). Variable 3 determines assignment of patient to the doctor, which is equal to selection of patients in the queue 3, and the variable 4 determines a vector of priority-queue 2 or queue 3 disciplines in the assignment of patients to the doctor, which is equal to First in First out (FIFO).

The results in test case 2 show the variable 1 determining the size of the queue 2 = 2 patients. Variable 2 determines a vector of decision variable values priority-queue 1 disciplines in the assignment of patients to queue 2, which is equal to Alternative Methods (P1, P2, P3, P1, P2, P3 . . .). Variable 3 determines patients' assignment to the doctor, which is equal to selection of patients in the queue 3, and the variable 4 determines a vector of priority queue 2 or queue 3 disciplines in the assignment of patients to the doctor, which is equal to Shortest Processing Time (SPT).

The results in test case 3 show the variable 1 determining the size of the queue 2 equal 2 patients. Variable 2 determines a vector of decision variable values priority-queue 1 disciplines in the assignment of patients to queue 2, which is equal to Alternative Methods (P1, P2, P3, P1, P2, P3 . . .). Variable 3 determines assignment of patient to the doctor, which is equal to selection of patients in the queue 3, and variable 4 determines a vector of priority-queue 2 or queue 3 disciplines in the assignment of patients to the doctor, which is equal to Longest waiting time (LWT).

Table 9. Best parameter values.

	Optimised value			
	Variable 1	Variable 2	Variable 3	Variable 4
Test case 1 N = 80 patients	2	4	2	1
Test case 2 N = 90 patients	2	4	2	2
Test case 3 N = 100 patients	2	4	2	3
Test case 4 N = 120 patients	4	1	3	1
Test case 5 N = 130 patients	5	1	2	1
Test case 6 N = 150 patients	4	1	2	1

Table 10. Comparison of simulation and optquest.

	Performance measuresaverage waiting time of patient			
	Optquest	Simulation model	Confidence interval 95%	Difference (%)
Test case 1 N = 80 patients	83	115	[80,120]	27.82%
Test case 2 N = 90 patients	116	137	[110,140]	15.32%
Test case 3 N = 100 patients	108	142	[100,150]	23.94%
Test case 4 N = 120 patients	220	335	[200,350]	34.32%
Test case 5 N = 130 patients	240	399	[200,400]	39.84%
Test case 6 N = 150 patients	285	450	[200,500]	36.66%

The results in test case 4 show the variable 1 determining the size of the queue 2 equal 4 patients. Variable 2 determines a vector of decision variable values priority-queue 1 disciplines in the assignment of patients to queue 2, which is equal to First in First out (FIFO). Variable 3 determines assignment of patient to the doctor, which is equal to selection of patients in the queue 3, and the variable 4 determines a vector of priority-queue 2 or queue 3 disciplines in the assignment of patients to the doctor, which is equal to First in First out (FIFO).

The results in test case 5 show the variable 1 determining the size of the queue 2 equal 5. Variable 2 determines a vector of decision variable values priority-queue 1 disciplines in the assignment of patients to queue 2, which is equal to First in First out (FIFO). Variable 3 determines assignment of patient to the doctor, which is equal to selection of patients in the queue 3, and the variable 4 determines a vector of priority-queue 2 or queue 3 disciplines in the assignment of patients to the doctor, which is equal to First in First out (FIFO).

The results in test case 6 show the variable 1 determining the size of the queue 2 equal 4 patients. Variable 2 determines a vector of decision variable values priority-queue 1 disciplines in the assignment of patients to queue 2, which is equal to First in First out (FIFO). Variable 3 determines assignment of patient to the doctor, which is equal to selection of patients in the queue 3, and the variable 4 determines a vector of priority-queue 2 or queue 3 disciplines in the assignment of patients to the doctor, which is equal to First in First out (FIFO).

In Table 10, for test case 1, our results show that the improvement of average waiting time of patients is by 27.82%, from 115 minutes to 83 minutes. For test case 2, our findings evidence that the improvement of average waiting time of patients is by 15.32%, from 137 minutes to 116 minutes. For test case 3, our outcomes indicate that the improvement of average waiting time of patients is by 94%, from 142 minutes to 108 minutes. For test case 4, our results show that the improvement of average waiting time of patients is by 34.32%, from 335 minutes to 220 minutes. For test case 5, our findings prove that the improvement of average waiting time of patients is by 39.84%, from 399 minutes to 240 minutes. For test case 6, our results show that the improvement of average waiting time of patients is by 36.66%, from 450 minutes to 285 minutes as depicted in Figure 3.

