# Process Improvement in a Private Hospital using Discrete Event Simulation
## The Case of Companion and Complementary Diagnostics

**Jorge Daniel Carvalho Mira**

**Department of Engineering and Management, Instituto Superior Técnico**
University of Lisbon, Portugal

December 2022

**Abstract**

Due to new health problems and the worsening of old ones, healthcare is needed more than ever. Knowledge motivates patients to live healthier as science advances. Thus, many healthcare units have battled to handle rising demand while maintaining service quality to improve patient satisfaction and profitability. Simulation models may analyse patient flow and identify ways to improve resource efficiency and reduce waiting time. This study creates a hospital unit simulation model using data from Lisbon's Hospital da Luz Imaging Department. This model will replicate the everyday flow of patients and staff in this department and show how resource and examination room management affects the system. At the conclusion of the studies, numerous ideas are offered and debated, from level to level, to enhance service, resource, and patient performance, however it is verified that only the increase in one unit of examination rooms has a major beneficial influence on queue waiting times.

**Keywords:** healthcare simulation, process improvement, simulation models, operational research methods, discrete event simulation.

### 1. Introduction

Global competition in a growing industry often makes patients curious and apprehensive about healthcare [1]. Health consciousness and affluence have increased healthcare demand and demographic trends toward a healthier lifestyle. Thus, local businesses, including medical services, face a demanding environment. Due to hospital competition, patients now choose the best healthcare unit [2], [3].

Due to rising consumer expectations and demand for standard services, hospitals and healthcare units must improve their services to compete [4]. For this reason, healthcare units are facing many challenges. With demand increases, hospitals may dissatisfy patients with long lengths of stay due to excessive wait times [2]. Thus, a number of them have made significant efforts to improve hospital efficiency to reduce LOS and other issues like patient wait times, patient satisfaction, levels of spending, capacity, resource consumption, working conditions, staff morale, accessibility to error-free treatment, and medicines [5], [6]. Hospitals and other healthcare facilities use qualitative concepts and human experiences to improve. However, such strategies may not yield the big improvement one hopes for, and it is impossible to quantitatively predict their results [5].

In recent years, healthcare operations have improved with computer simulation to aid decision-making [7]. A simulation model may simulate the process and its dynamics under random distributions, show patient flow and care delivery methods, and provide performance evaluation forecasts [8]. With such a tool, healthcare management can evaluate existing procedures, study potential changes, experience situations that would not otherwise be possible without spending a lot of money on system development, training, and equipment, or investigate system variable relationships or trade-offs [2]. Healthcare simulation can also be used to compare situations or visualise processes. Simulating performance and efficiency can be done continuously.

This research aims to create a simulation model of an Imaging department inspired by contextualisation. This model will test various internal factor changes, such as a service's personnel and facilities, to examine system performance under different scenarios. Thus, for each tested combination, it will be possible to predict how the unit will behave and determine the number of resources needed to perform well for the decision-maker.

This study also evaluates human resource effectiveness in each scenario using the occupancy rate, which shows how much time a resource spends on an activity. When the resource allocated to a given number of activities decreases, the occupancy rate increases, but waiting times do not improve, indicating a trade-off. Finally, the model should help the department manage resources. This model's precision matches demand and supply, optimising resource allocation in time and space and reducing queue times.

## 2. Literature Review

Simulation models can be used to evaluate and improve performance and productivity. A simulation model is created to test and integrate with the organization's operational information systems [9]. This is done to examine a system's longitudinal behaviour and recommend changes while it works and generates dynamic data. Simulation's true value can be realised when simulation models are fully integrated into the current information system applications that support healthcare providers' daily operations [8].

### 2.1. Discrete-Event Simulation

Simulation models can be distinguished between static or dynamic, deterministic or stochastic and continuous or discrete. The most used simulation technique is discrete-event simulation, which combines dynamic, stochastic and discrete properties [10], which is the base of this research. Discrete-Event Simulation (DES) is a cheap, secure, and fast tool for analysing complex systems and assessing performance indicators. DES is an easy and adaptable computer-based modelling technique for decision-making that simulates the dynamic behaviours of complex systems and the interactions between people, communities, and their surroundings [11], [12], which reflects the system's actual behaviour [13]. Due to the large amount of data that most real-world systems must store and manage, recommends DES on a digital computer [14]. DES is better for modelling complex systems at the individual level than at the cohort level than aggregate models without interaction, such as decision trees or Markov models [12], [15]. It shows the flow of individual entities through discrete events (activities) in a system that evolves over time [14]. Due to resource scarcity, entities must line up between these events. These are queueing networks [16]. In a hospital simulation, entities are often transferred patients. This simulation allows traits to affect system progression and resource limits [11]. Thus, it accurately depicts how patient characteristics affect a health system.

Since DES results are samples from a distribution, multiple simulation runs may be needed to accurately measure output parameters. This is especially problematic in unstable systems when the arrival rate is near the service rate or activity time fluctuations are large [17].

DES models allow patients to be unique and interact with resource supply [2]. Although testing and running these models takes longer, they help model healthcare delivery systems, especially when resources are scarce [18].

### 2.2. Framework for Developing GE-DES in Healthcare Systems

The framework for Generalizable Discrete Event Simulation (GE-DES) for Healthcare Systems consists of four sections: (I) understanding the issue scenario, (II) establishing the modelling objectives, (III) choosing the model content and (IV) developing the model.

