An Optimization based on Simulation Approach to the Patient Admission Scheduling Problem: Diagnostic Imaging Department Case Study

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Abstract

The growing influx of patients in healthcare providers is the result of an aging population and emerging self- consciousness about health. In order to guarantee the welfare of all the healthcare stakeholders, it is mandatory to implement methodologies that optimize the healthcare providers' efficiency while increasing patient throughput and reducing patient's total waiting time. This paper presents a case study of a conventional radiology workflow analysis in a Portuguese healthcare provider. Modeling tools were applied to define the existing workflow. Re-engineered workflows were analyzed using the developed simulation tool. The integration of modeling and simulation tools allowed the identification of system bottlenecks. The new workflow of an imaging department entails a reduction of 41 % of the total completion time.

Background

In the past years, Portuguese healthcare providers (PHcP) observed a steady growing demand on services from the population [1]. The percentage of inhabitants using public health centers increased from 4 % of the population in 2006 to 30 % in 2010 [2]. In comparison, in the period from the year 2000 to the year 2007, there was a decrease of (a) 23 % in the number of public PHcP and (b) 5 % in the number of public health centers [2]. These reductions in the number of public PHcP led the Portuguese Health Ministry to create conventions with private PHcP to tackle the increasing demand for services, particularly for methods of complementary diagnosis and therapy (MCDT). However, the number of private PHcP only increased 5 % [2], which is clearly insufficient to support the increasing demand. Thus, it is fundamental that public and private PHcP optimize their services in order to avoid an uncontrolled cost situation and patient waiting times.

In Portugal, there are 565 PHcP that supply services in the domain of MCDT, of which 449 are private, 76 are public, and 40 are social [2]. Nowadays, the most executed MCDT is conventional radiology (CR). This type of MCDT comprises 73 % of the total MCDTs workload [2] as shown in Fig. 1. The obvious preference denoted for CR, associated to the increasing demand that this type of MCDT has been experiencing, clearly calls for optimization studies. Studies that apply modeling and simulation tools to clinical workflows to tackle the patient admission problem (PAS) can be found in literature. Such studies focus on the optimization of care delivery through the management of decisions on three levels: the strategic, the tactical, and the operational levels. These three levels of decisions can be defined in a hierarchical chain according to their potential impact on the service supply.

On a strategic level, decisions are considered to have a long-term effect in the process. Diwas [3] approached the PAS by studying the effect on operational performance of focus at the firm level, at the operating level, and at the process flow level. The authors were able to demonstrate a significant reduction on the patient length of stay by controlling selective patient admissions.

A study targeting the maximization of patient throughput, by means of a multi-criteria decision-making model, was proposed by Lee and Kwak [4]. In this work, satisfying solutions were derived using goal programming. In contrast, Vissers et al. [5] presented a framework to evaluate hospital admissions targeting the minimization of the patients' wait for admission by comparing hospital admission planning systems. A simulation model was built to examine the impact of extreme admission service concepts in a simplified hospital setting. In this work, the following service concepts for ad- mission planning were considered: maximum resource use (MRU), zero waiting time (ZWT), coordinated booked ad- mission (CBA), and uncoordinated booked admission (UBA). The goal of MRU is to maximize the use of resources without considering the impact for patients; ZWT aims for patient admission without any delay; UBA performs admission considering only the availability of the main resources, not considering resources such as beds and nursing staff; CBA is similar to UBA but considers all the resources. Both UBA and CBA are only based on the availability of resources, not attempting system optimization. The performance criteria considered were the utilization of resources, the average waiting time for patients, the percentage of canceled patients at the date of admission, the percentage of emergency patients that are rejected, and the percentage of days the target capacity use is exceeded. It was concluded that the best admission

concept is a mix between the extreme admission concepts studied as they have different impacts on the performance.

