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Improving performance in hospital emergency departments by using simulation

Vicente Manita Santos Mota

Master in Management of Services and Technology

Supervisors:
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BUSINESS
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Resumo

Nos últimos anos, departamentos de urgência há volta do mundo têm-se deparado com o mesmo problema, sobrelotação. Com o objetivo de tentar reduzir os tempos de espera de pacientes, os autores usaram a ferramenta de simulação de eventos discretos "SIMUL8" para criar um modelo generalizado de um departamento de emergência baseado numa análise indutiva de casos de estudo.

Com base nesta análise forma criadas e simuladas 34 variações do modelo base. Através da análise destes cenários foi concluído que melhorar alocação de recursos, ou aumentar os mesmos, são formas eficazes de diminuir os tempos de espera.

Palavras chave: Triagem, Sistema de Triagem de Manchester, Simulação de Eventos Discretos, SIMUL8

Códigos de Classificação JEL: I11, M10

Abstract

In recent years, emergency departments (ED) all over the world have been suffering from overcrowding. Tto deal with this issue by reducing patient waiting times, the researchers used the discrete event simulation tool “SIMUL8” to create a general model of an ED-based on an inductive case study analysis.

Based on this analysis, 34 different variations of the base model were developed and tested. Through analysing the results of these scenarios, it was concluded that improving resource allocation and increasing the number of resources available to be the best ways to reduce patient waiting times.

Keywords: Triage, Manchester Triage System, Discrete-event Simulation, SIMUL8

JEL Classification System: I11, M10

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Glossary

ABS – Agent-based Simulation

ATS – Australasian Triangle scale

CTAS – Canadian Triage and Acuity Scale

ED – Emergency Department

ESI – Emergency Severity Index

DES – Discrete Event Simulation

MTS – Manchester Triage System

OM – Operations Management

SATS – South African Triage Scale

SD – System Dynamics

1 Introduction

This chapter will introduce a succinct view of the problem that leads to this study along with its context and relevance in society. It will also identify the objectives of this thesis along with its scope and the methodology used. The last subsection will provide the thesis' structure.

1.1 Research Problematic and Research Problem

Triage is a concept that has been fundamental in the practice of emergency medicine for more than fifty years (Iserson & Moskop, 2007). However, in recent years, Emergency Departments (ED) all over the world have been suffering from overcrowding (Hoot & Aronsky, 2008). This increasing number of patients creates the need for fast and accurate triage (Ghanes et al., 2015). Simulation in particular has become an effective tool in determining the most effective allocation of healthcare resources to improve patient flow and minimizing costs (Chouba et al., 2019). Also, using both optimization and simulation tools allows for more efficient decision making when determining optimal ED configurations.

Healthcare needs have been growing and healthcare services have become larger, more complex and more costly (Everborn, Flisberg, & Ronnqvist, 2005; Wang, 2009). Coupled with the intrinsic uncertainty of healthcare demands and outcomes this dictates that healthcare policy must be based on evidence of its potential to address said stochastic problems (Katsaliaki & Mustafee, 2011) they create a situation in which the use of simulation becomes a clear solution as it can be used to forecast the outcome in a change of strategy free of cost (Wierzbicki, 2007).

Barjis (2009) looks at the potential of modelling and simulation in healthcare and sees in them major potential in cost reduction, decision support (due to allowing for better-informed decision making) and as a way of tackling increased complexity created by the extreme mobility of patients.

Over the last ten years many studies have been done on the use of both simulation and optimization to improve the allocation of human and material resources in health care

(Ahmed & Alkhamis, 2009a); (Baghery, Abgarmi, Yousefi, & Alizadeh, 2017); (Steward, Glass, & Ferrand, 2017).

In Portugal, the Manchester Triage System (MTS) is the most common system used in EDs all around the country (Mackway-Jones, Marsden and Windle, 2014)

Considering this information, this thesis will focus on the current situation of triage in hospitals using the MTS and look for ways to decrease waiting times in the ED.

1.2 Research Gaps

Robinson (2008) identifies the difficulty of dealing with many different consumers with a wide variety of needs as one of the main challenges of service operations management when it comes to B2C (Business to Consumer) services, which is the case for a hospital. This issue often causes congestion in the service process.

To find new ways for overcoming these problems, a theoretical model of how a hospital's ED should function, based on the use of the MTS, will be created. This a problem mentioned in a paper about the evolution of triage (Robertson-Steel, 2006), the issue of how to sort patients following the allocation of priority levels during triage and whether to phase in, use appropriate time banding or simply wait for there to be no critical cases before dealing with minor injuries.

1.3 Objective

The purpose of this project is to, through the analysis of previous case studies, develop a theoretical simulation model of a hospital's ED. This model will then be used to test different combinations of internal factors (*e.g.* number of beds) and their ability to deal with the patients coming in.

Based on the context outlined in section 1.1, a literature review focusing on three main areas was conducted. First, on services, service operations management and its role in healthcare services management. Secondly, the beginning and present of triage were studied, along with papers on the MTS in order to understand the current reality in this type of triage and have a better way of identifying the issues behind overcrowding.

Finally, a look at simulation, some of its different types and on how to develop a conceptual model, all of them key in creating an accurate simulation model.

Since this thesis will be using an inductive approach in creating a simulation model of an ED-based on previous cases. The expected outcome will be the creation of hypotheses based on the developed model to be compared to existing literature and/or tested in future studies.

1.4 Research Questions

Eisenhardt (1989) identifies the need for an initial definition of the research questions as a means of avoiding being overwhelmed by the volume of data. To achieve the goals of the thesis, two research questions were defined as follows:

RQ1) What is the flow of a patient through an ED?

RQ2) What can be done to reduce waiting times in an ED?

1.5 Methodology

Exploratory research describes phenomena and attempts to explain why behaviours are the way they are, it enables us to understand the very nature of what we are looking at (Adams, Khan, Raeside, & White, 2012). Its primary purpose is to develop preliminary ideas about an issue or phenomenon and move toward refined research questions (Neuman, 2014). This thesis will be using exploratory research to develop enough understanding to create a simulation model of an ED that can be used to create hypotheses on its functioning to be tested in later studies.

The data needed to develop such a model will be gathered through an inductive approach. This type of approach's objective is developing a theory that begins with concrete empirical evidence and works toward more abstract concepts and theoretical relationships (Neuman, 2014). In inductive methods of data collection the researcher usually (1) systematically observes the phenomena under investigation, (2) searches for patterns or themes in the observations, and (3) develops a generalization from the analysis of those themes (Lodico, Spaulding, & Voegtle, 2006).

An investigation of case studies pertaining to ED functioning will be the first step taken in this thesis, its goal will be to gather the necessary quantitative data. The data gathered will pertain mostly to mapping the system flow, to determine the time it takes for each task, the population details and the number of resources available in an ED. After it is gathered, analysed and its patterns determined, this data will be used to develop the simulation model. From it, hypotheses to be tested in future studies will be created.

1.6 Structure

The structure of this project is divided into the following chapters:

Chapter 1: Introduction

Includes a brief contextualization of the problem, including research gaps. Identifies the objectives, research questions, methodology used and structure of this thesis.

Chapter 2: Literature Review

Through an analysis of previous investigations and existing literature, this chapter studies the existing theories on the relevant subjects.

Chapter 3: Conceptual Framework

Defines the concept, maps research and synthesizes the relevant aspects that emerged from the literature review in a schematic manner.

Chapter 4: Methodology

Explains the methodology adopted and the steps taken during the thesis development.

Chapter 5: Conceptual Model

Creation of a conceptual model representative of a real ED. Identifying relevant inputs and outputs of the simulation.

Chapter 6: Data Collection

Analysis of data obtained from previous studies.

Chapter 7: SIMUL8 Model Results

Identification and results of the base model and scenarios tested. Also contains an analysis of these results.

Chapter 8: Conclusion

Discusses the results of the analysis and connecting them to existing literature. Presents the conclusions reached, identifies the limitations of the thesis and suggest topics for future research.

2 Literature Review

The purpose of this chapter will be to show the theoretical foundations upon which this thesis will stand. This chapter starts by focusing on services. Afterwards, it focuses on triage, its beginning and evolution, and then the MTS specifically, in the end, it also looks at the different types of simulation and their uses as well how to create a conceptual model.

2.1 Services

Before looking at what service operations management is, we must first understand what services are. According to Bayraktar (2016) "service" is used to describe almost 80% of economic activities in developed countries, this is mentioned as a reason to why there is no single definition of what a service is. However, a consensus seem to be emerging around the idea that a service is an activity in which the costumer also performs an active role and which involves the treatment of said costumer or something belonging to him/her (Johnston & Kong, 2011).

Ravindran et al. (2018) identifies four key differences between goods and services:

- Intangibility: You cannot touch or see a service. Per example, you cannot see the knowledge gained by a student during a lecture.
- Perishability: Unlike services, goods can be produced ahead of time and stored. Empty seats on an airplane hold no value once the airplane takes off.
- Proximity: Most services must require physical proximity to its costumers (e.g. going to a movie or buying groceries). However, online services and back office operations are the exception as they do not require proximity.
- Simultaneity: Most services are created and consumed at the same time. Presence of a costumer is required in service production.

As it observes every one of these four conditions, treating patients in a hospital can be considered as a service.

Karmarkar (2004) mentions how competitive advantages can be enhanced through service and it is clear that competitive advantages lead to a superior performance (Lusch, Vargo, & O'Brien, 2007).

2.1.1 Service Operations Management

Now that we understand what services are and how important service operations management can be, it is time to provide a definition for service operations management: “Service operations management is the term that is used to cover the activities, decisions and responsibilities of operations managers in service organisations. It is concerned with providing services, and value, to customers or users, ensuring they get the right experiences and the desired outcomes. It involves understanding the needs of the customers, managing the service processes, ensuring the organisation’s objectives are met, while also paying attention to the continual improvement of the services. ” (Bayraktar, 2016, p. 12).

The definition above mentions how service operations management pertains to managers in services organizations, Daskin (2011) identifies healthcare as a service industry and therefore, hospitals as service organizations. With this in mind, the following sections will first look at process improvement (mentioned in the definition) and afterwards in the role of service operations management in healthcare.

2.1.2 Process Improvement

Competitiveness is the ability to compete which can arise from the process of an organization (Ajitabh & Momaya, 2003). Therefore, continuous improvement of production processes based on customer demands is necessary to increase or maintain competitiveness (Tamás, 2017). Only carrying out continuous improvements and adapting to external environment changes is enough to maintain long-term success (J. P. Womack & Jones, 1997). This is something that is also mentioned in the definition of service operations management given.

Bendell (2005) mentions how, to improve said processes and maintain competitiveness, some companies have been using the Lean Thinking approach.

2.1.2.1 Lean Thinking

Originating in Japan in the Toyota Motor company, lean is considered to be a radical alternative to the traditional mass manufacturing and batching principles maximize efficiency, quality, cost and speed (Radnor, Holweg, & Waring, 2012). According to Holweg (2007) this way of thinking has since spread from Japan to the rest of the world in part due to the book "The Machine That Changed the World" by James P. Womack, Jones, & Roos (1992).

The core philosophy behind Lean is to continually improve a process by removing non-value added steps or "waste". Womack and Jones (1996) however define the five "Lean Principles" to be followed when looking to remove "waste":

- Specify the value desired by the customer;
- identify the value stream for each product/service providing that value and, challenge all of the wasted steps;
- make the product flow continuously;
- introduce 'pull' between all steps where continuous flow is impossible;
- continuously strive for perfection through the systematic identification and removal of "waste".

Section 2.1.3.1 will look at the role of Lean in healthcare management.

2.1.3 Healthcare Services Management

Healthcare service management has to link together two different sets of interest, those focused on providing health services to the population and those focused on providing services to the individual (Packwood, 1997). This same paper also describes the different operational values of each ideology. Those focused on the population pay more attention to equality, equity, economy and resource management. Meanwhile, those focused on the individual pay attention to the needs of each patients and tend to disregard economic and resource constraints.

This clash of ideologies ties into Berry (2019) which identifies the cost pressure and need for quality service demanded by our societies, mentioning the urgent need for innovation as a solution. However, it is widely accepted that there is a trade-off between customer satisfaction and productivity (Rust & Huang, 2012). Despite the existence of this trade-off, Wirtz (2019) mentions some organizations that have been able to achieve both cost effectiveness and service excellence and identifies doing this as an objective for organizations worldwide.

Wirtz (2019) also mentions how, currently, the service sector and healthcare in particular seem to be in an inflection point when it comes to productivity gains, identifying as particularly promising innovations robotic, artificial intelligence, Internet of Things, wearable technology, analytics and geo tagging.

2.1.3.1 Lean in Healthcare

It is quite common for the principles of Operations Management (OM) to be used in the healthcare industry. Looking at the issues created by overcrowding and congestion in an ED Batt and Terwiesch (2012) consider the how ED physicians will order fewer tests if the ED is more crowded and Batt and Terwiesch (2015) analyse how overcrowding leads to a higher likelihood of patients leaving without being seen. Finding solutions to issues like these, caused by overcrowding, has been a common theme in healthcare OM literature. Among these proposed solutions we can find the idea of streaming patients based on the likelihood of admission (Saghafian, Hopp, van Oyen, Desmond, & Kronick, 2012); prioritizing patients based on probable resource usage (Saghafian, Hopp, Van Oyen, Desmond, & Kronick, 2014); introducing an expedited patient care queue to control admission to inpatient units (Helm, Ahmadbeygi, & Van Oyen, 2011); and using predicted future patient arrival as well as proactive admission control to effectively manage congestion (Xu & Chan, 2016). These suggestions are used as a way to reduce the “waste” of waiting (delay) identified as one in Westwood, Moore and Cooke (2007).

2.2 Triage

The idea of triage first appeared in the late seventeen hundreds during the Napoleonic wars to deal with the increased number of deaths and injuries associated with modern warfare. And that is exactly what triage did for some years. It was a tool used for war scenarios and introduced the ideas of patient sorting and care at the scene into the world. The system then continued developing mainly in military situations in the 19^{th} and 20^{th} centuries (Robertson-Steel, 2006).

During the early 20th century, organized medical systems started to emerge and with them so did triage which was a key component of care in emergency departments. In that time, however, triage was less standardized and thus more subject to the nurse's opinion. Its role was essentially the same as today: determining possible waiting times and sequence in which the patients should be seen, and if applied in the field it served for determining the speed of transport and which facility a patient should be transported to (Robertson-Steel, 2006).

Triage has evolved much from its inception, these innovations were created mainly in wartime scenarios. In the US civil war implementation of a triage system greatly reduced mortality from one year to the other. In WWI a new concept was introduced, unlike before where priority went to the most injured, except for those that were beyond hope. With the increase in casualties due to new weapons like mustard gas or machine guns, medical personnel also started to take into account the time needed to treat an injury and if it took too long (and that meant other patients might die) then that patient would also be disregarded. Nowadays, the mass evacuation of wounded is much more accessible and the scarcity of medical resources less likely. Creating a whole new set of options for on-field triage. However, the creation of weapons of mass destruction can render war triage virtually irrelevant due to the sheer number of casualties inflicted in an instant (Iserson & Moskop, 2007).

Currently, triage systems in civilian context with widespread adoption include the Australasian Triangle scale (ATS), Emergency Severity Index (ESI), Manchester Triage Scale (MTS), South African Triage Scale (SATS) and Canadian Triage and Acuity Scale (CTAS). All of these triage systems share some core elements: They all use a 5-level priority system that aims to assign higher priority to patients in critical need of care and assign appropriate waiting time limits for each priority level. However, they have some key differences, for example, the role of provider judgment, with the CTAS and MTS assigning less importance to it and focusing more on detailed clinical discriminators (Hinson et al., 2019).

Christ, Grossman and Winter (2010) identify the ED as "the crucial interface between the emergency medical services and the hospital" and shows how they are increasingly being chosen as the primary entry point into the healthcare system. It also mentions how triage aims to solve the problem inherent with an inability to accurately predict the volume of patient admissions: the possibility of overcrowding. The authors also identify the five-level triage systems as the gold standard in emergency healthcare.