(I) understanding the issue scenario is divided into four steps: study population, evaluating the system performance, status quo process map, and experimental decision factors. The information gathered for each of the four domains is intended to guide modelling operations. Decision factors reveal model inputs. The comprehensive process mapping lists relevant components to help select model content. The modeller must understand the topic to build an accurate model that addresses the concerns [19]. To determine if DES is the best option, consumers and subject matter experts must understand and express the problem [20].

(II) establishing the modelling objectives describe how simulation research analyses alternative system configurations based on a performance metric to aid client decision-making. Typically, configuration options are constrained by hospital money, physical space, and laws [21]. Modelling objectives, level of detail, and generality may be interrelated. [22]. More detail may make a model less generic. Objectives are classified either general (run-time and visualisation needs, development effort, and re-use flexibility) or modelling (answering "what are the most important issues to be addressed by experimenting with the model?") [23]. The generic and reusable content of the ED model is related to the general objectives. The primary function of selected models determines their modelling objectives.

(III) in selecting model content, the framework distinguishes between model scope, which identifies model boundaries by including or

omitting a representation of parts of the system under investigation as model components, model detail (or depth of the model), which focuses on characteristics [24], and identifying model assumptions and simplifications [20]. Before evaluating the extent and amount of complexity of the suggested simulation model, its use should be questioned [19]. Variability, interconnectedness, and complexity of the modelled system determine simulation selection. DES is the most applicable system applicable because most operational systems are queuing systems. In addition to these reasons, the issue scenario, modelling objectives, experimental factors, and responses will determine whether simulation is the right method. Conceptual simulation models have not been discussed much yet. Different modelling strategies are possible. Simulation-specific conceptual model begins here.
(IV) healthcare decision-making involves complex social interactions. Thus, healthcare service delivery and patient flow management issues are hard to define. Understanding the healthcare process is essential for making sound, defensible decisions and achieving success [25]. Consequently, the issue must be developed from the service delivery perspective. After defining the problem, identifying inputs, outputs, assumptions, and entities, and reviewing, the model can be developed. Quantitative data (observations) are saved in databases or recorded on any form of storage media (records), while qualitative data can be collected by direct observation of the system and expert interviews [26]. Doctors, nurses, consultants, administrators, and managers are hospital experts [27]. The hospital information system records patient treatment route, arrival method, referral type, and discharge or admission time [25]. Staff enter patient data (e.g., administrators, doctors, and nurses through the stages of patient care). Hospital records lack precision and uniformity due to healthcare system restrictions. Before extracting data, data mining must extract the most dedicated group of documents. Expert and clinician observations and interviews are used to gather model inputs. This clarified many system issues.

## 3. Case Study Formulation and Analysis

This chapter explains all of the information provided by the Imaging department management at Hospital da Luz regarding the unit under study for developing the plan and subsequent conceptual model.

### 3.1. Service Functioning Description

Hospital da Luz Imaging offers about ten types of examinations. The decision-maker suggested Mammography, X-Ray, MRI, CAT, and Ultrasound reduce waiting times. The department has two Mammography equipment that can simultaneously examine two patients. The department also has four X-Ray appliances, six MRI machines, three CAT devices, and eight Ultrasound scanners, allowing the same number of patients. Each office has its exam equipment. Regarding the health personnel assigned to supervise and conduct each examination, it is necessary to have one technician in Mammography, X-Ray, MRI and CAT; one assistant in X-Ray, MRI, CAT and Ultrasound; and a physician in Ultrasound. In addition, only a secretary is required to perform the check-in of the patient.
The patient gets a ticket at a check-in location to start the journey. The unit has two entrances with check-in counters. Exams are inserted in zones A (Imaging) and B (Ultrasound). Mammography, X-Ray, MRI, and CAT examinations define zone A, while Ultrasound defines zone B. Patients must enter the entrance room concerning the zone they will examine. A patient with zone A and zone B examinations will enter any zone and be directed to a waiting room after check-in. In case of the patient enters zone A but has an examination scheduled in zone B, the check-in service is usually done there, but after the service, the patient will go to the other waiting room.
The patient must wait until the healthcare personnel responsible for the examination summoned them. The duration of each exam is predetermined and corresponds to the time slot provided for each patient. This period will include completing the exam and all associated activities (preparation of equipment, instructing the patient, and filling out the medical report, if necessary, among others). By the end of this period, the patient will leave the office to make room for the next one. The patient's number of exams does not affect the prescribed duration for all exams except MRI, i.e., if the patient has two MRI exams, the specified period will be doubled.
After leaving the office, the patient can wait for another exam or leave the unit. In the first scenario, he will go to the waiting area for the other exam and repeat. The patient does not return to the queue because all scheduled exams of the same type are done simultaneously.

### 3.2. Objectives

As stated before, the decision-maker's primary objective is to decrease patients' general average waiting time in the examination queue. However, sub-goals can be set to help achieve the main goal and act as a stage. Sub-objectives may include reducing the average queueing and maximum time for check-in and examination activities separately; increasing the number of facilities inside the unit to have a more significant patient flow (fewer patients in queues) so they can be treated more quickly to boost patient satisfaction and to increase the occupancy rate of each resource to increase profitability.

### 3.3. Key Performance Indicators

Performance metrics must be established after problem definition and understanding objectives. These will determine the system's performance throughout the project by assessing the degree to which the predetermined objectives have been met. Like the pre-objectives, the KPIs must measure service quality to reduce waiting times in service queues.