On a tactical level, decisions imply medium term changes on the process. Arenas et al. [6] proposed a linear programming exact algorithm for PAS in operating rooms with the purpose of minimizing the patient length of stay in waiting lists. PAS in operating rooms was also addressed by Vanberkel et al. [7] who studied the bed occupancy and patient length of stay in the recovery ward using stochastic models. Patrick and Puterman [8] addressed PAS using discrete event simulation to minimize unused capacity subjected to an overtime constraint.

On an operational level, the solutions have a short-term effect on the process. The barrier between the tactical and operational level decisions is very thin; however, on the operational level, the rules are applied to day-to-day decisions. In 1970, Kolesar [9] suggested a Markovian decision model for hospital admissions scheduling, while Adan and Vissers [10] and Ceschia and Schaerf [11] studied admission scheduling through the analysis of bed utilization rates. Adan pro- posed a linear programming model where the objective was to maximize patient throughput and resource utilization in orthopedic surgery. The best results were obtained when giving the maximum weight to operating theater use. The model was able to generate a good admission profile without violating restrictions. However, because the model did not consider emergency patients, the optimization level achieved was small when compared to the real scenario. Ceschia and Schaerf [11] presented a multi-neighborhood local search model applied to a dynamic system in which admission and discharge dates are not defined a priori. The new local search methods proposed were an improvement on previous works in terms of quality and computational time of the solution. Ahmed and Alkhamis [12] presented a study in an emergency department for which the objective was to maximize patient throughput and reduce patient length of stay. Using discrete event simulation, the authors obtained an increase of 28 % in patient throughput and a reduction average of 40 % in patient waiting time. A method based on optimization and simulation was used in the analysis of surgery scheduling by Persson and Persson [13]. The aim was to analyze the effects of new legislation to assure that patients are scheduled for surgery within 90 days from the request. The results of this study reveal an average reduction of 16 weeks for high priority patients and an average increase of 2 weeks for low priority patients. A goal programming model, subjected to both hard and soft constraints, was used by Topaloglu [14] to schedule residents at an emergency department. The model revealed a better fitting to the soft constraints than the model used in the real world scenario. PAS considering walk-ins was approached by Su and Shih [15]. The term "walk-ins" refers to patients that come into the provider without an appointment. The problem considered an outpatient clinic, where the walk-ins represented 72 % of the patients, and the objective was to minimize the patient throughput time and maximize the clinic's utilization rate. Simulations were run for four different scenarios: (a) patient's sequence followed the scheduled order, (b) elective patients first and walk-ins last, (c) elective and walk-ins were sequenced in an intercalated manner, and (d) the optimal time between patient arrivals was found for time intervals of 3, 5, 7, 9, and 11 min. Li et al. [16] proposed a method for patient scheduling to sonography in a radiology department. The model considered patient priorities in real time and aimed the minimization of patient waiting and to resolve the waiting room overcrowding. The model implementation allowed the department to reduce patient waiting time from an average of to 20.30

min and reduce significantly the number of waiting patients.

When considering problems with PAS, researchers appear to assume (as in the aforementioned papers) that admission and discharge time is known a priori. However, in real scenarios, imaging clinics have to adjust the patient admissions in real time as the service becomes available. On the other hand, the time of discharge is constrained by admission time but also by the process duration. Therefore, a dynamic problem is proposed here in which the times of admission and discharge are not known in advance. A simulation tool was developed for the validation of the scheduling results. In this paper, a modeling and simulation analysis of an imaging department in a private PHcP is presented. System bottlenecks and limitations were identified and the original workflow re-engineered for optimization. The PHcP is located in Portugal, but its name is not revealed for ethical reasons.