Now, in the 21st century, the issue that needs resolving is the creation of an integrated triage system which encompasses ambulance service, pre-hospital care, general providers and advice centres that can be adopted universally (Robertson-Steel, 2006).

In Portugal, the MTS is the most common system used in EDs all around the country (Mackway-Jones, Marsden and Windle, 2014). It is also a part of the recommended five-level triage systems, which are considered to be valuable and reliable (Schaaf, Funkat, Kasch, Christoph, & Winter, 2014)

The MTS was created in 1996 by the Manchester triage group, they noticed that every day EDs were facing a large influx of patients with completely different issues and that therefore it was "absolutely essential that there is a system in place to ensure that these patients are seen in order of clinical need, rather than in order of attendance."(Mackway-Jones, Marsden, & Windle, 2014).

In this system, patients in an ED are initially screened by a nurse trained in the MTS. The nurse uses the 52 flowchart diagrams backed by the MTS in which a patient describes his/her symptoms and the nurse follows the chart in order to assign the patient with one of five priority levels. These priority levels determine the maximum amount of time allowed before the patient is seen by a doctor. Patients categorized into the highest priority (red) order must be seen immediately. The following two levels (orange and yellow) will have recommended time allowances of 10 and 60 minutes respectively. A patient assigned the fourth highest priority (green) will have a time allowance of 120 minutes and the lowest level priority patients (blue) will have time allowances of 240 minutes, henceforth these will be called MTS levels 1 to 5 (with 1 being the highest priority). The flowcharts mentioned above were created around six general discriminators: life threat, conscious level, haemorrhage, temperature, pain and acuteness. The flowcharts also take into account the age of patients (Weiss et al., 2004). In figure 1 we can see one of these flowcharts used to determine the MTS level of a patient presenting with symptoms for asthma.

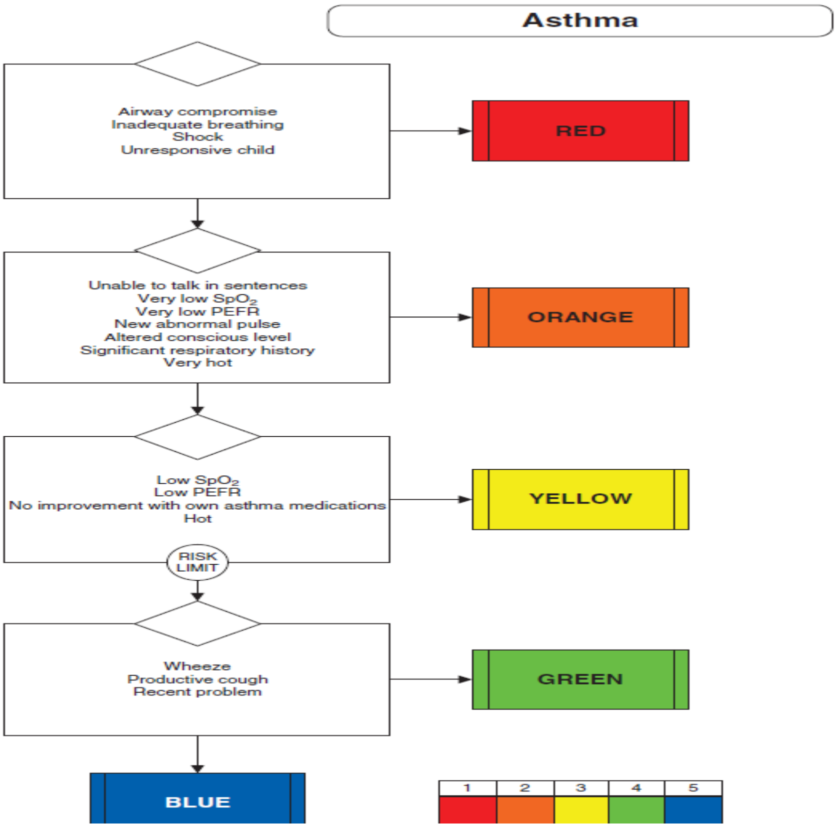

Figure 2.1 - Example of an MTS flowchart pertaining to patients with symptoms related to asthma. Source: Mackway-Jones, Marsden and Windle (2014)

Since its widespread adoption, the MTS has been the subject of many studies aiming to test its validity in several scenarios:

The MTS, when studied without a focus on patients with specific conditions, was shown to be able to not only correctly prioritise the care of higher acuity patients but also accurately predict the evolution of patient conditions while in the facilities (Júnior, Salgado, & Chianca, 2012). In addition, when compared to an institutional protocol that raised the classification level when there were disagreements on classification the MTS was found to be more inclusive (Souza & Toledo, 2011).

Santos *et al.* (2013) concluded that both hospitalization and death were more likely in high priority patients (red or orange) compared to low priority (yellow, green or blue) by 5 and 5.5 times respectively. This paper also determined that the MTS was a good discriminator in the use of diagnostic tools in the ED.

Martins et al. (2009) acknowledged the importance of the MTS when distinguishing between patients with a low and high risk of death in the short term and in identifying patients requiring 24h hospitalization.

Wulp, Schrijvers and Stel (2009) and Storm-versloot et al. (2011) both tried to compare the MTS with the Emergency Severity Index (ESI). The results of both papers determined that both tools were useful in predicting entry into ED and that they had similar validity. However, the MTS had a lower rate of undertriage.

Undertriage into yellow and orange priority levels were a serious issue with the MTS. This was especially the case in elderly patients as the symptoms manifested atypically (Wulp, Baar, & Schrijvers, 2008).

The MTS was reported being moderately sensitive in paediatric patients but that in this age-group overtriage was much more common that undertriage (Seiger et al., 2011). This same report also mentions how specific modifications should be done to the MTS specifically for situations of paediatric care.

2.3 Simulation

Saunders, Makens and Leblanc (1989) said that system simulation is an infinite potential tool to plan how to allocate resources without changing the actual resources in the system. It is used to analyse and describe the behaviour of a system, as well as aiding in designing a real system (Mandahawi, Shurrab, Al-Shihabi, Abdallah, & Alfarah, 2017).

Kelton (1999) defined system simulation as a process to recreate the actual system through computer technology. The author suggested that “The real meat of a simulation project is running your model(s) and trying to understand the results. To do so effectively, you need to plan ahead before doing the runs, since just trying different things to see what happens can be a very inefficient way of attempting to learn about your models’ (and hopefully the systems’) behaviours’”. While also mentioning how simulation can, if well planned, yield valuable information with little effort and in little time.

2.3.1 Stochastic Models

A stochastic model utilizes random number generators to simulate chance or random events. "When one studies a stochastic process, he is interested in the average level of activity, deviations from this level, and how long these deviations last, once they occur” (Maguire, 1972). Stochastic systems typically use Monte Carlo methods, which rely on the assumption that probabilistic components have distributions that can be used to obtain inputs for the computation through a random number generator. Therefore, although a single run of the simulation would not be representative of the model outcomes, running the simulation a large number of times will yield output values following a distribution that will characterize the model's behaviour (Harrison, Carroll, & Carley, 2007).

2.3.2 Deterministic Model

Unlike stochastic models, deterministic models will have no probabilistic elements and therefore only a single run need be made for each given model, as the same inputs will always yield the exact same result (Harrison et al., 2007).

Stevens *et al.* (1996) define computer experiments using deterministic models as unreplicated, factorial experiments. Where an unreplicated experiment occurs when there is only one independent sampling of each treatment.

2.3.3 Dynamic Simulation Models:

A complex system can adapt to changes in its local environment, behaves in a non-linear fashion and is composed of other complex systems (a good example would be the human body). Additionally, the system's behaviour is different from that of its individual parts. Unlike more conventional methods, dynamic simulations incorporate the complexity of a system and anticipate changes in said complex systems (Marshal *et al.*, 2015). This type of system is used when trying to create mathematical representations of processes and systems. Their goal is to study different interventions and experiments to the system and analyse their consequences over time, leading to a better understanding of the system processes and allowing for better-informed management and policy design. (Harrison et al., 2007).

Marshal *et al.* (2015) identify three modelling methods of dynamic simulation as the most appropriate when evaluating system interventions in healthcare:

2.3.3.1 System Dynamics (SD)

SD was developed in the 1950s “with the goal of using science and engineering to identify the core issues that determine the success and failure of corporations (Marshall *et al.*, 2015).

This model focuses on modelling the behaviour of the system as a whole, rather than modelling the behaviours of actors within the system (Battersby & Forrester, 1963). SD simulates the processes that lead to changes in the system over time (Harrison et al., 2007). The core elements of SD are accumulations, rates, time-delays and feedback. An important characteristic of these systems is nonlinearity caused by the existence of feedback processes, meaning that an effect is seldom proportional to its cause (Marshall *et al.*, 2015). Qudrat-ullah (2012) identifies as the most important part of SD modelling the identification of how structure and decision policies help to generate patterns of behaviour in the system. He also defends that the most appealing feature of SD modelling is linking observable behavioural patterns in a system with micro-level structures and decision-making processes.

2.3.3.2 Discrete Event Simulation (DES)

Discrete evens systems are dynamic systems in which time passed through the occurrence of events at either regular or irregular intervals. Therefore, it resembles real-world production and as such it has been used in a wide array of areas, such as banking, manufacturing and distribution systems (Mandahawi et al., 2017). It has even been used in healthcare applications, for example, a model was developed to improve radiation therapy planning processes (Werker, Sauré, French, & Shechter, 2009).

DES is used to study queueing processes and networks of queues focusing on resource utilization (Siebers, Macal, Garnett, Buxton, & Pidd, 2017). DES focuses on four main concepts: events, entities, attributes and resources.

- Events are something that happens at determined time points and can affect entities and/or resources;

- Entities are objects that have attributes and consume resources when there is an event. They are passive entities as they have no initiative to make decisions and instead things are done to them as they move through the system;
- Attributes are the unique characteristics of each entity; they can change over time or not;
- Resources are the objects that provide a service to the entities.

Essentially, DES is a simulation in which entities with specific attributes and availability to a group of resources are subject to change as they pass through the system and experience events at set time points.

DES is considered to be well suited to problems in which capturing the changing attributes of entities is particularly relevant, per example patients and their condition (Marshall *et al.*, 2015), hence its popularity and widespread acceptance by decision-makers in healthcare operations planning (Noorain, Kotiadis, & Scaparra, 2019). This is why, in this thesis, SIMUL8, which uses DES, will be utilized.

2.3.3.3 Agent-based Simulation (ABS)

ABS is a simulation method for modelling dynamic, adaptive, and autonomous systems (Gunal, 2017). This model is used to discover systems by using both deductive and inductive reasoning. The main elements of ABS are the agents, the simulated environment and the simulation environment Agents are the entities looking to achieve their goals through interactions with other agents and/or the simulated environment. The simulated environment is where both agent and non-agent entities are encountered, in ABS there must be at least one simulated environment. The simulation environment is an environment for simulating ABS models, it controls the specific simulation time advance and provides message passing facilities and directory services (Gürcan, Dikenelli, & Bernon, 2013).

ABS is commonly used to predict the behaviour of large populations, through the coding of predefined behaviours into agents it looks to predict how a population following said behaviours and the environment in which it resides would adapt and evolve over time (Marshall *et al.*, 2015).

Aspect	Method: System dynamics	Discrete-event simulation	Agent-based modeling
Type of problems	Strategic, operational	Operational, tactical	Strategic, operational, tactical
Perspective	System-oriented, emphasis on dynamic complexity (top–down)	Process-oriented, emphasis on detail complexity (top–down)	Individual-oriented, dynamic and detail complexity (bottom–up)
Resolution	Homogeneous entities, continuous policy pressures and emergent behavior	Individual heterogeneous *passive* entities, attributes, and events	Individual heterogeneous *active* agents, decision rules
Origin of dynamics	Deterministic endogenous fixed structure	Stochastic endogenous fixed processes	Agent–agent, agent–environment interactions and adaptive behavior of agents
Handling of time	Continuous	Discrete	Discrete
Approach	Exploratory and explanatory	Explanatory	Exploratory and explanatory
Basic building blocks	Feedback loops, stocks, and flows	Entities, events, queues	Autonomous agents, decision rules
Data sources	Broadly drawn: qualitative and quantitative	Numerical with some judgmental elements	Broadly drawn: qualitative and quantitative
Unit of analysis	Feedback loops and stocks' dynamics	Queues, events	Decision rules, emergent behavior
Mathematical formulation	Differential equations	Mathematically described with logic operators	Mathematically described with logic operators and decision rules
Outputs	Understanding of structural source of behavior modes, patterns, trends, relevant structures, aggregate key indicators	Point predictions, performance measures	Detailed and aggregate key indicators, understanding of emergence due to individual behavior, point predictions
Model maintenance	Upkeep may require large structure modifications, global	Upkeep may require process modifications, global. Allows for local modifications regarding individual heterogeneity	Upkeep may require simple local modifications
Development time	Dependent on the problem, purpose, and scope of the model; these models may require less time to be developed	These models are more data intensive. This requires more time regarding obtaining data and data analysis to prepare model inputs. Programming and calibration are usually very time consuming	These models can be data intensive, which requires data analysis and time to obtain the data. Programming and calibration are usually very time consuming
Cost	In general, SD is less costly than are DES and ABM. This involves data requirements, and skill sets needed	Because of costs associated with data and skill sets required, these methods tend to be more costly than is SD	If the model is data intensive or requires primary data collection, costs may increase. Skill sets required may also increase the costs

ABM, agent-based modeling; DES, discrete-event simulation; SD, system dynamics.

Figure 2.2 - Comparison of Dynamic simulation modelling methods. Source: Marshall et al. (2015)

In Figure 2 we can see a comparison between the three types of simulation mentioned above. The table shows how time-consuming and how costly each simulation is and at the same time what the perspective of each is. It can be used as a faster way of comparing each type of simulation and determine which is more useful for a specific problem.

2.3.4 Model Design

A simulation for a hospital's ED can have a lot of different levels of detail and complexity. It can be quite simple if it focuses solely on queues and triage, and it could be expanded to include things like seating area, empty beds, available staff, medical supplies' availability, etc. To determine the scope of the model created for this thesis, the steps outlined to create a conceptual model in chapters 5 and 6 of Robinson (2008) will be used.

Proper development of a conceptual model is the key in expressing the context, elements, relationships, limitations and purpose of the simulation study (Cetinkaya, Verbraeck, & Seek, 2010). The conceptual model will determine the data requirements, the speed with which the model can be created, the speed of experimentation, the confidence in the results and the validity of the model (Robinson, 2008). A well-designed model will increase the likelihood of the simulation meeting its objective considerably.

Robinson (2008) Considers the key components of the model to be:

- Objectives: the purpose of the model and modelling project.
- Inputs: those elements of the model that can be altered to affect an improvement in, or better an understanding of, the real world; otherwise known as the experimental factors.
- Outputs: report the results from simulation runs.
- Content: the components that are represented in the model and their interconnections.
- Assumptions: made either when there are uncertainties or beliefs about the real world being modelled.
- Simplifications: incorporated in the model to enable more rapid model development and use.

2.3.5 Representing the Conceptual Model

Being able to visually represent the conceptual model is very important when creating one, Robinson (2008) suggests four main methods of representation:

- Component list;
- Process flow diagram;
- Logic flow diagram;
- Activity cycle diagram.

2.3.5.1 Component List

This provides a list of all the components in a model along with some detail on each of them. Although it is very simple, it does not provide a visual representation of the model and is, therefore, less suited to capture complex logic and the process flow.

2.3.5.2 Process Flow Diagram

We can view the process flow as a complex network with split, parallel, closed and re-entrant services (Li & Howard, 2010). A diagram of this process flow shows each component in the system along with some detail on it. These components are shown in a sequence. The visual representation makes it easier to understand the model. Many simulation options use this method, including SIMUL8.