The average and maximum queueing time for each check-in service or examination and resource occupancy rate are used for this. These metres will be reviewed after several system runs to determine if the system is improving or deteriorating.

### 3.4. Activities

Activities represent a period with a given duration. Refers to a group of operations that modify the state of an object. Although activities and events are often used interchangeably, they have distinct meanings in the context of simulating. An event is a change in the system's state caused by an activity, with the event serving as the consequence and the activity as the cause.

Each activity that will be analysed is associated with each service under study. In this case, there will be seven activities, corresponding to: Mammography, X-Ray, MRI, CAT, Ultrasound and Imaging and Ultrasound Check-ins.

### 3.5. Assumptions

To design the model, some basic assumptions were needed to guide its construction, analysis, and solution-finding. The issue was formulated without mentioning these assumptions, which helped create the model and assume the right conditions for modelling.

**1.** A patient only goes through the check-in procedure only once each day for an unlimited number of examinations.

**2.** A patient who has records on several days will be considered as one new patient each day they attended the unit.

**3.** Every patient exits the department having had at least one examination.

**4.** The patient waits in the queue for an examination for as long as is required.

**5.** The patient who enters the unit on a particular day is required to be seen on the same day and, therefore, must depart the unit on the same day, never being permitted to remain there from day to day.

**6.** A patient is only permitted to take one examination at a time.

**7.** The duration of each examination activity corresponds to the slot provided for the patient (and its associated resources).

### 3.6. Sketch of the Conceptual Model

The model to be developed can be divided into two sections. The first section covers the time between patients' entrance (when they take the

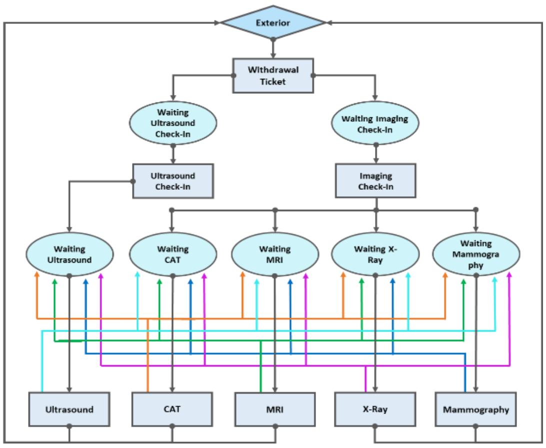



***Figure 1** – Base schema of the model that will be implemented in SIMUL8.*

ticket from the kiosk) and their departure from the check-in service to join a queue for an examination. Thus, the second section of the model covers the rest of the journey, from the patients' check-in to their exit from the system, focusing on their passage through various examinations. Patients are directed to the imaging or ultrasound service when they arrive in the first section of the model. Each zone has a check-in activity service and a queue. Patients are sent to sub-service queues after abandoning check-in. The imaging service has four sub-services: mammography, x-ray, MRI, and CAT, but only one for ultrasound: ultrasound. After the examination, the patient can choose to enter another queue or leave the system. The model's life cycle diagram and SIMUL8 design overview are shown below.

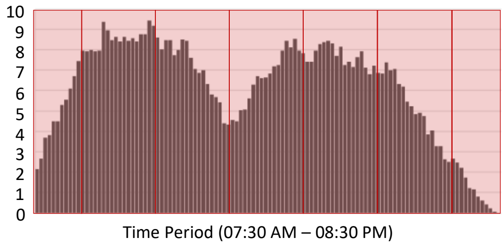
## 4. Data Treatment

This phase focuses on collecting data and how it was treated to implement in the conceptual model.

### 4.1. Patient Entries

The department accepted patients Monday through Friday from 7:30 AM to 8:30 PM. Since the system runs for 13 hours, it is necessary to divide it into several time intervals to better analyse the events in each and maintain tracking control for validation later. *Graphic 1* presents the histogram relatively to the number of arrivals in the function of the extracted timestamps divided into 112 bins

(classes). This represents the average number of patients arriving at the unit during this period.
By dividing the total hours of running per the number of classes, it was obtained that each bar is equivalent to seven minutes. Through the graph, it was possible to divide it into seven intervals over time, and in each interval the bars show the same behaviour, as shown in the figure.




***Graphic 1*** *– Histogram of the average number of arrivals per time interval per day (112 bins).*

Through the graph, it was possible to divide it into seven intervals over time, and in each interval the bars show the same behaviour, as shown in the figure. Thus, each bar block corresponds to a period, with five periods of 2h and two periods of 1.5h, the latter representing the extreme hours. Using the provided information, it is possible to determine how many patients visit each block daily. By placing the values corresponding to each time, the Chi-Square test is conducted to verify whether the set of values is consistent with a Poisson process [28], using SPSS Statistics [29]. For each block, it is then calculated the average arrival rate.
To convert the average arrival rate per hour into the interval between arrivals, in minutes, the inverse process described by expression (1) was used, which is the exact value that must be entered into SIMUL8. The interval length is the base unit of measure, in this case is 60 minutes.

$$Interarrival\ Time = \frac{Interval\ Length}{Arrival\ Rate} \tag{1}$$

A process with a Poisson distribution can have exponential interarrival times. Swapping between these distributions is similar to the formula above. A Poisson process's inverse mean is the parameter $\lambda$ of an exponential distribution.