Methods

System Description

The CR process in the selected PHcP is described in a sequence of three sets of tasks, as illustrated in Fig. 2. These sets, denoted as modules, include different tasks performed by different resources and are defined as (a) admission module: representing the administrative tasks performed to book ex- aminations and admit the patient in the day of the exam, (b) exam module: representing the examination itself and all the tasks related to its accomplishment, and (c) billing module: representing the administrative tasks related to patient billing. The PHcP works 8 h and performs a maximum of 39 CR examinations per day. The CR department is composed of (a) human resources, comprised of six physicians, one radiology technician, one radiology assistant, and four administrative; physical resources, which are one waiting room, three changing rooms, one control room, and one exam room; and technical resources, such as one digital modality. Two human resources in the CR department are shared with other MCDT departments, namely: (a) one radiology technician that performs CR, orthopantomography, and densitometry and (b) one radiology assistant that participates in the computed tomography, orthopantomography, densitometry, and ultra- sound scanning.

The objective of the present research work is to find the workday configuration that maximizes patient throughput and minimizes process total completion and patient total waiting time. Workday configuration is defined as the order by which patients are admitted. The process comprehends 16 tasks as summarized next and shown in Fig. 3.

The patient arrives at the clinic and refers to the reception to be admitted. During admission, the patient provides the administrative personnel additional demographic data and is guided to the waiting room. The administrator logs the patient's data in the system and prints out the corresponding record. The patient's data is then sent to the radiology information system that sends the relevant information to the modality work list. This work list is available to the CR technician on the modality, informing them of the patient's arrival. As soon as the CR department is available, the patient is guided by the radiology assistant from the waiting room to the changing room and

informed of clothing changing requirements. The radiology technician then takes the patient to the examination room and positions him/her on the equipment table. After the examination has been performed, the patient redresses and refers to the reception before leaving the clinic.

Modeling Approach

To assess the real needs of the PHcP, and model the case study with the required accuracy, it is essential to know the Portuguese and International guidelines, protocols, and best practices [17–22]. This knowledge supports the workflow re- engineering and presents the fundamental issues, such as resource, process interactions, and tasks definition.

According to the scheduling theory, if patients and re-

sources are considered as jobs and machines, respectively, the CR process is described as a set of

n jobs $J_j(j=1,\cdots,n)$ and m machines $\{M_1,\cdots,M\}$. Job j is composed of n_j tasks

linked by precedence constraints. This problem can be formu- lated as follows:

Notation

Problem Size Parameters

J Set of processes to be scheduled (index j)

M Set of available resources (human, physical, and technical) and patients (index m)

Process Parameters

A Set of tasks from process j (index i)

$\varepsilon_{i,j}$ Operation mode of task i from process j, assumes the value w or o whether waiting is allowed or not, respectively.

Resources Parameters

$R_{m,i,j}$ Imposes the choice of resource m to perform task i from process j to the one chosen to perform a previous task in process j.

$\eta_{m,i,j}$ Occupation mode of resource m in task i from process j takes the value of zero waiting (*zw*) or non-zero waiting (*nzw*) as the occupation mode is, respectively, continuous, and the task $A_{i,j}$ must start immediately after task $A_{i,j-1}$ is finished on resource m or discontinuous and task $A_{i,j}$ does not have starting time constraints related to resource m.

$P_{m,i,j}$ Processing time of resource m to perform task i of process j. The index m is omitted in case the $A_{i,j}$ processing time does not depend on the resource

Decision variables

$t_{0_{i,j}}$ Task i from process j starting time

$t_{f_{i,j}}$ Task i from process j ending time

$\Delta t_{w_{i;j}}$ Task i from process j waiting time. Waiting time is added before the task i when the entire set of resources needed to execute it are not available and $\varepsilon_{i,j}$ takes the value w. If $\varepsilon_{i,j}$ takes the value o, all the tasks from process j are deallocated until one that allows waiting is found.

Thus, all the tasks associated to the CR process in the PHcP were object of characterization according to these parameters, allowing the use of a stochastic scheduling algorithm for simulating the process.

To better understand the resources utilization and workload at the studied department, 21,056 CR examinations, which took place from January 1st 2007 to May 30th 2009, were investigated and characterized. The collected data is presented in Fig. 4. An in loco study permitted the quantification of the time parameters and the characterization of the operation and occupation mode for each task of the CR process.