2.3.5.3 Logic Flow Diagram

This diagram represents the logic of the system rather than the process flow. While the process flow diagram shows how the entities move through the system, the logic flow diagram shows why they do so in that order.

2.3.5.4 Activity Cycle Diagram

This method is considered to be somewhere in between the process flow and the logic flow diagrams because they describe, in part, the logic of a model while also providing a visual representation. Robinson *et al.* (2010) identify their usefulness in identifying events, entities and activities.

3 Conceptual Framework

The conceptual framework is the researcher's idea of how the research problem will have to be explored (Upadhyay, 2015). It allows researchers to define the concept, map research and synthesize the relevant aspects that emerged from the literature review in a schematic manner (Rocco & Plakhotnik, 2009). With this in mind, the conceptual framework (Figure 3.1) was created with a basis on the literature review. Through an analysis of previous studies, the goal will be to collect data on the variables shown in Figure 3.1. The data collected will first be used to identify how an ED functions and develop a conceptual model for the simulation, through the use of information on patient flow. Then it will serve to determine the distribution functions that will be introduced into the model when developing the simulation. The model creation will be done through the use of a discrete-event simulation tool called SIMUL8 as it is a type of simulation that is widely accepted in healthcare due to its usefulness in capturing the changing attributes of entities (*see section 2.3.3.2).* Afterwards, this model will be used to look at the relationships between different factors in the ED and develop theories based on the observed relationships. These theories will then be compared to existing literature. From this comparison, suggestions for future studies will emerge.

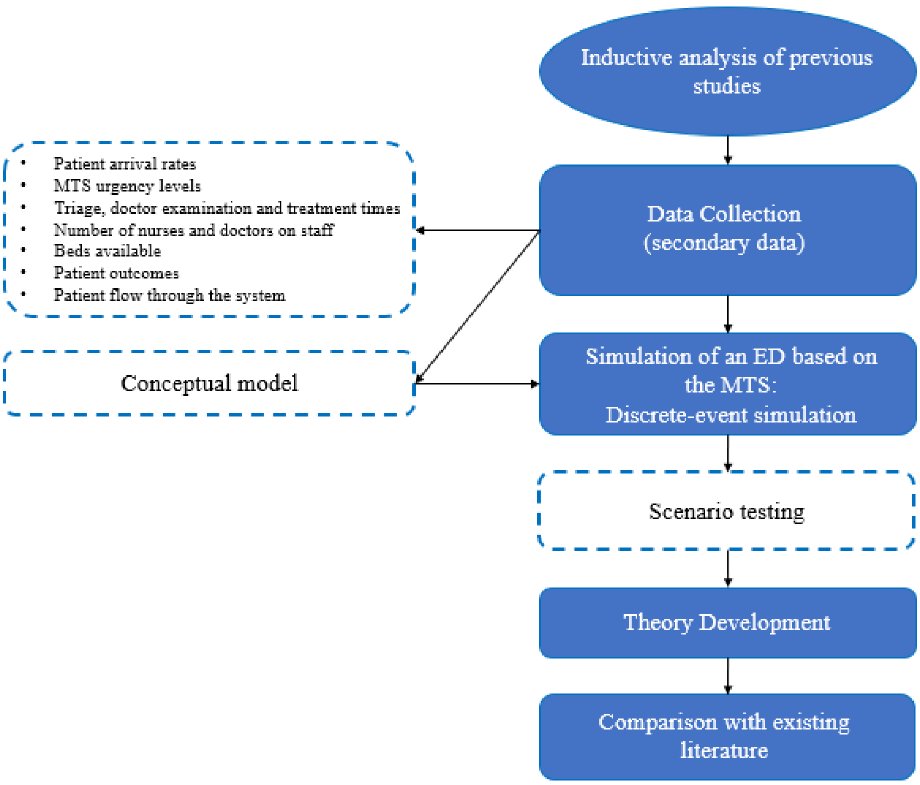

Figure 3.1 - Conceptual Framework

4 Methodology

This chapter aims to present this thesis' methodology. The first step will be to take a look at existing case studies on the functioning of EDs and take the relevant data from them. Afterwards, the data collected will be analysed and used to develop a simulation model. From this model many different scenarios will be tested and with the results, theories will be generated.

4.1 Inductive Analysis of Case Studies

Eisenhardt (1989) defines this approach as a research strategy which focuses on the dynamics present within single settings. This type of research consists of analysing existing cases without any preconceived notions, and theory building based on this analysis. Its primary purpose is to develop preliminary ideas about an issue or phenomenon and move toward refined research questions (Neuman, 2014). This thesis will be using exploratory research to develop enough understanding to create a simulation model of an ED that can be used to create hypotheses on its functioning to be tested in later studies.

This analysis will consist of four steps:

1. Collecting data;
2. Developing the simulation model;
3. Analysing results and theory development;
4. Comparison with existing literature.

4.1.1 Collecting Data

The data collection was done through an inductive approach of existing case studies on ED functioning, the data collected can therefore be considered as secondary as it is "data collected from a source that has already been published" (Kabir, 2016, p. 205). As suggested in Eisenhardt (1989), the case selection was done through theoretical sampling where the papers chosen were the ones that provided relevant information to be introduced into the simulation model. The data collected from these papers was both qualitative and quantitative, and aimed at understanding the patient flow through the system and how long each activity takes.

4.1.2 Development the Simulation Model

The simulation model was developed as suggested in Robinson (2018) by first developing a conceptual model of the simulation (*vide section 5*). The focus here will be to map the patient flow through the system.

After designing the conceptual model, the actual simulation model was created using the simulation tool SIMUL8. Based on the data collected from previous studies, this model attempts to represent the average reality of an ED. In this model, the time between arrivals of patients and the time it takes for each activity to be performed was introduced into the system.

Due to the seemingly large differences in time it takes for each activity depending on the case study looked at, a series of scenarios was created with the goal of recreating these different realities.

4.1.3 Analysing results and theory development;

This step consists of comparing the results of the different scenarios of the simulation and developing theories based on them. These results focus mainly on the time patients spend waiting while in the system.

4.1.4 Comparing with existing literature

An essential part of theory building, the comparison of the emergent theories with the extant literature involves asking what the theory is in accordance with, what it contradicts and why (Eisenhardt, 1989).

From this comparison along with the theories developed, the suggestions for future studies will emerge.

5 Conceptual Model

Designing an appropriate conceptual model is seen as one of the most important parts of simulation (Cetinkaya et al., 2010; Robinson, 2008). In order to do so, this thesis will follow the steps suggested by chapters 5 and 6 of Robinson (2018). Figure 5.1 provides an outline of a framework for conceptual modelling. It focuses on four key elements:

1. Develop an understanding of the problem situation;
2. Determine the modelling objectives;
3. Design the conceptual model: inputs and outputs;
4. Design the conceptual model: the model content.

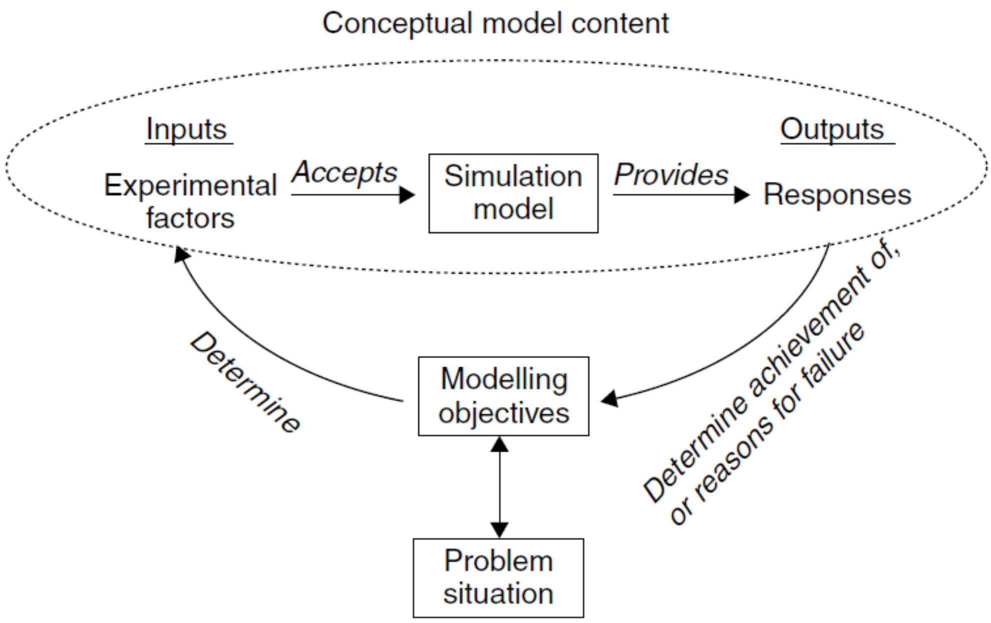

Figure 5.1 - Framework for Conceptual Modelling. Source: Robinson (2008)

5.1 Problem Situation

The problem addressed in this thesis is the issue of overcrowding identified in Pereira *et al.* (2001); Amorim *et al.* (2019) and numerous other papers. Weiss *et al.* (2004) looks at a lot of possible reasons for overcrowding such as an inadequate nurse-patient ratio or ineffective policies when diverting patients. Amorim et al. (2019) considers some of the main reasons for it to be mismanagement of patient flow, lack of access to inpatient beds, demand from patients for specialized care instead of primary care, absence of or reduced access to primary care, and structural failure of the healthcare system to manage population health.

5.2 Modelling Objectives

The objective of this simulation will be to explore the way an ED works and figure out the relationship between elements of the system along with encountering ways of reducing patient waiting times and minimizing the number of patients exceeding their recommended time allowances, said allowance is determined by their MTS urgency level (*vide section 2.2*).

5.3 Inputs and Outputs

Hospitals could be viewed as simple input-output systems whereby patients arrive from different sources, take different treatment routes, and are discharged (Gunal, 2017). Before introducing any information into the simulation, the researcher will try to gather data on several inputs that will help in identifying said sources and routes. Those variables will be:

- Patient arrival rates
- MTS urgency levels
- Triage, doctor examination and treatment times
- Number of exams needed
- Exam times
- Number of nurses and doctors on staff
- Number of beds available
- Patient outcomes
- Patient flow through the system

By inputting the mentioned variables into the simulation model, the outcomes which will be analysed are:

- Time spent in queues;

- Time spent in the system;
- Resource utilization

5.4 Model Content

Having identified the model's inputs and outputs, the modeller can identify the content of the model itself. In this section, both the scope and the level of detail of the model will be specified through Tables 5.1 and 5.2 respectively. According to (Robinson, 2008) the scope of the model must be sufficient to provide a link between the inputs and outputs, and the level of detail must be such that it represents the components defined within the scope and their interconnection with the other components of the model with sufficient accuracy.

Table 5.1 - Model Scope

Component		Include/exclude	Justification
Patients		Include	Flow through the system
Staff	- Nurses	Include	Input, required for resource utilization
	- Doctors	Include	Input, required for resource utilization
	- Janitorial staff	Exclude	Not relevant for waiting times
	- Receptionist	Exclude	Disregarded due to lack of information
Supplies	-Testing	Include	Important in determining time in the system
	- Beds	Include	Input, required for resource utilization and determining space in the ED
	- Medical Supplies	Exclude	Not relevant for waiting times, assume there are no shortages
Queues		Include	Required for waiting time and queue size response

Table 5.2 - Model Level of Detail

Component		Include/exclude	Comment	Source
Patients	Patient inter-arrival times	Include	Modelled as distribution	(Ortiz Barrios & Felizzola Jiménez, 2016; Weng, Cheng, Kwong, Wang, & Chang, 2011)
	Patient age and gender	Exclude	Lack of data to accurately correlate with MTS level	(Moreira, 2010; Zachariasse et al., 2017)
	Patient issue/disease	Exclude	Lack of data to accurately correlate with MTS level	(Steiner et al., 2016; Zachariasse et al., 2017)
	Patient MTS level	Include	Determines priority in queues	(Anziliero, Dal Soler, Silva, Tanccini, & Beghetto, 2017; B. Martins & Filipe, 2020)
	Mode of arrival	Include	Assume all urgency category 1 come through ambulance and skip triage	(Brenner et al., 2010; Mandahawi et al., 2017)
	Outcome	Include	Model exit points	(Maningas, Hime, & Parker, 2006; Steiner et al., 2016)
Nurses	Triage time	Include	Modelled as distribution	(Improta et al., 2018; Weng, Tsai, Wang, Chang, & Gotcher, 2011)
	Absenteeism	Exclude	Assume perfect attendance	(Weng, Cheng, et al., 2011)
Doctors	Examination time	Include	Modelled as distribution	(Chen, Guo, & Tsui, 2020; Weng, Cheng, et al., 2011)
	Treatment time	Include	Modelled as distribution	(Chen et al., 2020; Ramos & Paiva, 2017)
	Absenteeism	Exclude	Assume perfect attendance	(Weng, Tsai, et al., 2011)
Tests	Testing time	Include	Modelled as distribution, assume materials required are always available	(Brouns et al., 2019; Mandahawi et al., 2017)
Beds	Number of beds	Include	Relevant in determining space in the system	(Nishi, Polak, & Cruz, 2018; Zeinali, Mahootchi, & Sepehri, 2015)
Queues	Queuing	Include	Required for waiting time and queue size response	(Mandahawi et al., 2017; Weng, Cheng, et al., 2011)
	Queue behaviour	Include	Assigning priorities depending on MTS level	
	Capacity	Exclude	Assume no capacity constraints	

5.5 Representing the Conceptual Model

As part of the project specification, it is important to have a means for representing the content of the conceptual model (Robinson, 2008). This section will therefore represent the conceptual model using the methods explained in section 2.3.4. The diagrams that will be shown have been developed through the analysis of previous case studies and how they describe the way their observed ED works. The articles used for determining the patient flow through the system were Martin *et al.* (2011); Schaaf *et al.* (2014); Storm-Versloot *et al.* (2014); Rutman *et al.* (2015); Mandahawi *et al.* (2017); Improta *et al.* (2018); Amorim *et al.* (2019); and Martins and Filipe (2020). All these cases identify the main path through the system as follows: Arrival > Triage > Doctor consultation/exams > treatment > discharge/admission. Doctor consultation and exams are considered as one for two reasons: firstly, because exam need varies from patient to patient, some might not even require it; secondly, because they are interconnected in the sense that a patient must first have a consultation before being sent for testing, and then must return for another consultation. However, while they all share this overall path, some of them are more complex than others. Something to be considered when developing the simulation in this thesis is the existence of a separate room for patients who come in by ambulance and are given a MTS level 1 (red) urgency level (Amorim et al., 2019; Mandahawi et al., 2017; Schaaf et al., 2014). Another possibility to be looked at a possible solution is creating another separate room to deal only with patients who have MTS levels 4 and 5 of the MTS and allocating doctors and nurses to it (Mandahawi et al., 2017).