***Table 1*** *– Rate of patient per hour and interarrival time, in minutes.*

| Time Slot | Poisson Arrival Rate (patients/h) | Exponential Interarrival Time (min) |
|---|---|---|
| 07:30 AM – 09:00 PM | 35.366 | 1.697 |
| 09:00 AM – 11:00 PM | 57.219 | 1.049 |
| 11:00 AM – 01:00 PM | 47.486 | 1.264 |
| 01:00 AM – 03:00 PM | 41.445 | 1.448 |
| 03:00 AM – 05:00 PM | 51.528 | 1.164 |
| 05:00 AM – 07:00 PM | 39.002 | 1.538 |
| 07:00 AM – 08:30 PM | 13.453 | 4.460 |

The proportion of patients in each block who went to one of the check-ins is shown in Table 2, below.

***Table 2*** *– Proportion of patients that proceeded to one of the services per time slot in the moment of arrival.*

| | % Of Patients | |
|---|---|---|
| **Time Slot** | **Imaging** | **Ultrasound** |
| 07:30 AM – 09:00 PM | 81.192 | 18.808 |
| 09:00 AM – 11:00 PM | 77.792 | 22.208 |
| 11:00 AM – 01:00 PM | 77.856 | 22.144 |
| 01:00 AM – 03:00 PM | 83.572 | 16.428 |
| 03:00 AM – 05:00 PM | 77.009 | 22.991 |
| 05:00 AM – 07:00 PM | 77.963 | 22.037 |
| 07:00 AM – 08:30 PM | 92.714 | 7.286 |

### 4.2. Check-In Service

With the data set relating to the duration of this activity, and to prevent possible outliers from entering the data analysis, they are identified for later removal, using the quartile method [30].
The decision-maker determined that two minutes of activity was the bare minimum, and subsequent calculations to identify outliers led to the elimination of durations greater than 19 minutes. Thus, the set of valid values is inserted into a vector, and the probability distribution that best fits the values is calculated using the SPC For Excel software.
Consequently, the time set followed a log-normal distribution with a mean of 7.527 and a standard deviation of 3.648.

### 4.3. Imaging and Ultrasound Services

The duration of the activities remains constant regardless of the number of exams performed, with the exception of the MRI examination, whose duration is added the number of times a patient takes is examined. Each activity will have this durations (in minutes): Mammography (15), X-Ray (10), MRI (40), CAT (20), and Ultrasound (15). This step also aims to determine the probability that a specific patient will use each service. These calculations are crucial because they will enable the simulation to determine whether the patient will choose one route or another depending on the actual use of each service.
The percentage distribution of patients per exam is therefore calculated. It was found that, of the total number of patients admitted, 11% were in Mammography, 32% in X-Ray, 17% in MRI, 20% in CAT and 42% in Ultrasound. The sum of the percentages exceeded 100% because there were patients who underwent multiple exams during

their hospital stay. Therefore, the patient has two options: leaving the unit after the examination or moving to a different waiting queue. For each combination of two exams, the probabilities of the patient taking both on the same day had to be determined (intersection probability). This was determined by dividing the number of patients who utilised the two examinations in combination by the total number of admitted patients. Similarly, the probability that the patient had only undergone one exam on the same day was determined.

After determining the individual and intersection probabilities, it is possible to calculate the conditional probability, using the expression (2) that indicates the likelihood that a patient has participated in one examination while also participating in another. The conditional probability is equal to the intersection probability divided by the individual probability. Note that the probability that a patient has been on an Ultrasound knowing that they have been on a Mammography is not equal to the probability that a patient has been on a Mammography knowing that they have been on an Ultrasound.

$$P(A \mid B) = \frac{P(A \cap B)}{P(B)} \tag{2}$$

The results of these probabilities may be seen on the original document, at *section 7.3.*, *Table 8*, they can be calculated manually using the formula above.

## 5. Model Development

Once gathered, data (from observations and interviews with experts) is combined to conceive the conceptual model using SIMUL8, where processes and activities could be defined. The conceptual model guides the actual simulation model, which contains more system detail. Besides that, it serves as a communication mechanism for validating the model. The implementation of the model in SIMUL8 may be seen at the original document in Figure 1A from the annexes section.

### 5.1. Simulation Clock

Establishing the system's unit of measurement was crucial before simulation. The minute was chosen to evaluate the acquired outcomes because most of the information is presented in minutes and the pre-established performance metrics use this time unit as a reference. On working days, the simulation runs from 7:30 AM to 9:00 PM, for 13 hours and 30 minutes long.

### 5.2. Components of the Model

Seven weekly-pattern shifts were created. Each time slot of the arrivals is covered by a specific shift.

The system uses resources throughout the simulation. They require non-specialist staff (or equipment). In general, several activities share a resource, with the others on active standby until it is used by another. Technicians, assistants, physicians, and secretaries will understand this research's four potential resources for examination-related activities. Knowing their system roles does not matter. The only important information is how many resources of each type are needed for each activity that depends on them and when they are no longer needed.

Labels add system control. Work items can be labelled before or during the simulation. Activities can examine and change the label's value. In this context, the labels will serve as a trail for each patient, indicating the latest exam they passed and the other tests they have taken, with the latter incrementing the exam-specific label each time the patient enters this activity. This will also serve as a debug to determine if the patient repeated an examination since they should not re-enter the queue where they have already been before. Labels will prevent these incidents. Therefore, two labels representing each activity are necessary to develop this logic.

### 5.3. Activities

Below is a list of model activities and how they were modelled. For a more detailed explanation, it is recommended to see the original document. The explanation of some fictional activities was also described.