The collected data was used in the definition of the task's time distribution and in the identification of possible variable dependencies. In this way, the collected data was segmented according to the type of exam and patient's age, the factors that most influence the processing time, and fitted to a normal distribution $X \sim (\mu, \sigma)$. A nonparametric goodness of fit test confirmed the hypothesis of data normality, as shown in Fig. 5; the Kolmogorov−Smirnov test was selected since an ordinal level can quantify each data value, and its distribution is well-defined and completely specified, as shown in Fig. 6.

Results

Modeling tools permit the identification of process bottle-necks and their causes and allow for the system optimization. Bottlenecks are defined as constraints, $B_{i,j}$, in a process where, for some reason, the normal operation is constrained. In the following, we show results for two scenarios: *Scenario 1* corresponds to the implemented workflow, whereas *Scenario 2* denotes the new workflow.

The workflow implemented at the selected PHcP, illustrated in Fig. 3, further denoted as Scenario 1, was analyzed, characterized, and simulated. For the simulated workload, the maximum workload capacity of the CR department was used, according to Fig. 4. The simulation inputs are as in Table 1.

Total completion (C_{max}) denotes the final instant of the last task to end and was used to characterize the efficiency of the process (note that $C_{max} \geq tf_{ij}, \forall i,j$). Total waiting denotes the sum of the patients' waiting time and was used to characterize the process quality, and it is given by $C_{max} \geq tf_{ij}, \forall i,j$.

The reference case was defined for a time between patient arrivals of 10 min set by the PHcP.

The results obtained for Scenario 1, given in Table 2 show that the simulation relative error is 2 %, for a time between patient arrivals of 10 min when compared to the reference.

The simulation results for different times between patient arrivals for the current workflow are depicted in Fig. 7. The results obtained for Scenario 1 show that the optimum is reached at a time between patient arrivals of 5 min, with a total completion reduction of 57 % when compared to the reference and an average patient waiting of 15.4 min.

The in loco observation of the CR process accomplishment according to the Scenario 1 workflow

allowed the identification of the bottlenecks, such as the overload of patients in the waiting room. Simulation results revealed that the factor causing this bottleneck is the sharing of human resources; the radiology assistant also participates in the computed tomography, orthopantomography, densitometry, and ultrasound scanning activities and is not always available to call patients to the CR on time. Simulation also confirmed that the radiology technician is often non-operational for the same reason. The simulation identified this optimization opportunity.

Taking into consideration the literature recommendations [15, 16] and the causes for the Scenario 1 workflow bottle- necks, a new workflow was proposed denoted Scenario 2. In Scenario 2, it was considered that the radiology assistant does not participate in the CR process. The tasks that were previously assigned to this assistant were now assigned to the radiology technician. The simulation results confirmed that Scenario 2 resolves the bottlenecks previously identified. The simulation input parameters were the same considered for Scenario 1 in the characterization of the tasks.

The total completion and total waiting of Scenario 2 are given in Table 3. According with these results, for a time between patient arrivals of 10 min, the transference of the tasks from the assistant to the radiology technician resulted in a relative reduction of 8 % of the patients' total waiting time despite the average total completion time being now 2 % longer (relative deviation). Moreover, a human resource was released from the CR process that can now make other complementary diagnostic and therapeutic activities.

The simulation results for different times between patient arrivals are analyzed in Fig. 8. For Scenario 2, an optimized time between patient arrivals of 5 min was also achieved. This scenario presents a gain of 41 % in the total completion time, when compared to the reference case, with an average patient waiting of 4.8 min.