5.5.1 Process Flow Diagram

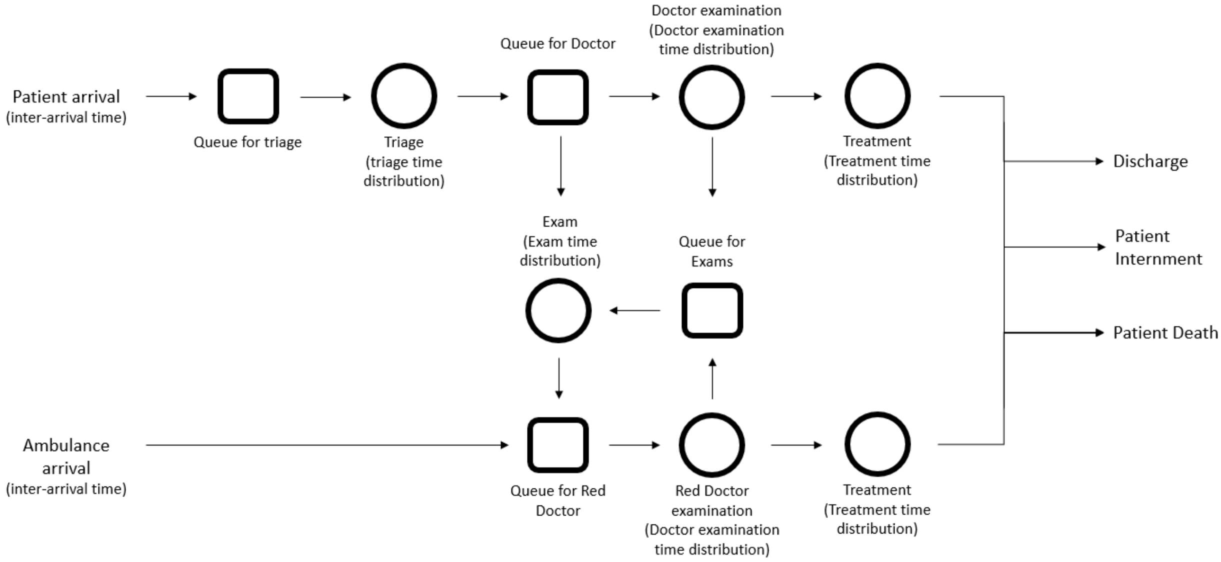

Figure 5.2 - Process flow diagram of the conceptual model
Source: Adapted from Robinson (2008) with information from Martin et al. (2011); Schaaf et al. (2014); Storm-Versloot et al. (2014); Rutman et al. (2015); Mandahawi et al. (2017); Improta et al. (2018); Amorim et al. (2019); and Martins and Filipe (2020)

Figure 5.2 is used to show in a more simplified manner the components of the system along with small details that are relevant to them. These components are shown in a sequence (as indicated by the arrows). The system will therefore have two entry points (by ambulance and by walk-ins) and three possible exit points (death, internment and discharge). In between these, patients will be seen in triage and afterwards by a doctor who, if need be, will prescribe exams and afterwards treat patients. If a patient comes in by ambulance it will be assumed that he is a category one patient and will therefore be sent directly to a specialized room and treated by a doctor assigned solely to MTS level 1 patients, these doctors will henceforth be called “red doctors” to differentiate from others treating MTS levels 2 to 5. In Figure 5.2, squares are used to represent dead states, where a patient waits for something to happen and circles represent active states, where a patient is acted upon (Robinson et al., 2010). The distributions mentioned next to the active states will be defined in the section dealing with data analysis as they will be created based on the result of said analysis.

5.5.2 Logic Flow Diagram

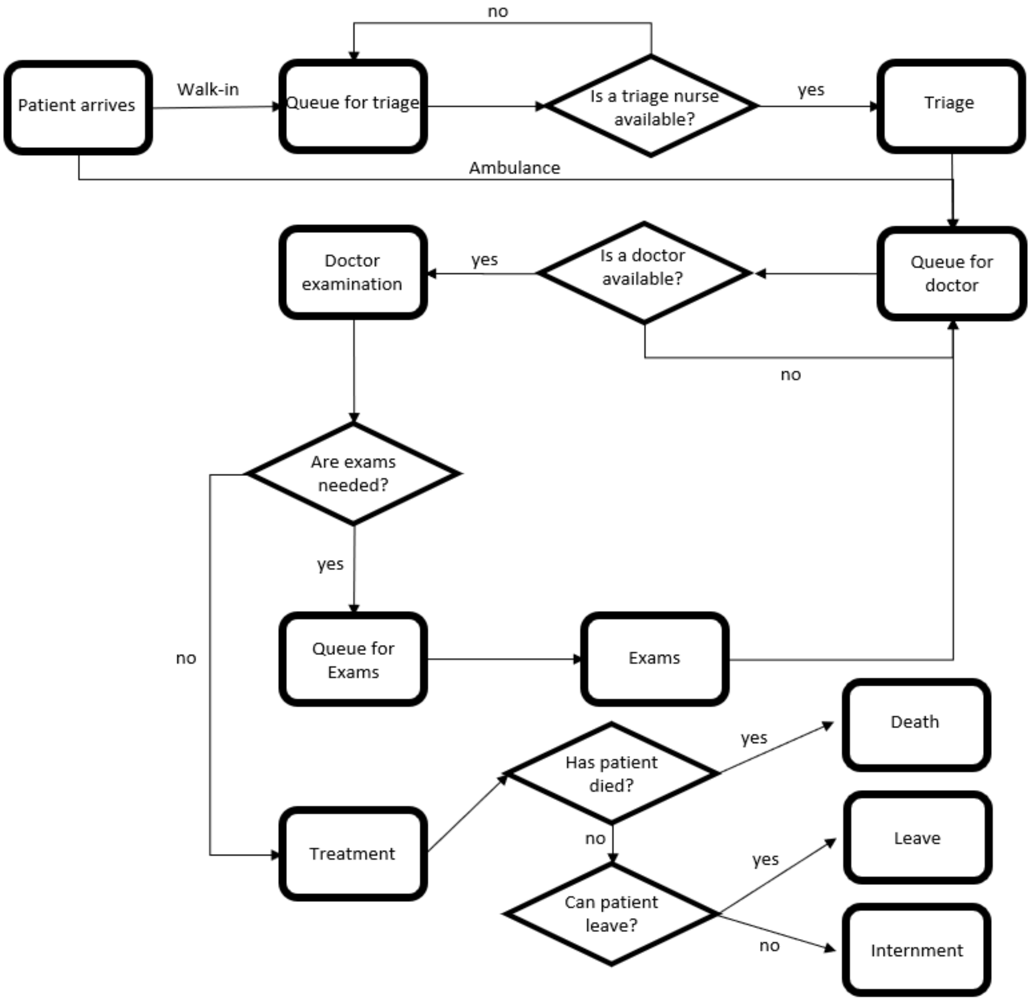

Figure 5.3 - Logic flow diagram of the conceptual model
Source: Adapted from Robinson (2008) with information from Martin et al. (2011); Schaaf et al. (2014); Storm-Versloot et al. (2014); Rutman et al. (2015); Mandahawi et al. (2017); Improta et al. (2018); Amorim et al. (2019); and Martins and Filipe (2020)

Figure 5.3 shows the logic behind the process flow diagram. It explains when and why patients move from one process to the other. In this diagram, the difference between red doctors and the other doctors is not shown as the logic behind their movement is the same once it reaches the queue for doctor examination. The only place where that difference can be seen in Figure 5.3 is in the arrow from "patient arrival" to "queue for bed/doctor" that shows the path for patients coming in an ambulance.

5.5.3 Activity Cycle Diagram

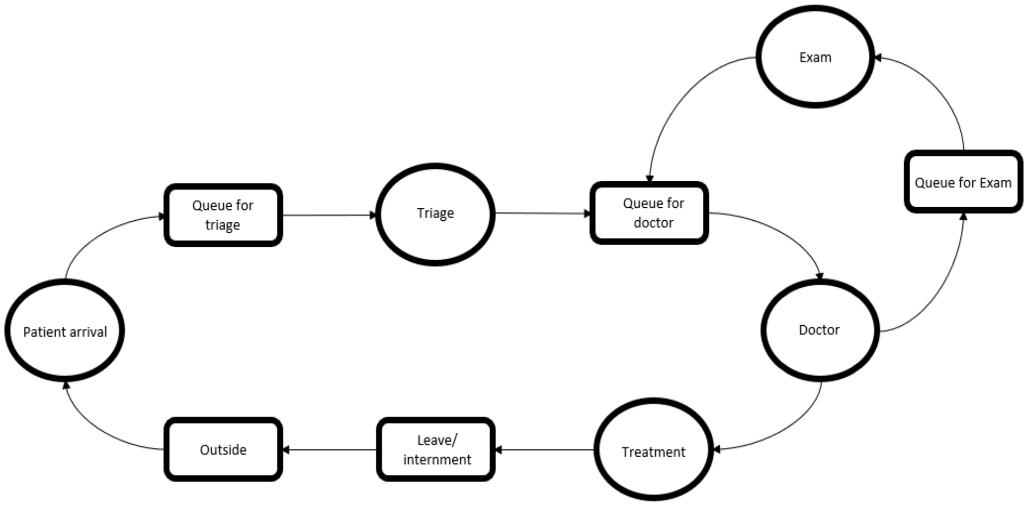

Figure 5.4 - Activity cycle of the conceptual model
Source: Adapted from Robinson (2008) with information from Martin et al. (2011); Schaaf et al. (2014); Storm-Versloot et al. (2014); Rutman et al. (2015); Mandahawi et al. (2017); Improta et al. (2018); Amorim et al. (2019); and Martins and Filipe (2020)

In Figure 5.4, just like Figure 5.2, rectangles represent dead states and circles represent active states. A dead state of ‘‘outside’’ the model is included to create a complete activity cycle, that is, customers come from and are returned to the ‘‘outside’’. Once again, to simplify the comprehension of the diagram, the distinction between MTS level 1 patients and the rest was not mentioned as the overall activities are the same with the exceptions of waiting in the queue for triage and the triage itself.

5.5.4 Assumptions

To develop this simulation, a series of assumptions had to be made. This section serves the purpose of identifying them. The following is a list of said assumptions:

1. All ambulance patients skip triage and go directly to a different room (Mandahawi et al., 2017), as there is a lack of information on the MTS levels of ambulance patients, it is assumed they have the highest urgency, level 1;
2. Receptionists and time spent registering a patient are not considered due to a lack of data on the subject; Martin et al. (2011) mentions the fact that patients go through receptionists but then also disregards them in his model;
3. Assume infinite queue capacity;
4. Every nurse is equally qualified (Weng, Cheng, et al., 2011);

5. Every doctor is equally qualified (Weng, Cheng, et al., 2011);
6. There is never a lack of the required medical supplies. “Emergency department planning and resource guidelines. Policy statement,” (2014) published in “Annals of emergency medicine” identifies more than forty items needed (not counting drugs), simulating all of them would overcomplicate the system and be outside of this model’s scope;
7. Assume exams depends solely on the availability of a nurse (due to lack of available data on testing machines) (Weng, Cheng, et al., 2011);
8. No problems in staff scheduling (Weng, Cheng, et al., 2011);
9. Patients don’t leave unseen, even with long waiting times (Weng, Cheng, et al., 2011);
10. Even though death normally could happen at any time, due to data constraints it will be assumed that patients can only die after going through the system.

6 Data Collection

Inductive analysis refers to approaches that primarily use detailed readings of raw data to derive concepts, themes, or a model through interpretations made from the raw data by an evaluator or researcher (Thomas, 2006). It is an analysis in which the researcher begins with an area of study and allows the theory to emerge from the data (Ozanne, Strauss, & Corbin, 1992). Despite a lack of availability of raw patient data, this chapter will be outlining the values observed and utilized by previous researchers on the inputs mentioned in Table 2 above.

The data collected comes from 29 different studies written in between 2006 and 2020.

6.1 Arrival Rates

When studying the arrival rates of patients in EDs, as with most other data collected, the information available and the way it was presented varied from study to study. Some authors chose to share the distributions they used at each time interval (e.g. Weng, Cheng, *et al.*, 2011; Mandahawi *et al.*, 2017) while others simply provided the number of observations and the time period. For the first ones, the 95% confidence intervals and averages for both days and hours have been calculated. For the second ones the confidence intervals were impossible to determine. Therefore, only the daily and hourly average rates were determined. Table 6.1 shows the results of this analysis.

Table 6.1 - Average daily and hourly rates of arrival for patients

Author	Daily			Hourly		
	-95%	Average	95%	-95%	Average	95%
(Weng, Cheng, et al., 2011)	127,1	129,5	131,8	5,3	5,4	5,5
(Mandahawi et al., 2017)	486,9	491,2	495,4	20,3	20,5	20,6
(Zachariasse et al., 2017)		684,9			28,5	
(Steiner et al., 2016)		80,2			3,3	
(Van Veen et al., 2008)		44,6			1,9	
(M. N. Storm-Versloot, Ubbink, Chin A Choi, & Luitse, 2009)		84,9			3,5	
(Santos et al., 2013)		210,2			8,8	
(Nishi et al., 2018)		547,9			22,8	
(Almeida & Vales, 2020)		321,6			13,4	
(Ramos & Paiva, 2017)		411,0			17,1	
(Improta et al., 2018)		92,0			3,8	
(Maningas et al., 2006)		158,7			6,6	
Average		263,6			10,98	

The last row shows the average of those studies, weighted regarding the number of observations from which the values were calculated. In the end we will have an average of 263,6 patients per day entering the system

Another factor that is considered relevant when forecasting patient arrivals are the days of the week (McCarthy et al., 2008; Wargon, Casalino, & Guidet, 2010; Whitt & Zhang, 2017). From these three studies, the percentages of all weekly arrivals that come in each day were calculated.

The final factor that will be used to determine the arrival rate to the ED will be the hour of the day. Many authors identify this as an important differentiating factor for arrivals (Chen et al., 2020; Green, Soares, Giglio, & Green, 2006; McCarthy et al., 2008; Weng, Tsai, et al., 2011; Whitt & Zhang, 2017). However, due to a lack of raw data, the difference between the arrival rates of each hour had to be determined through the graphics supplied by these papers.

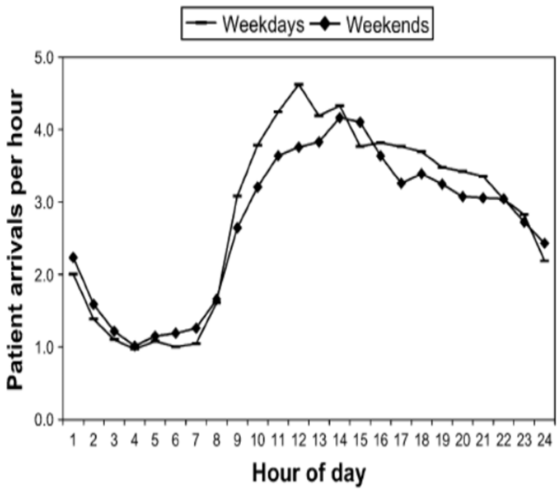

Figure 6.1 - Patient arrival pattern over a 24-h period. Source: (Green et al., 2006)

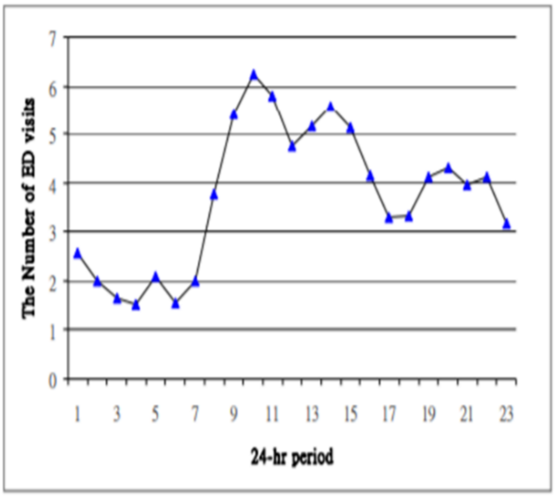

Figure 6.2 - Patient arrival pattern over a 24-h period. Source:(Weng, Tsai, et al., 2011)

The graphics pertaining to the arrival rates per hour from all five papers mentioned (e.g. Figures 6.1 and 6.2), although not exactly the same, all showed a low number of visits up until 7, then a sharp increase from then on usually peaking at around 11. From there it usually decays at a lower rate from hours 13 to 24. From the graphics of all five papers mentioned earlier, the arrival rates at every 2 hours were taken and an average calculated, from there the percentage of arrivals for each hour calculated. The results of this process can be seen in Table 6.2 and Figure 6.3.