**1. *Arrivals:*** This activity receives a distribution that specifies the interarrival time at each time slot, so all patient arrival information, including temporal distributions, must be stored here. This activity is, therefore, a time-dependent, with seven smaller exponential distributions comprising each time slot. The parameter of each smaller distribution is expressed in the second column of the *Table 1*. Here, all the created labels were set to zero along, to indicate that the patient has not been into any kind of examination. When designing the system, only one entry for all patients was considered. Next activity will cover dividing patients by entry zone.

**2. *Shift and Sep:*** Patients will be transferred to one of seven fictitious activities based on their arrival time. Thus, each shift created had to be assigned with each of these *Shift* activities, meaning each activity will only take patients during its assigned shift. Since percentages vary by slot, this was necessary to accommodate patients who choose Imaging or Ultrasound. Thus, each *Shift* activity is linked to two fictional activities, *Sep_I* or *Sep_US*, with percent mode enabled in the routing out of the first. *Table 2* shows the *Shift* activity input values according to the time slot.

**3. *Wait_Check_In:*** After getting the ticket at the checkpoint, the patient waits to be called to the service for check-in. Two queues of this type, *Wait_Check_In_I* and *Wait_Check_In_US*, one for each zone, are connected to one of the immediately preceding activities, *Sep_I* and *Sep_US*, respectively, and only pass patients designated for the respective services.

**4. *Check_In:*** Here, the log-normal distribution specified in the point 4.2. of this article is employed for the duration of both activities. Here, the resource responsible for this activities are defined, with the option to pick it up and release it when the patient exits the activity.

**5. *Go_Wait_Exam:*** This fictitious activity follows the patient from the check-in desk to the examination waiting room. In reality, a patient may be served at a service check-in and wait in the opposite waiting room of the other service with a 15% probability defined in the routing out dialogue. Patients who leave the *Go_Wait_Exam_I* activity have four pathways that match the four exam waiting rooms. Each examination's percentages had to be adjusted to the main service's patient count. Thus, 19%, 55%, 30%, and 34% of Imaging patients go to Mammography, X-Ray, MRI, and CAT, respectively, while 42% go to Ultrasound. This activity's routing dialogue includes the percentage values provided.

**6. *Wait_Exam:*** There are a total of five queues of this kind, each preceding the appropriate examination-related activity.

**7. *Exam:*** There are a total of five activities of this kind, each corresponding to one examination with the respective duration as a fixed distribution and with connected to the corresponding resources. The resources are required and released here, apart for the MRI, which is released ahead. The labels relatively to this examination is set to one. The labels relatively to the last exams of the other activities are set to zero to indicate that this was the last activity the patient has been.

**8. *Dispatch_MRI:*** This activity is responsible for moving the patient back to this examination, with a probability of 32%, which corresponds to the probability of a patient repeat that examination.

**9. *Other_Exam:*** The patient that finishes its examination, will have the option to moving to another queue or leave the unit. The conditional probabilities previously mentioned in *section 4.3.* are applied in the routing out of this activity. The MRI resources are released here.

**10. *Mammo*, *XRay*, *MRI*, *CAT* and *US*:** This fictitious queues are imposed only to apply visual code to prevent patients from entering the waiting queues where they have already been. In case a patient is sent to one of this queues, they will go back to the previous activity to re-sent them back again.

**11. *Exit_Mammo*, *Exit_XRay*, *Exit_MRI*, *Exit_CAT* and *Exit_US*:** This exit point receives the patients who abandon the unit.

**12. *Go_Wait*:** This fictitious activity directs the patient towards the specific queue to perform other examination.

## 6. Results Discussion and Presentation

Here, it is computed the initial and final conditions and evaluate the system. The results are examined and interpreted after proposing a formal solution search technique and presenting this methodology.

### 6.1. Initial Conditions

In order for the system to function, it is necessary to determine the minimum conditions. This will establish the minimum resource and activity values necessary for the system to execute minimally. For this computation, many simulations were run over days or weeks to extract the total number of arrivals and divide it by the total number of hours the system was admitting new patients based on the system's 13-hour workday. This resulted in an average of 38.385 patients/h each day.

To determine the minimum number of concurrent activities, it is necessary to multiply the patient average arrival rate by the simulated proportion of patients engaging in each activity and this value by its duration. According to the calculations, two Mammography activities must occur concurrently. Since there is one technician for each activity, exactly two technicians must be counted for this activity (*section 3.1.*). The other minimum number of activities and resources are: for X-Ray, three activities, i.e., (three technicians and three assistants); for MRI, six activities (six technicians and six assistants); for CAT, three activities (three technicians and three assistants); for Ultrasound, five activities (five assistants and five physicians); for the Imaging Check-In, four activities (four secretaries); and for the Ultrasound Check-In, one activity (one secretary) is the minimum required.

### 6.2. Warm-Up Period

After setting this minimum values into the SIMUL8, it is required to determine when each activity's occupancy rate and average queue waiting time stabilised to start collection results. Therefore, multiple runs were conducted weekly to determine that period of stabilization. According to *Tables 16A* to *26A* (and the complementary information from *Graphic 3A* to *13A*), the simulation results after 13 weeks seem to be stable after a period of small oscillations related to average waiting times. The warm-up period was defined to be 26 weeks (twice the 13 weeks verified) and 105,300 minutes to account for an extra safety margin to minimise the effects of those starting conditions.