Discussion

The purpose of this study was to demonstrate how modeling and simulation techniques can be applied to clinical workflows to increase their efficiency by maximizing the patient throughput and minimizing the patient length of stay. The study presented herein proposes a new technique to model clinical workflows. This technique allows the mathematical description of clinical workflows and their idiosyncrasies. By describing human resources according to their competences instead of their roles, considering that precedence relations are not workflow exclusive but may also relate to the information flow and by presenting a new definition of task, the proposed technique enables a more thorough analysis thus facilitating the identification and resolution of system bottlenecks. The CR process at the studied clinic was observed, and interviews with the acting human resources were carried out. The collected data was used to define Scenario 1 by applying the proposed modeling technique.

Scenario 1 was used to validate the developed simulation tool. The simulation results revealed a relative error of 2 % when describing the implemented process, for a time between patients' arrivals of 10 min, as used at the studied clinic. Given the low simulation error, the results from Scenario 1 were analyzed to identify system bottlenecks. This scenario was also used in simulation trials where the time between patients' arrivals varied in 1 min steps. These trials evidenced an optimum

for a time between patient arrivals of 5 min in which the total completion time was reduced by 57 % when com- pared to the reference.

In an attempt to resolve the identified system bottlenecks, Scenario 1 was re-engineered, based on the literature recommendations [15, 16] and defined as Scenario 2. Using the same human resource characterization as for Scenario 1, Scenario 2 was used in simulation trials where the time between patients' arrivals varied in 1 min steps, ensuring that the results were comparable with the ones from Scenario 1. The optimum was also reached for time between patient arrivals of 5 min in which the total completion time was reduced by 41 % when compared to the reference. However, the average patient waiting was reduced to 4.8 min.

Considering that the reduction of the total completion time opens up the possibility to increase the patient throughput, and that the reduction of both total completion time and patients' total waiting time evidence a lower patient length of stay, it is argued that the effectiveness of the developed tools in the workflows analysis and re-engineering increases the overall efficiency.

Conclusion

Two workflow scenarios of conventional radiology were com- pared in terms of total completion time and total waiting time, as a function of the time between patient arrivals. Scenario 1 describes the implemented workflow at the studied PHcP, while Scenario 2 is the proposed new workflow.

The results obtained for Scenario 1 show that the total completion time may be reduced by 57 % when compared to the reference for a time between patient arrivals of 5 min. For the new workflow (Scenario 2), the total completion time is also reduced significantly (41 %), with an average patient waiting of 4.8 min (which compares to 15.4 min of Scenario1). The results obtained for Scenario 2 show that it is possible to increase the patient throughput and reduce the costs associated with the CR process.

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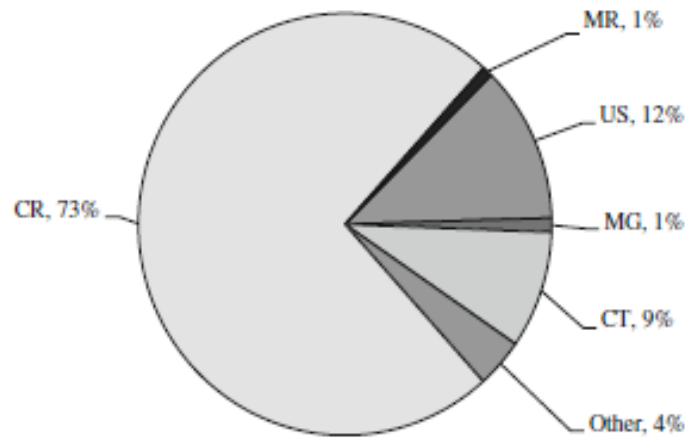
Fig. 1 Fractional number distribution of the most common complementary diagnostic and therapeutic methods: *CR* conventional radiology, *MR* magnetic resonance, *US* ultrasound scanning, *MG* mammography, and *CT* computed tomography
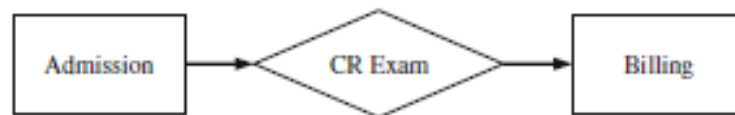