Table 6.2 - % of total arrivals in each hour

Interval	0-2	2-4	4-6	6-8	8-10	10-12	12-14	14-16	16-18	18-20	22-24
% of arrivals	6,4	4,4	3,7	4,0	8,4	13,4	11,7	11,3	10,3	9,1	9,4

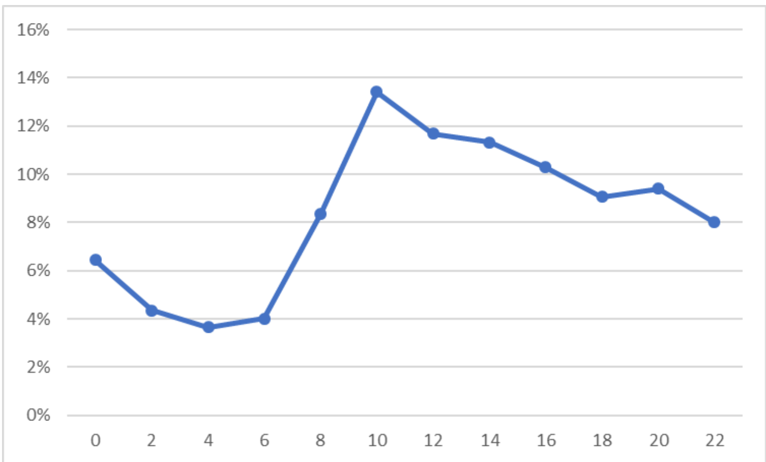

Figure 6.3 - % of total arrivals in each hour

6.2 Manchester Triage System (MTS) Levels

Probably one of the most important factors to be able to predict, the MTS level assigned to each patient will have a direct influence in the doctor examination, test and treatment times, as well as in the number of tests needed and the probability of each outcome.

To determine the likelihood of each urgency level, various studies have been analysed and the percentages of each level calculated, as shown in Table 6.3. The authors did not mention the standard deviations of their results.

Table 6.3 - % of patients assigned to each urgency level

Author	Red	Orange	Yellow	Green	Blue	Total observed
(Zachariasse et al., 2017)	0,7%	15,6%	36,4%	45,5%	1,8%	288 663
(Steiner et al., 2016)	0,9%	25,8%	40,5%	30,0%	2,8%	2 407
(Gräff, Latzel, Glien, Fimmers, & Dolscheid-Pommerich, 2019)	1,6%	15,8%	36,1%	41,9%	4,5%	20 836
(Van Veen et al., 2008)	1,5%	21,4%	36,2%	40,1%	0,8%	13 554
(Santos et al., 2013)	0,4%	14,7%	34,5%	46,5%	3,9%	23 615
(Mandahawi et al., 2017)	1,1%	2,3%	36,0%	33,7%	27,0%	445
(Cicolo & Peres, 2019)	0,5%	4,1%	18,7%	62,2%	14,5%	7 720
(B. Martins & Filipe, 2020)	0,5%	6,0%	37,3%	55,0%	1,1%	276 279
(Anziliero et al., 2017)	0,5%	6,6%	17,8%	71,4%	3,6%	136 153
(Whitt & Zhang, 2017)	0,4%	8,5%	39,0%	50,7%	1,3%	324 022
Average	0,57%	9,95%	34,94%	52,64%	1,91%	

In the average given by Table 6.3 to each colour, the weight of each paper was determined by the number of observations, meaning that studies with more observation will have a higher weight in the average. These values will be the ones introduced into the simulation when determining the urgency level assigned to a patient.

6.3 Resources

In an actual ED, the resources needed would include all staff (janitorial, receptionists, doctors, nurses, etc.) as well as the seats available in waiting rooms, the beds available, the testing machines, the laboratory equipment and the general medical supplies needed for treatments and tests. However, not all resources can be included in a simulation due to how complex it would become. Günal & Pidd (2010) mentions how the more complete and detailed a model is the more limited it is. While very useful for the specific situation it is modelling it is not usable for different situations. Therefore, the resources on which this study will focus are the number of beds, nurses and doctors available.

The medical supplies needed are excluded due specifically to how much more information would be needed (since there are so many different types of supplies, each with different lower utilization rates). The number of machines is excluded due to lack of information however, this is compensated in the simulation by assuming that a nurse is always required when doing tests (*vide section 5.5.4*).

6.3.1 Beds

A lack of beds has been consistently cited as a major source of ED crowding (Hamrock, Paige, Parks, Scheulen, & Levin, 2014), hence its inclusion in the model. When it comes to collecting data on the number of beds available in an ED, two approaches were taken. The first consisted of dividing the number of Portuguese ED beds (830, according to Instituto Nacional de Estatística, 2019) by the number of hospitals with an ED, 82 (Campos, 2014). This resulted in a rounded average of 9 beds per ED. The second approach used previous studies that mentioned the number of beds available and compared them to the patients per year in each of those EDs. Then, it used the average patients per bed and applied it to Portuguese reality. Table 6.4 shows the results of said research.

Table 6.4 - Patients per bed

Author	Patients per year	Nº of beds	Patients per bed
(Weng, Cheng, et al., 2011)	63 843	60	1 064
(Nishi et al., 2018)	200 000	178	1 124
(Maningas et al., 2006)	57 980	389	149
(McCarthy et al., 2008)	55 000	41	1 341
(Graves et al., 2018)	70 000	40	1 750
(Hamrock et al., 2014)	59 000	25	2 360
	50 000	20	2 500
(Weng, Tsai, et al., 2011)	32 000	53	604
(Zeinali et al., 2015)	52 000	10	5 200
Average			1788

As can be seen in Table 6.4, from this research an average of 1 bed available for every 1788 patients in a year was found. On its own, this number might seem a bit strange but it can be explained that oftentimes each patient spends only a couple of minutes in a bed to treat minor issues, in the end, this means that each bed will be used by an average of 5 patients in any given day. Using the number of ED visits from INE (2019), we will have an average of 83 550 visits to an ED per year, which means that it would need 46,7 beds per ED to have the same 1788 patients per bed (83550 / 1788 = 46,7).

The fact that the Portuguese average and the average found in the studies are so distinct is something that could be relevant therefore, simulations with both values will be performed to determine how relevant this difference is.

6.3.2 Nurses

This simulation will be following in the footsteps of Zeinali, Mahootchi and Sepehri, (2015) by trying not a single combination of allocation of nurses but many different scenarios. It will also take into accounts having a different number of nurses per shifts.

The nurses present in an ED are divided into two categories, triage nurses and regular nurses. Triage nurses are the ones who have had training on the MTS and are therefore able to correctly triage patients. The amount of nurses in charge of triage at any given time is usually just one (Brenner et al., 2010; Weng, Tsai, et al., 2011). However, this study will look at the effects of having two instead of one and see how it may impact waiting times. Table 6.5 shows the number of nurses available in the EDs studied in different papers.

Table 6.5 - Number of nurses available

Author	Number of nurses
(Olofsson, Gellerstedt, & Carlström, 2009)	30
(Weng, Cheng, et al., 2011)	7 to 9
(Brenner et al., 2010)	10 to 13
(Weng, Tsai, et al., 2011)	8 to 9
(Zeinali et al., 2015)	1 to 6

In table 6.5 the first paper seems to be an outlier among the five. However, this is due to the fact that the number 30 pertains to the total number of nurses in the staff, while to the rest of the papers it is only the number of nurses available at any given time in the ED. If we divide the 30 by the 3 shifts (assuming an equal number of nurses per shift) it would give us 10, a number in line with the others observed. In the table we can see how 4 out of the 5 papers were also experimenting with different configurations for the ED, this is similar to what will be done in this simulation: trying out a varying number of nurses.

Each day will feature three shifts of eight hours starting at 00:00, 08:00 and 16:00. The shifts were divided like this because three shifts seem to be the most common configuration and looking at the arrival rates of Figure 6.3 these seem like the best hours to separate the shifts so that the arrival rates are somewhat consistent throughout the shift.

With the first shift being the one with the least patients and the second the one with the most. However, since the difference between the second and third shift is relatively small, the same number of staff for both shifts will be assumed. This schedule while be applicable for both nurses and doctors.

6.3.3 Doctors

When choosing the number of doctors, we will follow the same logic as with the number of nurses, it will depend on shifts and many scenarios will be tried out. Table 6.6 gives us the number of doctors available at any moment as mentioned in each of those papers.

Table 6.6 - Number of doctors available

Author	Number of doctors
(Weng, Cheng, et al., 2011)	7 to 9
(Cicolo & Peres, 2019)	7
(Brenner et al., 2010)	5 to 6
(Weng, Tsai, et al., 2011)	4 to 8

From this table we realize that the suggested number of doctors ranges between 4 and 9; in SIMUL8 we will try to determine an optimal solution.

6.4 Time Distributions

6.4.1 Triage Time

The triage time is about the time a patient spends with the triage nurse where at the end he/she is assigned an MTS level. The fact that the MTS level is assigned during triage invalidates the time distributions given by some papers (Anziliero et al., 2017; Chen et al., 2020; Marja N. Storm-Versloot et al., 2014) as they separate the triage times by MTS level. In this simulation, the same triage times will be used for every patient. Although exponential distributions are considered to be a good approximation of service time (Swamidass, 2000), not every paper available uses it. The distributions found in Table 6.7 will be the ones used.

Table 6.7 - Triage time distributions (min)

Author	Distribution	Time (min)	
		Mean	Standard Deviation
(Martin et al., 2011)	Normal	3	3
(B. Martins & Filipe, 2020)	Exponential	2	
(Improta et al., 2018)	Exponential	7	
(Mandahawi et al., 2017)	Triangular	1,3,5	
(Weng, Tsai, et al., 2011)	Triangular	7,8,10	

6.4.2 Doctor Examination Time

For this distribution, we will have a scenario where the examination time depends on the MTS level and then three more where the same distribution is used for every patient. This is due to the lack of data separating the times per colour, this may be because it is not relevant or simply because it was not the objective of the papers found to determine that correlation. Table 6.8 shows the distributions to be used.

Table 6.8 - Doctor examination time distribution times (min)

Author	Red	Orange	Yellow	Green	Blue
(Chen et al., 2020)	Uniform (60)	Uniform (30)	Triangular (8;9;10)	Triangular (6;7;8)	Triangular (3;4,5;6)

	Distribution	Time (min)
(Ahmed & Alkhamis, 2009b)	Triangular	8;16;24
(Weng, Tsai, et al., 2011)	Triangular	4;8;12
(Improta et al., 2018)	Exponential	13

As can be seen, the difference in time for each paper seems to be quite substantial, hence each will be simulated and its effects on the simulation analysed.

6.4.3 Tests Time

The time spent on testing will go hand in hand with the number of tests necessary. To determine testing time there will be three different scenarios based on the different options seen in the literature.

Table 6.9 - Testing time scenarios by case study used

Scenarios	Number of tests	Testing time
1	(Weng, Cheng, et al., 2011)	(Mandahawi et al., 2017)
2	(Brouns et al., 2019)	(Mandahawi et al., 2017)
3	(Brouns et al., 2019)	(Weng, Cheng, et al., 2011)
4	(Weng, Cheng, et al., 2011)	(Weng, Cheng, et al., 2011)

The scenarios in Table 6.9 were created from among three different case studies, the number of tests simply because the values were different and testing both options could prove to be useful (Table 6.10). The testing time varies because while Weng, Cheng, *et al.* (2011) changes the time it takes for each subsequent test to be conducted, Mandahawi *et al.* (2017) use a triangular distribution of (15,20,30) for every test.

Table 6.10 - Number of tests per colour

Author	Nº of tests	Red	Orange	Yellow	Green	Blue
(Weng, Cheng, et al., 2011)	1	15,48%	18,01%	20,53%	21,46%	45,38%
	2	39,89%	41,30%	42,71%	49,77%	35,71%
	3	23,27%	21,68%	20,09%	11,67%	16,81%
	4	11,42%	10,59%	9,75%	9,33%	2,10%
	5	6,42%	5,37%	4,32%	4,67%	0
	6	3,52%	3,06%	2,60%	3,10%	0
(Brouns et al., 2019)	Mean	3,4	1,5	1,5	0,9	0,9
	SD	1,7	1,1	1,1	0,9	0,9
	None	9,8%	4,1%	20,3%	41,6%	41,6%

Before anything else, it is very important to mention how both papers were missing some data. Weng, Cheng, et al. (2011) on the orange patients and Brouns et al. (2019)on blue patients. For the first one an average of the colours red and yellow was used, for the second one, the same values as the ones from green were assumed. Although this is not necessarily similar to reality it was the best that could be done to complement the data. Relevant for the design of the simulation is also the fact that scenarios 1 and 4 assume that every patient requires at least one test.

Table 6.11 shows the time distribution of each test that will be used in scenarios 3 and 6. Compared to the other distribution used, T(15,20,30), the first test will be quicker, but the rest will most likely be slower.

Table 6.11 - Time distribution for each test(min). Source:(Weng, Cheng, et al., 2011)

Test Number	Time (min)
1	Exponential(3.4)
2	Exponential (107.4)
3	Exponential (55.6)
4	Exponential (75,3)
5	Exponential (49,8)
6	Exponential (49,8)

6.4.4 Treatment Time

The treatment time relates to the period in between the second doctor examination (first if there were no exams needed) and the exit from the system (either through discharge or admission). Four different scenarios will be tested, the first two using different times for each MTS level, the second and third maintaining the same distribution for every patient.

Table 6.12 - Treatment time distributions (min)

Author	Distribution	Red	Orange	Yellow	Green	Blue
(Chen et al., 2020)	Triangular	(0,4;8)	(0;2.1;24)	(0;2.1;45)	(0;2.5;60)	(2;5.42;60)
(Marja N. Storm-Versloot et al., 2014)	Exponential	131.4	131.4	120	30.6	22.8
(Mandahawi et al., 2017)	Triangular	5,10,20				
(Ramos & Paiva, 2017)	Average	300				

The reason for all four scenarios being tested is the differences between them. Between the first two in the second two, the difference is how the first two differentiate between MTS levels. Afterwards is the fact that all four of them suggest quite distinct treatment times, ranging from 0 to 300 minutes.

The difference between them is not explained but it could be due to different ways of measuring per example, considering the recovery time versus not it in an observation unit within the ED as treatment.

In the paper by Storm-Versloot *et al. (*2014), no information on the treatment time of patients assigned to urgency level one was available as they did not include any such patient in their study. Therefore, in order for it to be used in the simulation, it was assumed that treatment time for those patients was the same as the one for urgency level two patients.

6.4.5 Outcome

There are three possible outcomes for the patient journey: discharge, admission and death. The healthy patients are discharged and exit the system that way, the ones admitted into the hospital leave the ED to go to other departments, therefore leaving the simulation scope. The third outcome is death; it may come at any point in the simulation. For each outcome, their likelihood will depend on the MTS level assigned to the patient. Tables 6.13 and 6.14 show the likelihoods of admission and death respectively, otherwise, all patients are discharged.

Table 6.13 - Likelihood of admission

Author	Red	Orange	Yellow	Green	Blue	Total Observed
(Steiner et al., 2016)	33,3%	7,6%	3,4%	0,8%	0%	2 407
(Santos et al., 2013)	59,2%	12,3%	4,7%	1,3%	0,3%	24 721
(Moreira, 2010)	21%	28%	9%	1%	3%	32 022
(Maningas et al., 2006)	38,0%	18,4%	9,1%	1,5%	0,4%	7 077
(Brouns et al., 2019)	72,2%	29,6%	11,4%	2,8%	NA	6 108
Weighted average	24,86%	26,64%	8,72%	1,06%	2,70%	

The likelihood of admission for each MTS level was calculated by determining the weighted average of the results given by the papers in table 6.13 (the weight of each value was proportional with the total number of observations in the corresponding paper). The case study of Moreira (2010) has a considerably higher amount of patients observed when compared to the other four, hence its increased weight on the average. The last paper on the table did not include information on patients assigned the blue colour during triage, therefore it was not used to calculate that average. The weighted average is showing the likelihood of a patient being admitted depending on his MTS level per example if a patient is assigned the level 3 (yellow) he has an 8,39% chance of being admitted.