### 6.3. Terminal Conditions

The results collection period must be determined after the warm-up period. Thus, it is supposed to examine, across different time intervals, the variation related to all the KPIs considering the resources and activities at their minimum. To ensure confidence interval precision around the simulation results' estimated mean, each experiment's number of trials was first determined. Thus, 5% mean value accuracy is applied. This implies that a genuine KPI result will fall within its minimum and maximum values 95% of the time. The software demonstrated that three trials were enough, but five were added for safety. Therefore, each data collection period will include five runs from the same experiment, each with some variability due to random numbers regulating its behaviour. The mean and values within each KPI's confidence interval will be displayed in SIMUL8's results manager. Then, the collection periods for results are arbitrarily set at 5, 10, and 20 weeks. This duration was altered following each trial's five executions. The objective is to compare KPI confidence intervals across periods of data collection. After running the system for each period, the variations between each KPI's upper and lower bound are computed. Observations indicate that the variances of each confidence interval decrease as the period of data collection lengthens, indicating that the system becomes more stable over time. Therefore, it makes sense to analyse the system over longer collection periods. Long-term system operation necessitates consideration of the CPU's computationally intensive tasks. Thus, it was sufficient to establish a collection period of 20 weeks.

### 6.4. Solution Searching Technique

In the initial phase of the analysis, the number of replicas and resources will be maintained at their minimum values, except for the activity and its associated resources that are being studied, whose quantity will vary between executions. Then, it will be observed how increasing replicas and resources in each activity affects the KPIs for the queues under analysis. The number of replicas of an activity and resources will be increased by one unit throughout the subsequent three runs, starting from the point with the number of resources being reduced to their absolute minimum. At the end of the three runs of experiments, the number of replicas whose transition from run to run had the highest performance will be preserved.

The system will be evaluated in parts. The system will be evaluated in segments. The first segment will be tested at each check-in, and only then will the other activities be studied based on the already optimised resources of the check-in activities, so as not to account for the bottleneck effect of the check-in activities, i.e., the flow conditioned by these activities.

<u>Imaging Check-In Service:</u> increasing the number of replicas from four to five had the same impact as increasing it from five to six, i.e., the benefit rose correspondingly. The effect is diminished when the number of replicas increases from six to seven. For this reason, it is preferable to abuse the system with six replicas.

<u>Ultrasound Check-In Service:</u> raising the number of replicas and associated resources from one to two proved to have the highest impact on the KPIs, rather than the other increases.

<u>Mammography Facility:</u> it was verified that the percentage of improvement is better with the increase from two to four three replicas. The second-highest benefit is reached when transition from three to four replicas.

<u>X-Ray Facility:</u> there was a more significant percentage difference when increasing from three to four replicas, which appears to translate into a better gain. Increasing the number of replicas from four to five yields the second-greatest improvement.

<u>MRI Facility:</u> the system is best improved by the rise from seven to eight facilities compared to the other increases. The second-highest improvement comes when the number of replicas is increased from eight to nine.

<u>CAT Facility:</u> this analysis reveals that the KPIs perform more optimally for the transition from four to five replicas, rather than for the transition from three to four (in both KPIs). The second-greatest benefit is reached when increasing from five to six replicas.

<u>Ultrasound Facility:</u> According to what has been seen, adding a sixth replica has a more substantial influence on the system than increasing from six to seven or even from seven to eight replicas. However, the second greatest benefit happens when raising the number from seven to eight facilities.

### 6.5. Results Interpretation

The KPIs improved most after the first run, when the minimum replicas and resources values were raised by one. Due to the increased replicas and resources in posterior executions, this advantage diminished over time. However, these improvements were significant, so it was possible to climb higher. The decision-maker will decide how much cost increase they are willing to accept to make this system change. After a few runs, certain KPIs show a small change between the last two runs, proving that the proportion of benefit decreases until eventually stabilises. This will come to a point where increasing the number of replicas and resources will no longer be beneficial in this context. Since the utilisation rate will drop when adding more activities and resources, increasing replicas or resources in this situation is not recommended. Thus, replicas and resources would be 1:1, queueing times would decrease, and the system would be undercrowded, benefiting patients.

When testing the model with all this individual improvements all combined, the KPIs have deteriorated as predicted. This conditioning in the waiting queues of these activities impeded regular flow when reviewing the KPI results for a particular activity while limiting the others to the bare minimum. Fewer patients circulated from these activities, reducing the waiting queue for the "optimal" activity (via other examinations). However, optimising all activities increases patient circulation between exams. More patients are examined, so more move to other waiting rooms.

Hence, for each activity, it may be necessary to raise a level to the number of replicas and resources that will yield the second-greatest benefit. Then, each activity's replica count will increase to reach the second-highest benefit and the respective resources will be readjusted. Therefore, the system was re-run using the number of replicas and accordingly number of resources for the second-highest benefit for the same period. The results showed decreased queueing times for all queues, so the KPIs performed better. Due to shorter wait times, this makes the system more convenient.

When queue KPIs improve for a single activity, resource efficiency decreases. Efficiency and occupancy rates are directly related. This implies that more resources must be wasted in a given period for operations to be efficient. Due to the increase in replicas, resources are less efficient throughout the experiments because there are more of them for the same number of patients on the waiting queue. As predicted, the same number of patients is more evenly distributed among resources, reducing their workload. The resource has more free time considering that the duration of each activity remains constant. More free time means more resource waste or unused.