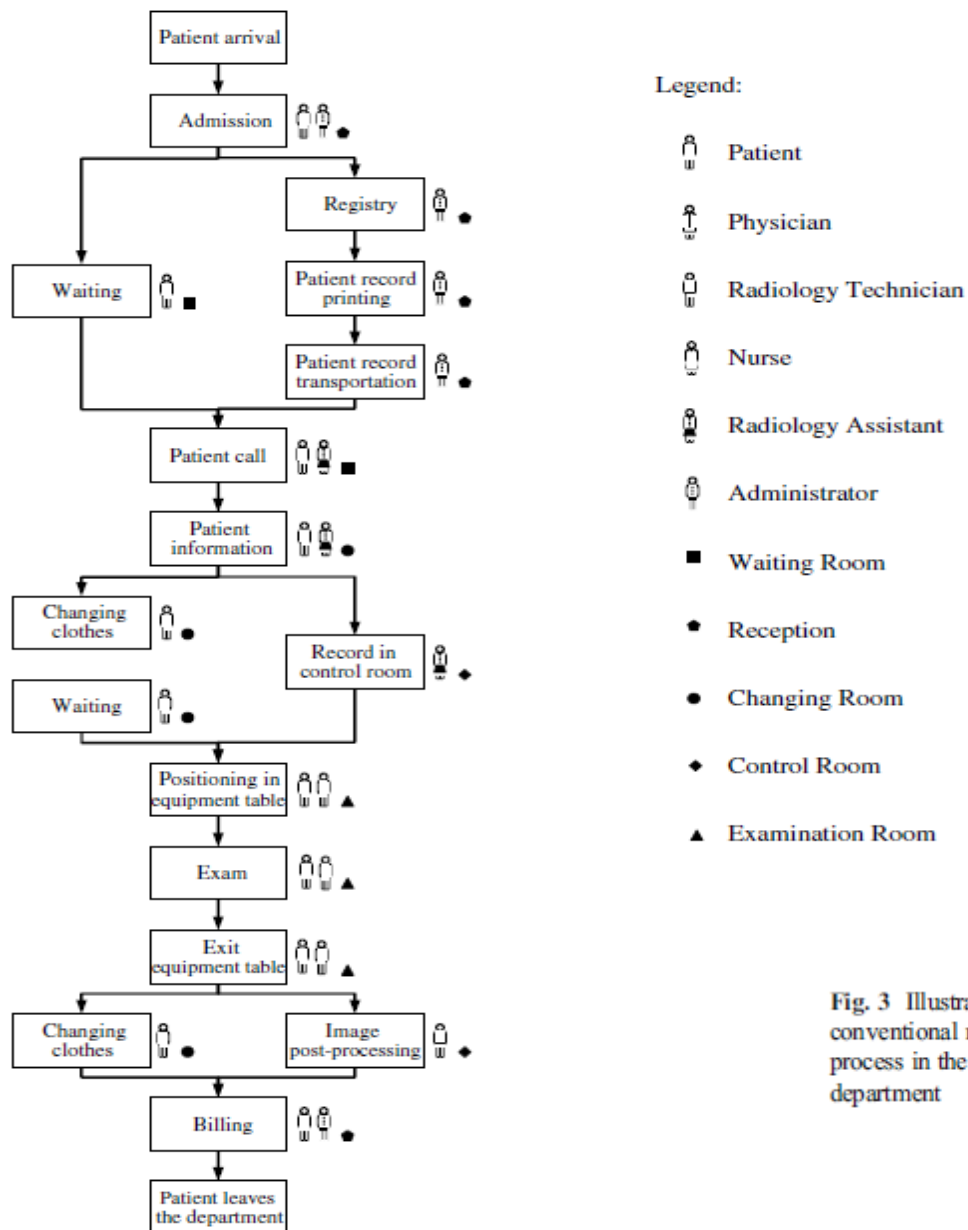**Fig. 2** Sequential modules of the conventional radiology process