In Table 11, for case 1, maximising satisfaction of the patients is by 30%, from 48 satisfied patients to 68 satisfied ones. For case 2, maximising satisfaction of the patients is by 53.94%, from 35 satisfied patients to 76 satisfied ones. For case 3, maximising satisfaction of

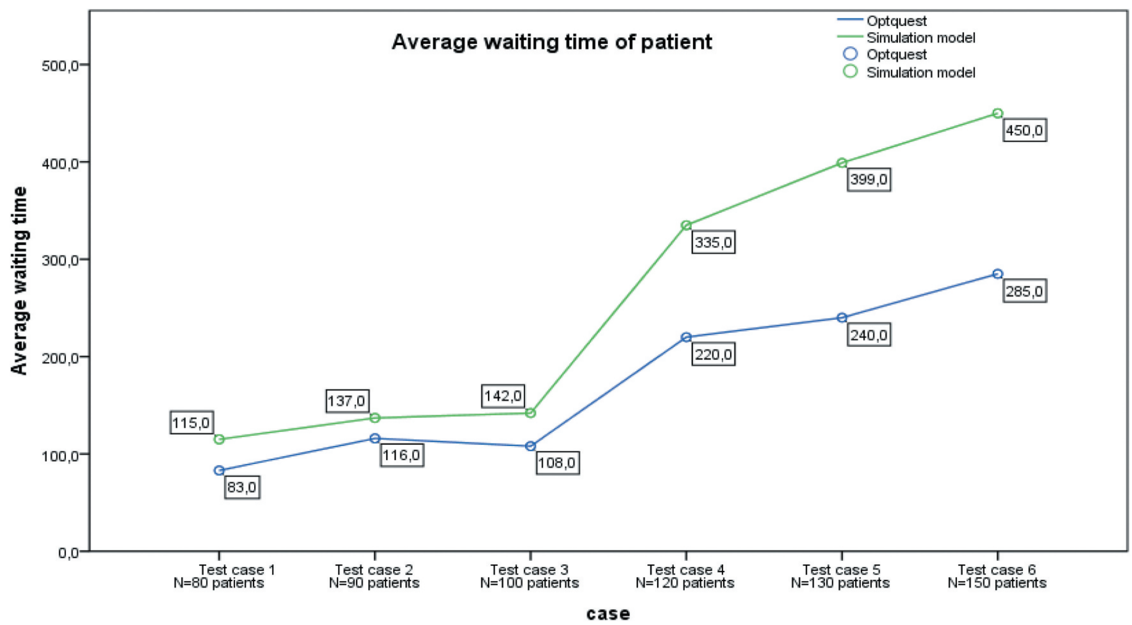


Figure 3. Improvement of the average waiting time of patients.

Table 11. Comparison of simulation and optquest.

	Performance measuresmaximising the function of patient satisfaction			
	Simulation model	Optquest	Confidence interval	Difference (%)
Test case 1 N = 80 patients	48	68	[20,80]	29.41%
Test case 2 N = 90 patients	35	76	[20,90]	53.94%
Test case 3 N = 100 patients	54	85	[20,100]	36.47%
Test case 4 N = 120 patients	78	110	[20,120]	30%
Test case 5 N = 130 patients	76	117	[20,130]	35.04%
Test case 6 N = 150 patients	86	130	[20,150]	33.84%

the patients is by 36.47%, from 54 satisfied patients to 85 satisfied ones. For case 4, satisfaction of the patients is by 30%, from 78 satisfied patients to 110 satisfied ones. For case 5, maximising satisfaction of the patients is by 35.04%, from 76 satisfied patients to 117 satisfied ones. For case 6, maximising satisfaction of the patients is by 33.84%, from 86 satisfied patients to 130 satisfied ones as depicted in Figure 4.