The system was set up to study the effects of reducing resources by type while maintaining activity levels to improve resource efficiency. When the number of activities remains the same but the having decreased the number of resources, resource utilisation is expected to increase. There is a visible trade-off between resource efficiency and service delivery. To deal with it, it is essential to strike a balance between the two and find a level of comfort where neither has advantages nor disadvantages. The value of the performance of the KPIs of the second-highest benefit was then used as a starting point, and three experiments were conducted, each with one less resource of each type than the previous experience, to determine how resource efficiency improved with the decrease in performance of the remaining KPIs. Mammography and MRI queues still have room for improvement, according to the results. However, the KPIs for other examination queues (except Ultrasound) show weak variances from the base experience. This is because check-in activities, which condition the system, have fewer resources. The system's second part flows slower because these queues are more crowded. The maximum queueing time for these queues improves dramatically.

Although the number of patients who wait longer than the average value is relatively small, it is still a case that merits consideration because the average waiting time is still low. Due to the physician shortage, the Ultrasound queue KPIs performed poorly, but it became clear that this resource is highly dependent on the system's overall performance. A second execution used the experiment's values with less than three resources and increased the number of physicians by two to avoid this issue. This shows that a reduction from 24 to 21 technicians increased their efficiency from 68.22% to 75.90% after a final general analysis based on the second-highest benefit. This resource's efficiency increased from 67.97% to 74.33% after reducing from 28 to 25 assistants. From 58.89% to 67.30%, efficiency dropped from 8 to 7 physicians. Productivity rose from 50.59% to 72.22% when 10 secretaries were cut to 7. The queues' performance was only slightly affected by resource efficiency, but some queues performed better than others, advising that this last solution may be the most appealing.

## 7. Conclusion and Future Work

This study focused on improving the services of Hospital da Luz Imaging's department. To meet patients' demands for better service and increase demand, the goal was to reduce wait times. The metrics for minimising these wait times were explored in various ways to provide solutions. After presenting these results, the decision-maker will be able to choose the best option to keep the system running.

The bottleneck effect on check-in activities often prevents exam waiting rooms from being overcrowded, which may be beneficial since limiting the check-ins may also reduce health staff (technicians, assistants and physicians). After considering this, as seen in the last experiment, reducing the number of resources did not affect examination queue performance other than improving resource efficiency, so it may be beneficial to do so.

As in the initial analyses of the previous chapter, the modeller must emphasise the importance of reducing the bottleneck effect to improve queue performance. System upgrades must be done in stages. If check-in delays patients, improving examination-related tasks is pointless.

The last analysis demonstrated that resource utilisation rate for all resources is about 70%, indicating that 30% of the time is spent waiting to be allocated to activities due to a lack of patients or resources. Studying when these resources are most needed and least needed can help improve their efficiency even more.

## References


[1] M. Li *et al.*, "Evaluating patients' perception of service quality at hospitals in nine Chinese cities by use of the ServQual scale," *Asian Pac J Trop Biomed*, vol. 5, no. 6, pp. 497–504, Jun. 2015, doi: 10.1016/J.APJTB.2015.02.003.

[2] F. Manzoor, L. Wei, A. Hussain, M. Asif, and S. I. A. Shah, "Patient Satisfaction with Health Care Services; An Application of Physician's Behavior as a Moderator," *Int J Environ Res Public Health*, vol. 16, no. 18, Sep. 2019, doi: 10.3390/IJERPH16183318.

[3] Clifford Bleustein, David B. Rothschild, Andrew Valen, Eduardas Valaitis, Laura Schweitzer, and Raleigh Jones, "Wait Times, Patient Satisfaction Scores, and the Perception of Care," *Am J Manag Care*, vol. 20, no. 5, 2014, doi: 10.37765/AJMC.

[4] E. Zarei, A. Daneshkohan, B. Pouragha, S. Marzban, and M. Arab, "An Empirical Study of the Impact of Service Quality on Patient Satisfaction in Private Hospitals, Iran," *Glob J Health Sci*, vol. 7, no. 1, p. 1, Jan. 2015, doi: 10.5539/GJHS.V7N1P1.

[5] J. Wang, J. Li, K. Tussey, and K. Ross, "Reducing length of stay in emergency department: A simulation study at a community hospital," *IEEE Transactions on Systems, Man, and Cybernetics Part A:Systems and Humans*, vol. 42, no. 6, pp. 1314–1322, 2012, doi: 10.1109/TSMCA.2012.2210204.

[6] J. Barjis, "Healthcare Simulation and its Potential Areas and Future Trends," 2011.

[7] N. Ö. Doğan and O. Unutulmaz, "Lean production in healthcare: a simulation-based value stream mapping in the physical therapy and rehabilitation department of a public hospital," *https://doi.org/10.1080/14783363.2014.945312*, vol. 27, no. 1–2, pp. 64–80, Jan. 2014, doi: 10.1080/14783363.2014.945312.

[8] D. M. Gaba, "The future vision of simulation in health care," *Qual Saf Health Care*, vol. 13, no. 1, pp. 2–10, 2004, doi: 10.1136/qshc.2004.009878.

[9] F. Darema, "Dynamic data driven applications systems: A new paradigm for application simulations and measurements," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 3038, pp. 662–669, 2004, doi: 10.1007/978-3-540-24688-6_86/COVER.

[10] D. Mourtzis, "Simulation in the design and operation of manufacturing systems: state of the art and new trends," *https://doi.org/10.1080/00207543.2019.1636321*, vol. 58, no. 7, pp. 1927–1949, Apr. 2019, doi: 10.1080/00207543.2019.1636321.