Patient arrival
↓
Admission
↓
Registry
↓
Patient record printing
↓
Patient record transportation

Waiting
↓
Patient call
↓
Patient information
↓
Changing clothes
Record in control room
↓
Waiting
↓
Positioning in equipment table
↓
Exam
↓
Exit equipment table
↓
Changing clothes
Image post-processing
↓
Billing
↓
Patient leaves the department

Legend:

Patient
Physician
Radiology Technician
Nurse
Radiology Assistant
Administrator
■ Waiting Room
Reception
● Changing Room
◆ Control Room
▲ Examination Room

Fig. 3 Illustration of a conventional radiology process in the studied department

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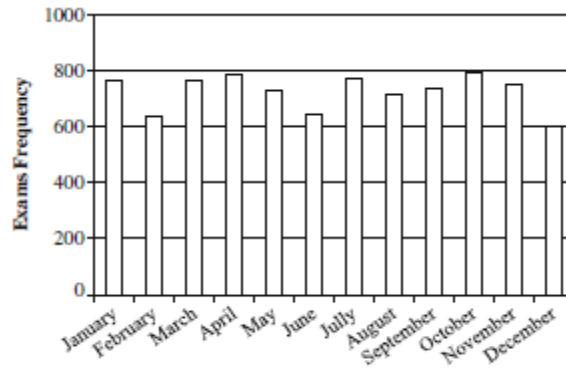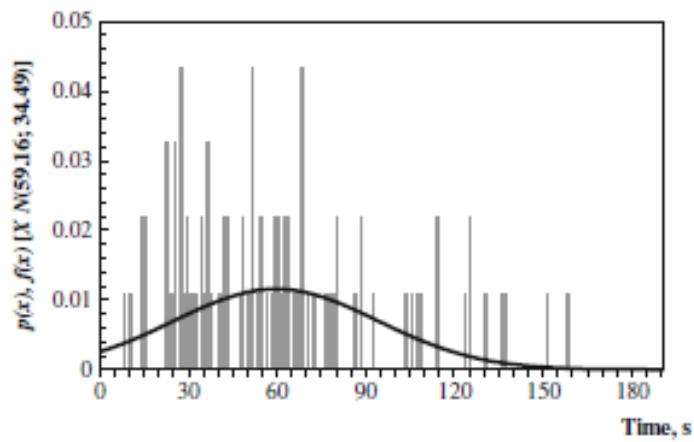
Fig. 4 Average monthly workload histogram

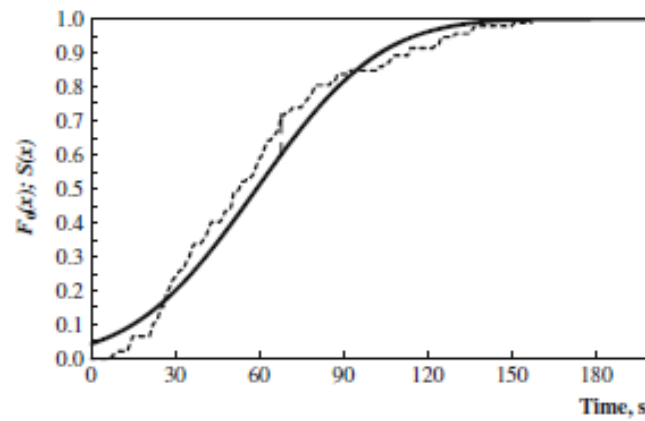**Fig. 5** Fitted normal distribution and actual data $X \rightarrow (\mu, \sigma)$