Table 6.14 - Likelihood of death

Author	Red	Orange	Yellow	Green	Blue	Total Observed
(Steiner et al., 2016)	19%	4%	3,1%	1,9%	3%	2 407
(Santos et al., 2013)	30,6%	3,3%	0,9%	0,3%	0,3%	24 721
(Moreira, 2010)	29%	1%	0%	0%	0%	324 022
(Brouns et al., 2019)	18,0%	0,2%	0%	0%	NA	6 108
Weighted average	28,30%	1,14%	0,08%	0,03%	0,04%	

The logic behind Table 6.13 is the same as that of Table 6.14 (explained in the previous paragraph) but this time it relates to the likelihood of death instead. As can be seen, the likelihood of death is much higher in patients assigned to MTS level 1 (Red).

In reality, as more time is spent waiting, the chances of admission and/or death increase (Mahmoudi, Swiatek, & Chung, 2017). However, since reliable data on the relation of between time spent waiting and patient outcomes could not be found, this theory has been disregarded when constructing the simulation model.

7 SIMUL8 Model

7.1 Why SIMUL8?

Before explaining the model developed and looking at the results, a brief explanation on why SIMUL8 was the simulation tool chosen for thesis is required. SIMUL8 uses discrete-event simulation which is widely accepted in the healthcare industry *(vide section 2.3.3.2)*. Additionally, this is a tool that is considered to be "a robust, user-friendly tool, which has proved to be adequate for implementing conceptual models and also for what-if analysis." (Vilas-boas, Suleman, & Moreira, 2015).

Within SIMUL8 itself, some of the capabilities that led to it being the chosen simulation tool were:

- Using different arrival rates depending on the time of day;
- Introducing resources and assigning them to different activities;
- Creating shifts and controlling the number of resources available per shift (e.g. number of doctors);
- Assigning labels to work items (patients) and setting different paths through the system depending on label assigned;
- Being able to choose the key performance indicators (KPIs) wanted;
- Setting up trials with however many runs the researcher wants and receiving a results list with the average and 95% confidence intervals of the KPIs determined.

The fact that the researcher already had previous experience using SIMUL8 was the final reason for choosing it for this simulation.

7.2 Base Model

7.2.1 Definition of the Inputs to the Base Simulation Model

Testing every possible combination of the different options mentioned in the Data Collection chapter would mean testing 64 000 scenarios. This is not feasible, therefore this thesis will choose one combination to function as a base model and then test different scenarios and compare the results. The only two components of the model that will not be changed are the assignment of MTS Levels and the likelihood of each outcome. The values used in both will be the ones mentioned in the previous chapter.

The following list will explain the values chosen for each of the variables defined in the previous chapter along with how they were introduced in SIMUL8 when creating the base model (all service distributions chosen were simply introduced in the activity properties):

- Arrival Rates: The arrival rates used will be the average of the papers of eleven patients per hour. The rates have, however, been adjusted to fit the percentage of arrivals by day and hour mentioned before;
    - Done by assigning a time dependent distribution that changes the arrival rates every two hours.
- Beds: The number of beds considered for the base model will be nine, with two of them always available for patients assigned MTS level 1;
    - Creation of the resources “beds” and “red beds”.
- Nurses and Doctors: After building the first model, a sensibility analysis will be performed and from there the values to be used in the rest of the scenarios will be decided. From the number of nurses, at least one will be put in triage and from the doctors, at least one will be assigned solely to treating MTS level 1 patients;
    - Creation of the resources “triage nurses”, “nurses”, “doctors”, and “red doctors” and determining the number of resources available depending on shifts (e.g. Figure A.12 seen in Appendix A).
- Triage: The triage time distribution will be an exponential with an average time of two minutes, following Martins and Filipe (2020). Exponential distributions are commonly used to determine service times (Swamidass, 2000) and of the two exponential distributions available this is the paper with the most observations;
- Doctor examination: In the base model, priority will be given to papers that differentiate between each MTS level as these should be closer to reality. Therefore, the distributions used to determine doctor examination will be the ones from Chen, Guo and Tsui (2020) described in Table 6.8;
- Tests: The number of tests will be determined using (Weng, Cheng, et al., 2011) as it has detailed information on the likely number of tests for each colour. Normally, the test times from the same paper would be used, however, since in this paper tests take too long when compared to the arrival rates this would create

a bottleneck that would heavily influence results from any activity or queue that come after it. Therefore, the distribution used will be a triangular (15,20,30) taken from Mandahawi *et al.* (2017);

- Treatment: Chen, Guo and Tsui (2020) will be delivering the distributions to be used in the treatment time as it is the only one that distinguishes by MTS level and has data available on all five levels.

7.2.2 Defining and Depicting the Base Simulation Model

Figure 7.1 provides us with an overview of the base model developed using SIMUL8. On the top part of the figure, we have the resources used in the simulation. Each resource is inside a coloured box. The activities that use any resource will also be inside a box of the same colour as the resource required. Most activities (blue squares with a gear) have a title either above or below them which explain what that activities they are. The exceptions are the ones in the dark green box which are lacking a title, these activities represent the tests (1 through 6) the patients are assigned.

Only three activities are independent from any resource: “Ambulance entries”, “Routing” and “Routing 2”. All three of these activities have a fixed activity time of zero seconds. They are not activities that exist in reality, they are instead added here simply to make the simulation work. “Ambulance entries” has this name because it is where MTS level 1 patients are sent, it is used to assign a label that will determine whether patients will have to go through some tests or not, this activity will only be of use in scenarios 24 and 25. “Routing” and “Routing 1” will be used as a way to route patients based on their MTS levels. This is necessary as SIMUL8 does not allow for routing out logic in queues. This meant that, if we required different activity times for each MTS level, then this was the method found to guarantee that each patient would move to the correct activity.

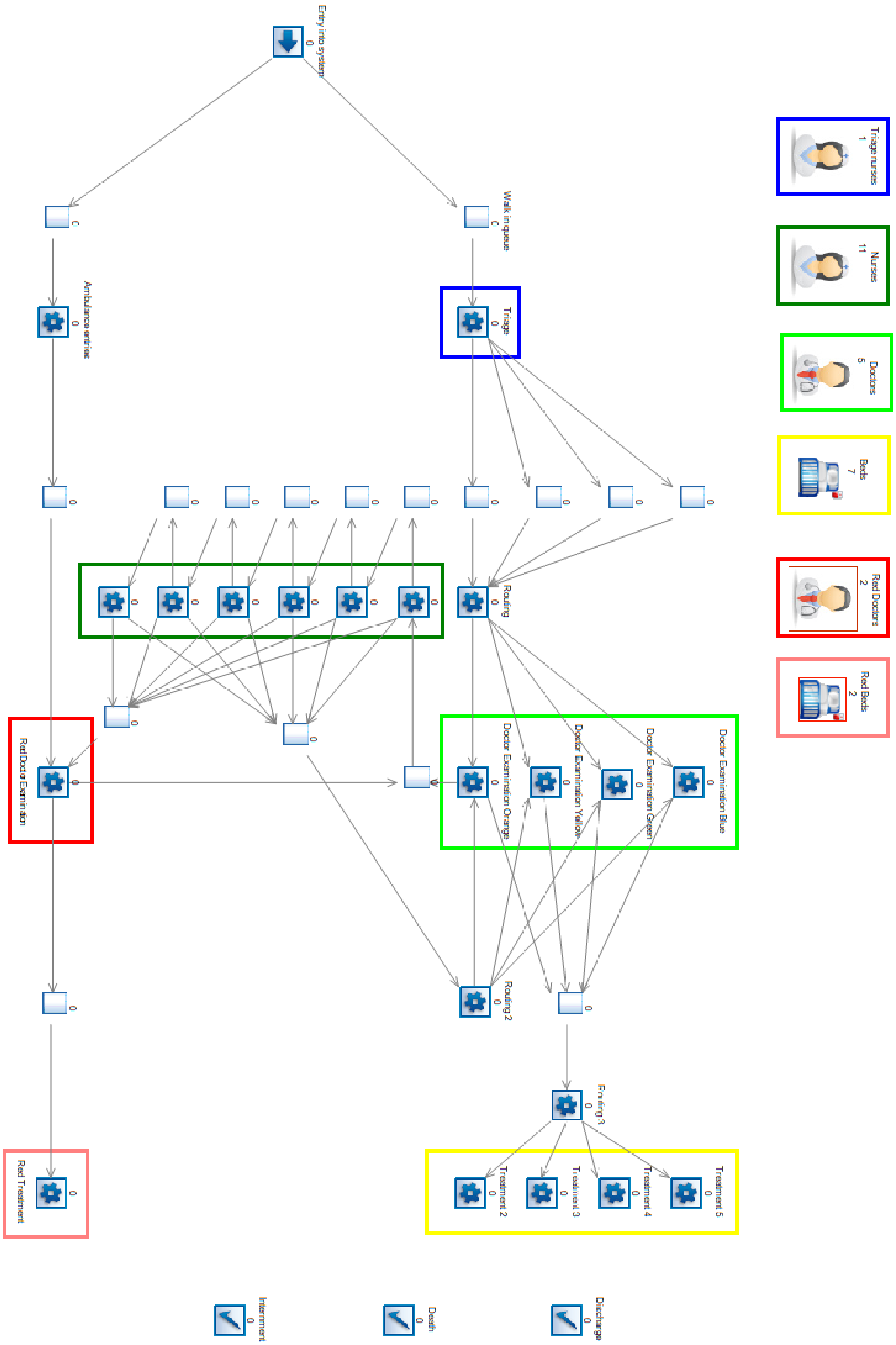

Figure 7.1 - Base Model in SIMUL8

7.3 Determining the number of Nurses and Doctors

When determining the number of nurses and doctors to be used in the base model fifteen scenarios (*vide table 7.1*) where simulated the relevant results are shown in Figures A.1 to A.6 (in Appendix A). These numbers include one nurse assigned to triage and two doctors assigned solely to MTS level 1 patients.

Table 7.1 - Scenario description

Scenario	Number of nurses		Number of Doctors	
	0h-8h	8h-24h	0h-8h	8h-24h
1	6	7	7	8
2	7	8	7	8
3	8	9	7	8
4	9	10	7	8
5	10	11	7	8
6	11	12	7	8
7	12	13	6	7
8	12	13	7	8
9	12	13	8	9
10	12	13	9	10
11	13	14	7	8
12	13	14	8	9
13	14	15	7	8
14	14	15	8	9
15	15	16	7	8

The MTS levels 5 and 4 patients' results are a bit less intuitive to understand than the rest. Looking just at Figures A.1 and A.2, a lower number of nurses would actually lead to lower waiting times. However, this is not true. To truly understand the results, one must also look at Table 7.2.

Table 7.2 - Queue for tests and patients who have not left the system in scenarios 1 through 15

Scenario	Average queue for tests			Patients in the system at the end of one week		
	-95%	Average	95%	-95%	Average	95%
1	368,44	377,33	386,22	756	757	759
2	272,25	281,17	290,09	561	563	564
3	180,95	189,37	197,79	367	369	371
4	155,12	168,03	180,94	172	175	178
5	20,71	23,88	27,06	43	47	52
6	8,08	9,05	10,01	23	30	36
7	0,33	0,37	0,40	27	42	56
8	3,32	3,73	4,13	11	20	29
9	4,75	5,31	5,88	16	21	26
10	5,37	6,08	6,78	16	21	27
11	0,98	1,13	1,29	9	17	26
12	2,05	2,41	2,76	12	17	22
13	0,37	0,44	0,50	7	17	27
14	0,90	1,08	1,26	12	16	21
15	0,15	0,17	0,19	8	17	26

The queue for tests being so large in the first four scenarios explains the perceived low waiting times, as many of the level 5 and 4 patients are still in the queue by the end of the week meaning that they are not counted when calculating waiting times. In this model, patients with a higher MTS level (less urgent) are always the last to be seen.

This is further shown when in scenario 5: as fewer patients are stuck indefinitely in the queue, the waiting times for level 5 patients increases to an average of 20 hours (the same happens for level 4 patients but in scenario 4 and to 4 hours) because more of them are now counted.

Looking at the graphs for the two less urgent patient categories, the comparison between scenarios 7 to 10 will also be relevant to understand the system. In all of them, the number of nurses remains constant and it is the number of doctors that varies. The interesting part is that as the number of doctors increases by one, from 7 (8h to 24h) to 8, the waiting time decreases greatly. However, as the same is done in scenarios 8, 9 and 10 the waiting time increases slightly. This happens because, as all patients take less time to pass through the doctor examination, they arrive at faster rates at the queue for testing and therefore, it takes longer for patients of lower urgency to be tested. Hence, for lower urgency patients, increasing the number of doctors past a certain point can be detrimental to waiting times if it is not accompanied by changes to the number of nurses.

For the rest of the MTS levels increasing the number of nurses will heavily reduce the waiting times up until 13 nurses. From there onwards, the waiting time still decreases but at a slower pace. When it comes to the number of doctors, increasing them seems to make little difference to the total waiting time as it reduces the waiting time for doctor examination but increases the one for tests. This happens because as they are seen faster by the doctor, the queue for tests will grow. This can be more easily seen in Figure 7.2 which shows the average size of the queue for tests depending on the scenario. Since the number of nurses is constant between scenarios 7,8,9 and 10 (12/13); scenarios 11 and 12 (13/14) and scenarios 13 and 14 (14/15). The only change between them is the increase of the number of doctors available, as can be seen, when the number of doctors increases the queue size for tests increases.

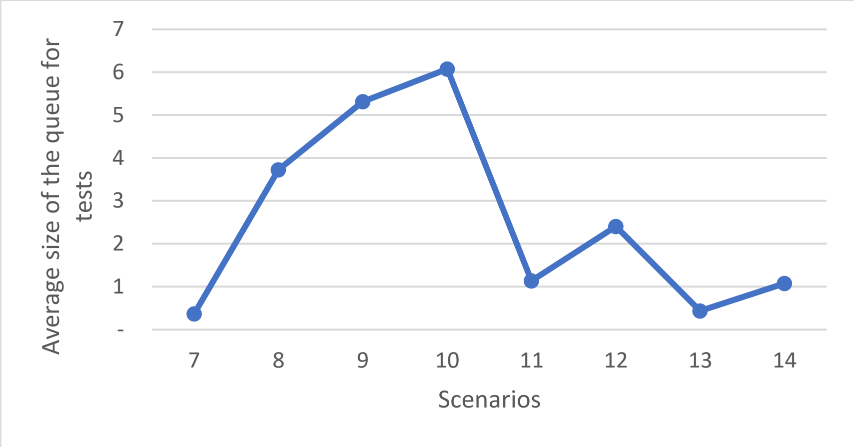

Figure 7.2 – Average size of the queue for tests in scenarios 7 to 14

Overall, the key takeaway from here is that while increasing the number of nurses will consistently decrease waiting times up to a point, increasing the number of doctors seems to not be relevant unless it is accompanied by an increase in the number of nurses as well.

One final interesting observation to mention is how the average waiting times for MTS level 1 seem to increase when the number of doctors is increase (e.g. from scenarios 8 to 9, 11 to 12 and 13 to 14). This may be happening due to the fact that this increased number of doctors will only be looking at the other four levels as level 1 patients always have two doctors exclusively assigned to treat them. This means MTS level 2, 3, 4 and 5 patients will be entering the queue for testing more frequently, increasing the time MTS level 1 patients will have to wait.

To prevent testing every other scenario with the existence of substantial bottlenecks or with unrealistic staff numbers, the scenario that will be used in the base model will be scenario 8 with either 12 or 13 nurses and 7 or 8 doctors (depending on shifts). These values have also been seen in previous literature as can be seen in Tables 6.5 and 6.6.

7.4 Arrival Sensitivity Analysis

The arrival rate of patients to the ED is subject to numerous outside factors, Otsuki et al. (2016) identifies seasonal changes as one such factor, and the recent pandemic created is an example of another. Therefore, before simulating the rest of the scenarios, a sensitivity analysis of the patients interarrival rate was done.

This sensitivity analysis picked the peak hours of patient arrivals, between 10:00 and 16:00 and looked at the different averaged waiting times per MTS level. Both decreases and increases of 10%, 20% and 50% to the interarrival times were simulated. Table A.1show us the result of these simulations. Results regarding the MTS level 5 patients were not included as even in the simulation with the most patient arrivals the number of level 5 patients was, on average, 0,9 with a 95% confidence interval of 0,56 to 1,24. Figure 7.3 gives us an easier to understand view of Table A.1 (in Appendix A) by showing the difference in average total waiting times for each level.