6. Conclusions and future research

This paper introduces a new approach with the aim of solving long waiting times for patients in the external department of orthopaedic surgery of Habib-Bourguiba Hospital of Sfax, Tunisia.

The external orthopaedic surgery department is represented by a simulation model developed with ARENA software aid, and supplemented with the gathered and fitted experimental data. The academic contribution of this research is a simulation-optimisation OptQuest based on Goal Programming using priority rules, combining stochastic parameters (random patient arrival) with measures of performance, including three types of patient satisfaction and average waiting time. The findings of the simulations model and optimisation provide evidence that the waiting time is reduced by 35% on average, while the patient satisfaction increases by 30%.

Eventually, we come to the conclusion that simulation and optimisation could help the healthcare sector without changing any processes and entities in a system. Through using Arena software, we have been able to conduct analyses and achieve the purpose of our study.For further development, we recommend that future researchers consider the following research directions:

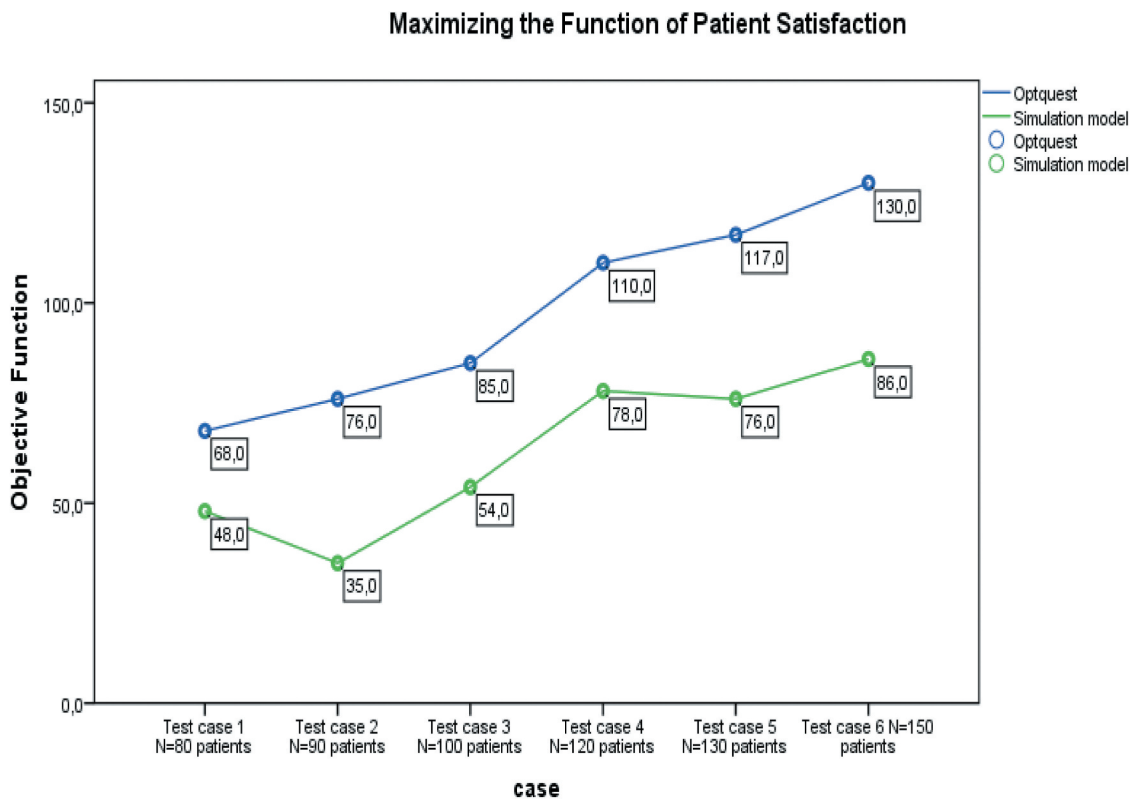


Figure 4. Maximising the satisfaction of patients.

- Considering approaches based on metaheuristics, namely taboo search, genetic algorithms, and simulated annealing, for solving patient-scheduling problems in deterministic cases.
- Examining a similar topic with the output of our results, using Optquest as input to a mathematical model in a deterministic case.
- Incorporating other performance measures through multi-objective simulation optimisation

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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