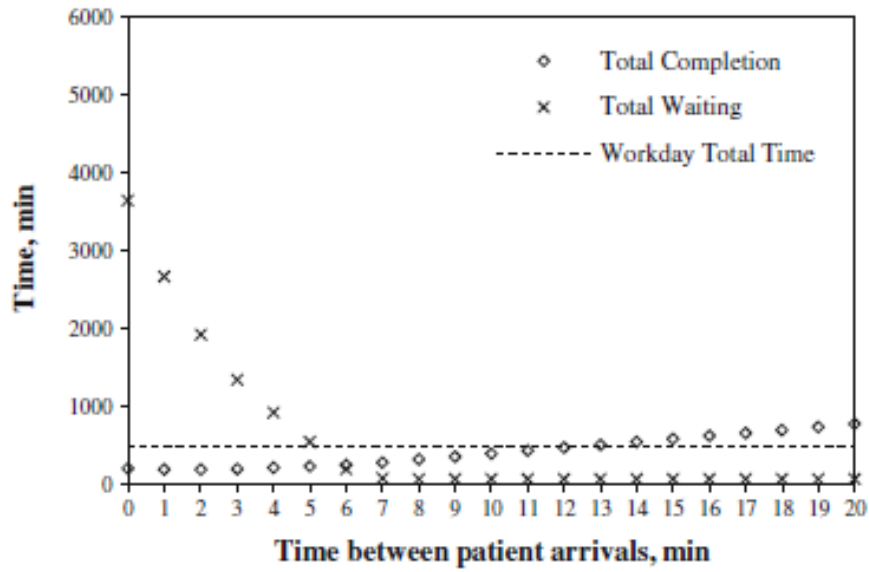**Fig. 6** Kolmogorov–Smirnov goodness of fit test of the collected data
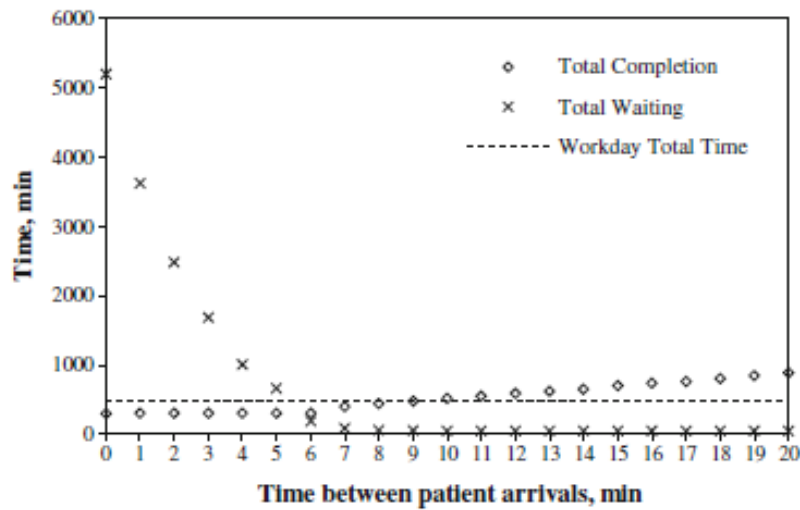
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Fig. 7 Simulation results for Scenario 1

Fig. 8 Simulation results for Scenario 2

Table 1 Input parameters to the simulator for an exam task. It is provided the average and standard deviation

$A_{i,j}$	$p_{i,j}$, s		$\varepsilon_{i,j}$
	$\mu_{i,j}$, s	$\sigma_{i,j}$, s	
Exam task	59.2	34.5	o

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Table 2 Total completion and total waiting results for Scenario 1 for a time between patient arrivals of 5 and 10 min and reference total completion time

Time between patient arrivals, min	Reference		
	Total completion hh:mm:ss	Total completion hh:mm:ss	Total waiting hh:mm:ss
5	–	03:44:47	09:01:00
10	08:42:45	08:30:49	01:01:16

Table 3 Total completion and total waiting results for Scenario 2 for a time between patient arrivals of 5 and 10 min

Time between patient arrivals, min	Total completion hh:mm:ss	Total waiting hh:mm:ss
5	05:08:25	02:48:00
10	08:40:23	00:56:34