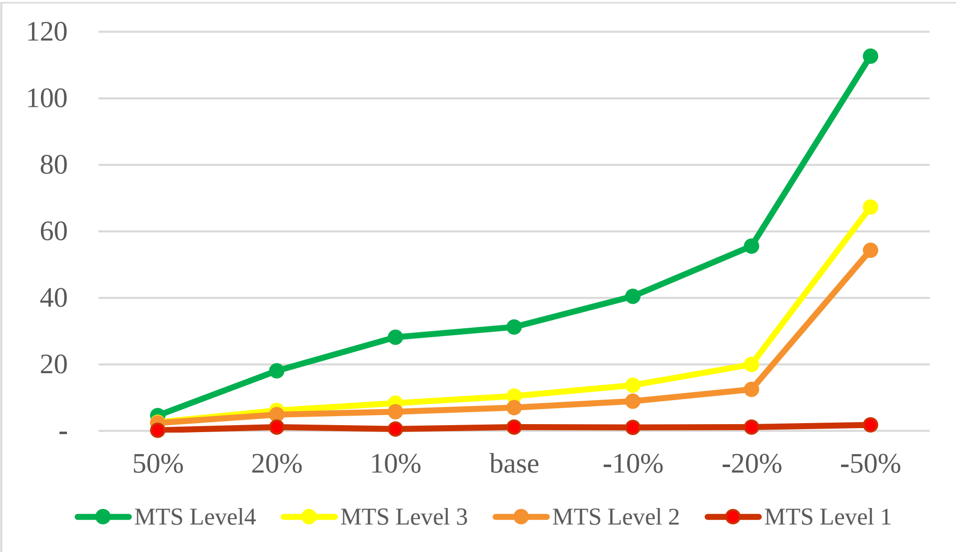

Figure 7.3 - Average total waiting times (min) depending on MTS level and on change to interarrival time

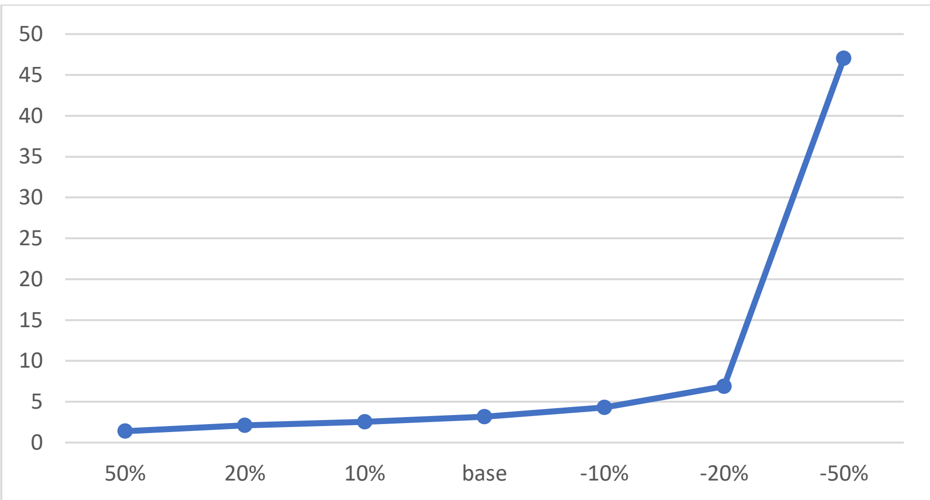

Figure 7.4 - Average time spent waiting for triage (min) depending on the change to interarrival time

The average waiting time seems to increase at a seemingly stable rate as the interarrival rate goes down. The rate is stable up until the interarrival time is reduced by half, here we see a sizable jump in total waiting time for every MTS level except for level 1. The reason why this happens is the waiting time for triage. When the interarrival time is this low, just one triage nurse is not enough to handle all patients. Hence, waiting times increase. MTS level 1 patients do not wait longer because they do not go through triage. Figure 7.4 shows us this difference in triage times, which, as can be seen, seems to match the lines from Figure 7.3. - Average time spent waiting for triage (min) depending on the change to interarrival time

7.5 Results Analysis

In this subsection, fourteen more scenarios will be tested using the distributions found in the literature (*vide chapter 6*). These scenarios will be divided into five groups. The first one contains only scenario 16 and it is related to the number of beds available. The second one looks at the different triage time distribution and is composed of scenarios 17 to 20. The third one changes the doctor examination times and encompasses scenarios 21, 22 and 23. The fourth one changes the number of tests and/or the test times, it is composed of scenarios 24, 25 and 26. The last one will be the one looking at different treatment times and how they affect the simulation in scenarios 27, 28 and 29. Table 7.3 provides us with the variables in which each scenario varies from the base model.

Table 7.3 - Scenario description

Scenario	Number of beds		Number of red beds		
16	37		10		
	Triage Times (min)				
17	Normal (μ=3;σ=3)				
18	Exponential(7)				
19	Triangular (1;3;5)				
20	Triangular (7;8;10)				
	Doctor examination times (min)				
21	Triangular (8;16;24)				
22	Triangular (4;8;12)				
23	Exponential(13)				
	Number of tests/test times (Table 11 scenarios)				
24	2				
25	3				
26	4				
	Treatment times				
	Red	Orange	Yellow	Green	Blue
27	Exponential (131,4)	Exponential (131,4)	Exponential (120)	Exponential (30,6)	Exponential (22,8)
28	Triangular (5,10,20)				
29	Average (300)				

7.5.1 Beds

Scenario 16 will simulate the ED with 47 beds instead of 9 (as proposed in subsection 5.3.1). The number of "beds" and "red beds" will be 37 and 10 respectively, to maintain the ratio used before of 7:2.

In this scenario, it becomes clear that in the base model, increasing the number of beds will have next to no impact as doing so diminishes the average waiting time of patients (of any MTS level) by less than one minute. The utilization percentages of "beds" and "red beds" will also drop from 45,69 and 0,19 to 9,41 and 0,04 respectively. This means that increasing the number of beds will not be useful if the utilization percentage was already low beforehand.

7.5.2 Triage Times

To look at the impact of triage times in the simulation, four different scenarios were tested. Table 7.4 and 7.5 show the relevant results taken from the simulations.

Table 7.4 - Comparison between results from the base model and scenarios 17, 18, 19 and 20

		base	17	18	19	20
Triage Average Waiting time (min)	-95%	1,58	7,73	1212,22	8,82	1779,13
	Average	1,67	8,50	1 271,09	3,61	1 818,30
	95%	1,75	9,27	1329,97	3,89	1857,47
"Triage nurse" utilization %	-95%	36,6%	58,9%	98,6%	53,8%	99,2%
	Average	37%	59,5%	98,8%	54,3%	99,4%
	95%	37,4%	60,1%	99,1%	54,7%	99,6%
Patients still in the system at the end of the week	-95%	20	20	428	20	634
	Average	23	23	430	23	642
	95%	26	26	432	26	649

Table 7.5 – Total waiting times (except for triage queue) per colour

			base	17	18	19	20
Average Total Waiting time (except triage queue) (min)	Blue	-95%	196,80	179,14	0,85	193,23	0
		Average	233,81	214,74	1,85	228,57	0
		95%	270,83	250,33	2,86	263,91	0,01
	Green	-95%	52,30	46,84	0,77	50,06	0
		Average	60,01	54,19	1,00	57,57	0
		95%	67,72	61,54	1,24	65,09	0,01
	Yellow	-95%	4,54	4,10	0,39	3,93	0
		Average	4,90	4,45	0,47	4,23	0
		95%	5,26	4,80	0,55	4,54	0
	Orange	-95%	2,55	2,40	0,27	2,36	0
		Average	2,76	2,62	0,36	2,58	0
		95%	2,98	2,83	0,45	2,80	0
	Red	-95%	1,46	1,57	0,05	1,68	0
		Average	2,41	2,53	0,96	2,55	0,61
		95%	3,37	3,50	1,87	3,42	1,26

Scenarios 17 and 19 tested triage times that, although slower than the base model, on average, managed to look at patients at a faster rate than patients would arrive at the system. This meant that even though there was an increase in the utilization percentage of the resource "triage nurse", the overall time spent waiting for each colour remained similar between these two scenarios and the base model, as can be seen in Table 7.5. This can be seen in Figures A.7, for scenario 17, and A.9, for scenario 19; (in Appendix A) where the maximum number of patients in the queue for triage is 16 and 6 respectively, therefore, triage does not seem to be an issue in these scenarios

In scenarios 18 and 20 using simply one triage nurse will be unsustainable. As can be seen in Table 7.4, taking this much time in triage will lead to average waiting times for triage of 21h and 30h. Figures A.8 and A.10 (in Appendix A) show us the number of patients in the queue for triage at any given point of the simulation for scenarios 18 and 20 respectively. Here it is important to note how the number does not increase at a constant rate. Since the interarrival time is not always the same, it would seem from these figures that when the interarrival time is at its highest (during the night) the queue for triage will decrease. However, this decrease is not enough to compensate for the increase during the day. In scenarios 17 and 19, since even during the day the queues are small, during the night there are almost no queues.

7.5.3 Doctor Examination times

Changing the time spent during doctor examinations will have the same effect we saw when changing the number of doctors available (*vide section 7.3*). As can be seen in Table 7.7, the locations where a patient will wait the most will change. However, the total queueing time seems to remain relatively unchanged. This happens because when the waiting time for the doctor examination reduces or increases the waiting times for tests does the opposite. As patients go through the doctor examination faster, they are also faster to arrive at the queue for tests meaning that the time spent waiting in this queue will increases.

This may make it seem like lowering the doctor examination times will be irrelevant, and even though when it comes to total waiting time this seems to be somewhat true, it will have a much more noticeable effect on the percentage of patients that wait for longer than the suggested amount of time per colour between triage and being seen by the doctor, this can be seen in Table 7.6. Here we see how, in scenarios increasing 21 and 23 the number of patients not seen within the time limit increases compared to the base model, with the exception being the MTS level 1 patients which are more likely to wait longer in the base model since, for this level, it is the scenario in which the doctor examination takes longer.

Table 7.6 - Percentage of patients queued above the suggested time limit in scenarios 21, 22 and 23

			base	21	22	23
Patients queued above time limit	Blue	-95%	0%	25,3%	0%	2,5%
		Average	0,6%	29,1%	0%	4,3%
		95%	1,2%	33,0%	0%	6,1%
	Green	-95%	0%	11,4%	0%	0,7%
		Average	0,1%	14,4%	0%	1,5%
		95%	0,3%	17,5%	0%	2,3%
	Yellow	-95%	0%	0%	0%	0%
		Average	0%	0%	0%	0%
		95%	0%	0%	0%	0%
	Orange	-95%	0%	0,2%	0%	0,3%
		Average	0,1%	0,5%	0%	0,6%
		95%	0,3%	0,7%	0%	0,8%
	Red	-95%	0,2%	0%	0%	0%
		Average	1,3%	0%	0%	0%
		95%	2,4%	0%	0%	0%

Table 7.7 - Comparison between results from the base model and scenarios 21, 22 and 23

			base	21	22	23
Average Waiting Time For Doctor Examination (min)	Blue	-95%	3,33	168,30	0,28	25,26
		Average	6,07	192,53	1,10	34,92
		95%	8,82	216,76	1,92	44,58
	Green	-95%	1,46	39,92	0,36	9,09
		Average	1,96	46,34	0,45	11,24
		95%	2,47	52,76	0,54	13,39
	Yellow	-95%	0,44	3,06	0,18	1,65
		Average	0,52	3,26	0,21	1,81
		95%	0,59	3,46	0,25	1,97
	Orange	-95%	0,29	1,63	0,12	0,95
		Average	0,34	1,74	0,14	1,05
		95%	0,39	1,86	0,17	1,14
	Red	-95%	0	0	0	0
		Average	0,28	0	0	0
		95%	0,57	0	0	0
Average Waiting Time For Tests (min)	Blue	-95%	193,27	45,76	195,78	167,71
		Average	227,11	62,20	228,30	200,20
		95%	260,96	78,64	260,83	232,70
	Green	-95%	50,28	18,88	51,03	44,05
		Average	57,37	22,22	58,12	50,50
		95%	64,46	25,56	65,21	56,95
	Yellow	-95%	3,73	2,86	3,74	3,66
		Average	3,95	3,06	3,98	3,86
		95%	4,16	3,26	4,22	4,07
	Orange	-95%	1,99	1,77	1,99	2,00
		Average	2,10	1,87	2,11	2,11
		95%	2,21	1,98	2,23	2,23
	Red	-95%	1,56	1,30	1,32	1,41
		Average	1,80	1,60	1,63	1,66
		95%	2,05	1,90	1,93	1,91
Average Total Waiting Time (except triage queue) (min)	Blue	-95%	196,80	224,52	196,17	195,30
		Average	233,81	269,42	229,68	239,07
		95%	270,83	314,32	263,18	282,84
	Green	-95%	52,30	72,84	51,62	56,87
		Average	60,01	84,19	58,85	66,20
		95%	67,72	95,53	66,07	75,54
	Yellow	-95%	4,54	8,83	4,08	6,79
		Average	4,90	9,49	4,38	7,35
		95%	5,26	10,15	4,69	7,90
	Orange	-95%	2,55	4,98	2,21	3,82
		Average	2,76	5,31	2,39	4,12
		95%	2,98	5,64	2,57	4,42
	Red	-95%	1,46	1,30	1,32	1,36
		Average	2,41	1,60	1,63	1,72
		95%	3,37	1,90	1,94	2,08

7.5.4 Number of Tests and Test Times

Regarding testing, scenario 24 tests assigning fewer tests to the patient and introduces the possibility of a patient going straight to treatment without any tests (in order to do so, a new label called "no tests " was created in SIMUL8 and the routing out from the Doctor Examinations was dependent on the results of that label as per Figure A.11, seen in Appendix A). Scenario 25 does the same and introduces a longer testing time. Scenario 26 returns to the same number of tests as the base model but maintains higher testing times. Since testing seems to be the main bottleneck of the base model, it would seem that lowering the number of tests would reduce the average waiting times considerably. At the same time, increasing the testing time will also some problems in the system leaving many patients unseen at the end of the week, all of this is shown in Table 7.7.

Table 7.8 - Comparison between results from the base model and scenarios 24, 25 and 26

			Base	24	25	26
Average Total Waiting Time (except triage queue) (min)	Blue	-95%	196,80	12,89	301,49	0,60
		Average	233,81	19,78	455,99	17,31
		95%	270,83	26,68	610,49	34,03
	Green	-95%	52,30	5,46	189,62	43,39
		Average	60,01	7,01	267,83	55,25
		95%	67,72	8,56	346,03	67,10
	Yellow	-95%	4,54	1,44	26,36	189,10
		Average	4,90	1,68	33,38	220,60
		95%	5,26	1,92	40,39	252,09
	Orange	-95%	2,55	0,88	7,87	13,50
		Average	2,76	1,03	8,59	14,14
		95%	2,98	1,18	9,30	14,78
	Red	-95%	1,46	0	5,78	9,78
		Average	2,41	0,36	7,85	12,09
		95%	3,37	0,86	9,92	14,40
Average Queue Size for Testing		-95%	5,59	0,01	12,00	442,53
		Average	6,36	0,02	20,16	457,16
		95%	7,13	0,03	28,32	471,78
Patients still in the system		-95%	19,91	9,76	42,24	928,26
		Average	22,73	12,77	46,27	934,43
		95%	25,56	15,77	50,29	940,61

As the results in the table above show, decreasing the number of tests required should reduce the average waiting time considerably, while at the same time increasing them too much could lead to higher than acceptable average queue sizes for testing. It is important to note that however useful it may be, reducing the number of tests assigned to patients may not be feasible.