[11] V. Alejandro Huerta-Torruco, Ó. Hernández-Uribe, L. Adriana Cárdenas-Robledo, and N. Amir Rodríguez-Olivares, "Effectiveness of virtual reality in discrete event simulation models for manufacturing systems," *Comput Ind Eng*, vol. 168, Jun. 2022, doi: 10.1016/J.CIE.2022.108079.

[12] J. Karnon, J. Stahl, A. Brennan, J. J. Caro, J. Mar, and J. Möller, "Modeling using discrete event simulation: a report of the ISPOR-SMDM Modeling Good Research Practices Task Force-4," *Med Decis Making*, vol. 32, no. 5, pp. 701–711, Sep. 2012, doi: 10.1177/0272989X12455462.

[13] M. Urbani, M. Brunelli, and M. Collan, "A Comparison of Maintenance Policies for Multi-Component Systems through Discrete Event Simulation of Faults," *IEEE Access*, vol. 8, pp. 143654–143664, 2020, doi: 10.1109/ACCESS.2020.3014147.

[14] A. M. Law, "Simulation Modeling and Analysis, FIFTH EDITION," 2015, Accessed: Jul. 13, 2022. [Online]. Available: www.averill-law.com

[15] X. Zhang, "Application of discrete event simulation in health care: A systematic review," *BMC Health Serv Res*, vol. 18, no. 1, pp. 1–11, Sep. 2018, doi: 10.1186/S12913-018-3456-4/FIGURES/5.

[16] S. Brailsford and N. Hilton, "A Comparison of Discrete Event Simulation and System Dynamics for Modelling Healthcare Systems," 2000.

[17] P. Renard, A. Alcolea, and D. Ginsbourger, "Stochastic versus Deterministic Approaches," *Environmental Modelling: Finding Simplicity in Complexity: Second Edition*, pp. 133–149, Jan. 2013, doi: 10.1002/9781118351475.CH8.

[18] J. J. Forbus and D. Berleant, "Discrete-Event Simulation in Healthcare Settings: A Review," *Modelling 2022, Vol. 3, Pages 417-433*, vol. 3, no. 4, pp. 417–433, Oct. 2022, doi: 10.3390/MODELLING3040027.

[19] S. Robinson, "Conceptual modelling for simulation Part II: a framework for conceptual modelling Conceptual modelling for simulation Part II: a framework for conceptual modelling Conceptual modelling for simulation Part II: a framework for conceptual modelling," *Journal of the Operational Research Society*, vol. 59, no. 3, pp. 291–304, 2008, doi: 10.1057/palgrave.jors.2602369.

[20] L. M. Boyle, A. H. Marshall, and M. Mackay, "A framework for developing generalisable discrete event simulation models of hospital emergency departments," *Eur J Oper Res*, vol. 302, pp. 337–347, 2022, doi: 10.1016/j.ejor.2021.12.033.

[21] S. Takakuwa and H. Shiozaki, "Functional analysis for operating emergency department of a general hospital," *Proceedings - Winter Simulation Conference*, vol. 2, pp. 2003–2011, 2004, doi: 10.1109/WSC.2004.1371562.

[22] M. M. Günal, M. Pidd, and M. Gu, "Discrete event simulation for performance modelling in health care: a review of the literature," *Journal of Simulation*, vol. 4, no. 1, pp. 42–51, 2010, doi: 10.1057/jos.2009.25.

[23] N. Furian, D. Neubacher, M. O'Sullivan, C. Walker, and C. Pizzera, "GEDMod – Towards a generic toolkit for emergency department modeling," *Simul Model Pract Theory*, vol. 87, pp. 239–273, Sep. 2018, doi: 10.1016/J.SIMPAT.2018.07.010.

[24] T. Monks *et al.*, "A framework to accelerate simulation studies of hyperacute stroke systems," *Oper Res Health Care*, vol. 15, pp. 57–67, Dec. 2017, doi: 10.1016/J.ORHC.2017.09.002.

[25] W. Abo-Hamad and A. Arisha, "Simulation-based framework to improve patient experience in an emergency department," *Eur J Oper Res*, vol. 224, no. 1, pp. 154–166, Jan. 2013, doi: 10.1016/J.EJOR.2012.07.028.

[26] J. C. Steuben, A. J. Birnbaum, J. G. Michopoulos, and A. P. Iliopoulos, "Enriched analytical solutions for additive manufacturing modeling and simulation," *Addit Manuf*, vol. 25, pp. 437–447, Jan. 2019, doi: 10.1016/J.ADDMA.2018.10.017.

[27] F. F. Baesler, H. E. Jahnsen, and M. DaCosta, "Emergency departments I | Proceedings of the 35th conference on Winter simulation: driving innovation," *Emergency departments I: the use of simulation and design of experiments for estimating maximum capacity in an emergency room*, pp. 0–190, Dec. 2003, Accessed: Jul. 09, 2022. [Online]. Available: https://dl.acm.org/doi/10.5555/1030818.1031081

[28] "Poisson Distribution | Brilliant Math & Science Wiki." https://brilliant.org/wiki/poisson-distribution/ (accessed Oct. 28, 2022).

[29] "End of support for SPSS Statistics 24.0.0." https://www.ibm.com/docs/en/spss-statistics/24.0.0?topic=tests-chi-square-test (accessed Oct. 28, 2022).

[30] "How to Find Outliers in Excel - AbsentData." https://www.absentdata.com/how-to-find-outliers-in-excel/ (accessed Oct. 28, 2022).