Important to note how the fact that 934 patients not leaving the system in scenario 26 has distorted the results. The average waiting times for "blue" and "green" patients seem to have reduced from the base model but this only happens because most of them are still in the queue at the end of the simulation. The only ones counted for those waiting times were the ones that entered at the beginning of the simulations and had much smaller queues still.

7.5.5 Treatment Times

As was expected, since it is the last part of the system the effect of increasing or decreasing treatment times will only affect the time spent waiting for treatment. This time will also depend on the number of beds available. Scenarios 27 and 29 increase treatment times considerably. This leads to a much higher number of patients left in the system. This value should lower if the number of beds increases. Table 7.8 shows the number of patients in the system at the end of the week, along with the utilization percentages of “beds” and “red beds”. The fact that that the utilization percentages of “beds” in scenarios 27 and 29 are almost at 100% is the reason why such a big queue is formed and why increasing the amount of those resources could lead to better results.

Table 7.9 - Comparison between results from the base model and scenarios 27, 28 and 29

		base	27	28	29
Patients still in the system	-95%	19,91	1245,01	19,02	1591,12
	Average	22,73	1 247,97	21,87	1 601,03
	95%	25,56	1250,93	24,71	1610,95
“beds” utilization %	-95%	45,31	98,28	29,75	99,05
	Average	45,69	98,47	29,98	99,09
	95%	46,06	98,65	30,21	99,13
“red beds” utilization %	-95%	0,16	5,27	0,48	12,15
	Average	0,19	6,35	0,55	13,97
	95%	0,21	7,43	0,62	15,79

7.5.6 Improvement Proposals

After analysing all 29 scenarios, some possible solutions for the ones with the highest average waiting times and/or more patients left in the system have been tested. The scenarios where the proposals have been simulated were 18, 20, 21, 27 and 29. The solutions and the logic behind them will be explained as we look through each of them separately. To be more easily identifiable, the simulations testing the solutions will henceforth be identified as scenario x.a (per example: scenario 18.a).

Scenarios 18.a and 20.a both employ the same solution. This is because the issue in both is the same, triage takes too long. Therefore, the solution tested is increasing the number of triage nurses during the day to 2, while maintaining only one during the night. Additionally, scenarios 18.b and 20.b were also created, in these scenarios the number of triage nurses was considered to be 2 during the night instead of the day, this was done to see the importance of accurate staff allocation and compare the results of increasing the number of nurses during the different shifts.

As the results of scenarios 18 and 20 from triage onwards are unreliable (due to the low number of patients that the triage queue) the values compared between the originals and the solutions were only the average waiting times for triage. As it shows in Table 7.9, increasing by one the number of triage nurses will lead to much lower waiting times. The increase will be much more relevant during the day, as can be seen, changing the number of triage nurses during the night meant a smaller difference in waiting times for triage, this should be due to the lower affluence of patients during the night. Important to note how we are assuming patients never leave due to waiting times. In reality, it is possible that patients would not wait for nighttime to be seen by a triage nurse.

However, this is something that should only be done if the waiting for triage takes too long.

Table 7.10 - Comparison between results from the scenarios 18, 18.a, 20 and 20.a

Scenarios		Triage Average Waiting time (min)	
	-95%	Average	95%
18	1 212,22	1 271,09	1 329,97
18.a	15,74	17,59	19,44
18.b	259,43	282,71	306,00
20	1 779,13	1 818,30	1 857,47
20.a	39,08	45,40	51,72
20.b	840,13	881,72	923,32

Of all the scenarios that varied the time it would take for the doctor examination to be performed, scenario 21 was the one to have the highest percentage of patients not seen within the time limit. As a solution for this, scenario 21.a simulates the creation of a separate queue for lower urgency patients (MTS level 4 and 5), which was suggested in Mandahawi *et al.* (2017). Therefore, having three different queues, one for level 1 patients, one for levels 2 and 3 and one for levels 3 and 4. The table below shows how doing this has both advantages and disadvantages, while the likelihood of a patient waiting longer than the number of minutes suggested by the MTS is lower for the less urgent patients, the average waiting time for patients seems to increase at the same time. Figure 7.5 Shows the changes made within SIMUL8: creating a new routing activity and a new resource "doctors 2" representing the doctors assigned to the new queue.

Table 7.11 - Comparison between results from the scenarios 21 and 21.a

			21	21.a
Average Total Waiting Time (except triage queue) (min)	Blue	-95%	224,52	244,89
		Average	269,42	305,09
		95%	314,32	365,29
	Green	-95%	72,84	129,43
		Average	84,19	148,24
		95%	95,53	167,05
	Yellow	-95%	8,83	17,82
		Average	9,49	20,78
		95%	10,15	23,74
	Orange	-95%	4,98	5,85
		Average	5,31	6,32
		95%	5,64	6,78
	Red	-95%	1,30	1,54
		Average	1,60	1,81
		95%	1,90	2,07
Patients queued above time limit	Blue	-95%	25%	5%
		Average	29%	8%
		95%	33%	10%
	Green	-95%	11%	0%
		Average	14%	0%
		95%	17%	0%
	Yellow	-95%	0%	3%
		Average	0%	4%
		95%	0%	6%
	Orange	-95%	0%	2%
		Average	0%	2%
		95%	1%	3%
	Red	-95%	0%	0%
		Average	0%	0%
		95%	0%	0%

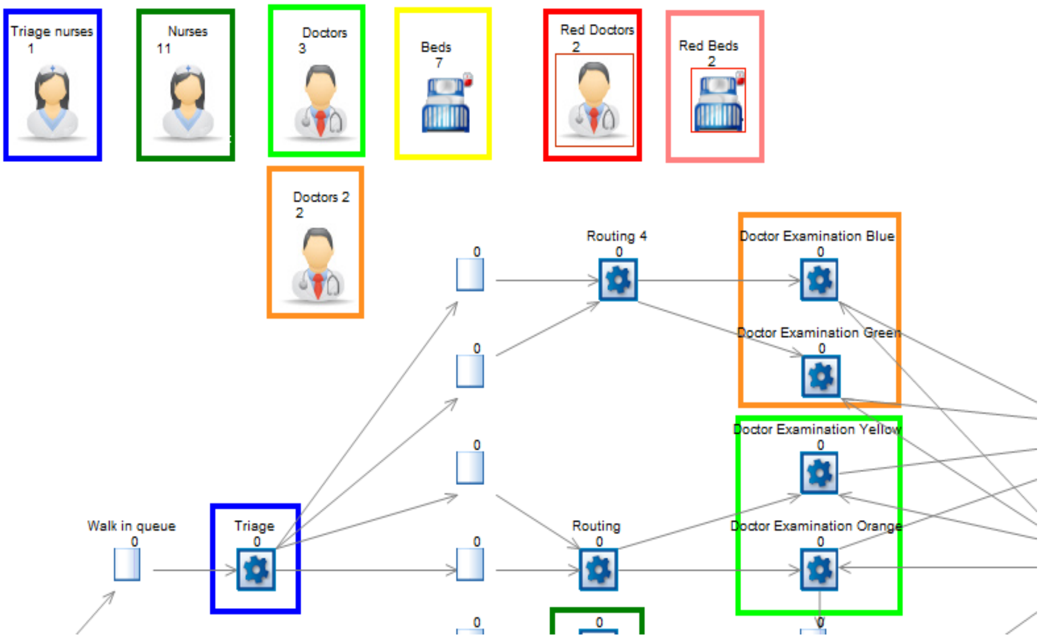

Figure 7.5 - Screenshot from SIMUL8 showing scenario 21.a

Scenarios 27.a and 29.a try to look at the possibility of increasing the number of beds as a solution for treatment times taking too long. The number of beds available was, therefore, considered to be 16 (doubled).

To compare the results between them we will be looking at the patients still in the system at the end of the simulation. We do this because in scenarios 27 and 29 this number is so large that it distorts waiting times across the simulation. Scenario 27.a will reduce the number of patients in the system by 1132 (from 1248 to 116) and 29.a reduces it by 227 (from 1601 to 1374). What these results show is that while increasing the number of beds available should reduce the queue sizes for treatment (and consequently the patients left in the system) the relation between how much the queue reduces and the number of beds added depends on each ED and the treatment times in it. Table 7.12 shows the results of these simulations.

It should be noted that, even though the results given by the SIMUL8 for average waiting times were not compared due to the reasons mentioned above, having a lower amount of patients in the system at the end of simulation, when the only change was increasing the number of beds, means patients must have spent less time in the system.

Table 7.12 - Comparison between results from the scenarios 27, 27.a, 29 and 29.a

		27	27.a	29	29.a
Patients still in the system	-95%	1 245	128	1 591	1 365
	Average	1 248	116	1 601	1 374
	95%	1 251	105	1 611	1 382

8 Conclusion

The chapter starts with a discussion on the results gathered in the previous section (*vide chapter 7*) and relate them to existing literature, as mentioned in the Methodology (*vide section 4.1.4*). Afterwards, it outlines the final conclusions reached along with possible answers to the proposed research questions (*vide section 1.4*). It then discusses the main limitations associated with this thesis, suggestions for future research (i.e. a proposal for future hypothesis supporting forthcoming studies) and identifies the contributions of the study.

8.1 Discussion

In this section, some considerations about the results obtained are considered.

The first conclusion to come from the analysis is that before attempting to develop solutions, one must correctly identify the issues within the system. As can be seen in the scenario analysis (*vide sections 7.3; 7,4 and 7,5*), the issue within the system can be a number of different things depending on the ED in question. The most influential issues when it comes to waiting times are resource bottlenecks also identified as a problem in Williams, Tai and Lei (2010). These bottlenecks can be any part of the system depending on the service times and on the resources available. This can be seen, per example, when comparing scenarios 21 and 23 (assuming a doctor examination service time represented by a triangular (8, 16, 24) distribution and an exponential (3) distribution respectively). By changing the service times, the bottleneck in the system changes from the doctor examination, in scenario 21, to testing, in scenario 23 (*vide section 7.5.3*).

A way to deal with the issue mentioned above and strive for long-term success is through the use of continuous improvement (*vide section 2.1.2*). The effectiveness of this way of thinking was seen when determining the number of nurses and doctors to use in the base model (*vide section 7.3).* Looking at scenarios 1 to 15, at first, increasing the number of doctors seemed to not decrease waiting times, increasing the number of nurses would be much more effective. However, as can be seen in the difference in average waiting times from scenarios seven to eight, after a certain number of nurses, increasing doctors would be the most influential decision. A manager constantly trying to improve should be able to realize the point of diminishing returns and change his policy from hiring nurses to hiring doctor, and vice-versa accordingly.

Besides simply increasing the number of resources available (which may not always be possible) diminishing service times has also been seen to be a way to decrease overall patient waiting times, this can be seen when comparing total waiting times between the scenarios 24 and 25 (vide section 7.5.4), while maintaining the number of tests, increasing the time they took also increased the waiting times for every MTS level. Comfere, Matulis, & O'Horo (2020) suggests using quality improvement methods such as Lean Thinking to accomplish this (*vide section 2.1.3.1*).

When simulating an increase in the number of triage nurses available, we noticed the importance of staff scheduling. Increasing the number during the nights a much smaller difference compared to during the day, when arrivals are at their highest (*vide section 7.5.6*). This is something that is corroborated by Evans, Gor, & Unger (1996) and Kumar & Kapur (1989).

Creating a separate queue for low priority patients was seen to increase waiting times *(vide section 7.5.6).* However, Garcia et al. (1995) observed the opposite, that doing so would reduce waiting times. More studies on this subject should be conducted to ascertain in which scenarios it could be useful.

8.2 Final Conclusions

The creation of a simulation model of an ED using the MTS, through the use of the DES tool SIMUL8, was the chosen theme for this thesis.

The reason for looking at the functioning of an ED was the issue of overcrowding identified in Ghanes et al. (2015) and Hoot & Aronsky (2008). Among these EDs multiple types of triages are used (*vide section 2.2*), the one chosen to be used in this thesis was the MTS (*vide section 2.2.1*) as it is the one most commonly used in Portugal (Mackway-Jones et al., 2014)

Simulation was the method chosen to address this problem because it is widely regarded as one of the most useful tools for determining resource allocation in EDs when trying reduce overcrowding (Barjis, 2009; Chouba et al., 2019).

Within simulation there were multiple methods of dynamic simulation available (*vide section 2.3.3 and its sub-sections*). Among these options the one determined to be the most appropriate was DES (*vide section 2.3.3.2*) as it is considered particularly relevant for healthcare simulation (Marshall, et al., 2015). SIMUL8 was the chosen simulation tool due to its capabilities and the researchers previous experience with it (*vide section 7.1*).

The research was done through the inductive research method (v*ide section 4.1.1*). Therefore, Research Questions were proposed at the beginning of the research a means of avoiding being overwhelmed by the volume of data, as suggested by (Eisenhardt, 1989).

RQ1) What is the flow of a patient through an ED?

This first question was chosen with the creation of the model in mind. In order to create a realistic model through the use of secondary data only a good understanding of the patient flow was required. In order to answer this question, the researchers followed the path suggested by Robinson (2008) on how to design and represent a conceptual model (*vide section 2.3.5 and its subsections*). The information required to create those representations was taken from Martin et al. (2011); Schaaf et al. (2014); Storm-Versloot et al. (2014); Rutman et al. (2015); Mandahawi et al. (2017); Improta et al. (2018); Amorim et al. (2019); and Martins and Filipe (2020). The result of this analysis identified the main path through the system as Figure 9.1.

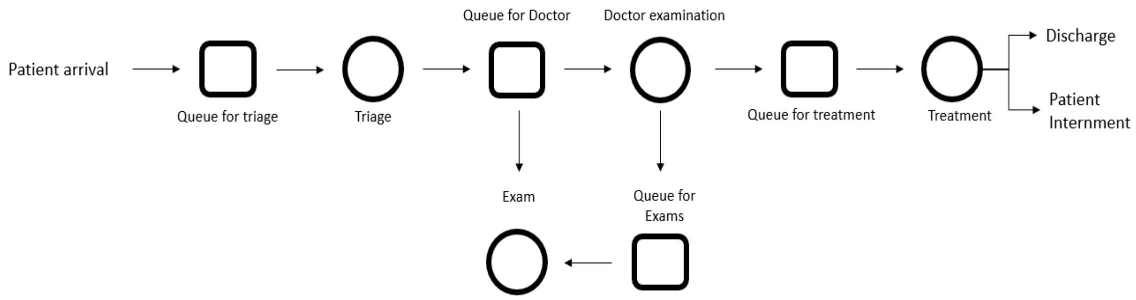

Figure 8.1 - Patient flow through the system

To explain Figure 9.1: the patient arrives in the system and enters the queue for triage; triage is performed by a nurse trained in the MTS; after triage the patient is assigned an

MTS that determines his priority in the following queues and is sent to the queue for the doctor examination; after the doctor examination patients, if need be, are sent to do some tests, otherwise they are sent to the que for treatment; after going through the assigned test the patient is once again sent to the doctor examination and then sent for treatment; after treatment the patient either leaves the hospital or is sent to internment in a different department. It is also important to note that a patient can die at any point during the system. More detailed information on how this path was adapted into the simulation model can be seen in sections 5.5.1, 5.5.2 and 5.5.3.

RQ2) What can be done to reduce waiting times in an ED?

As mentioned in the discussion (vide section 8.1) there can be no single answer for this question. The fact that through the analysis of previous papers we were able to create 14 scenarios by changing only one of the activities service time from the base model (*vide section 7.5*) shows that every single ED will have its own specific solutions. However, there are a couple of generalizations that can be derived from the results collected:

- Since patients tend to arrive more commonly during the day (vide section 6.1),taking this into account when allocating staff and, therefore, having more active staff during the day seems to improve ED functioning and reduce waiting time (*vide section 7.5.6*).
- Increasing the resource available for an activity will reduce average waiting times in that activity, even if it may not reduce average total waiting times in the system (*vide section 7.3*). The same can be said for reducing service times (*vide section 8.1*)

It should also be mentioned once again that due to the fact that there are so many different realities in EDs, in addition to the recent technological developments that could influence the industry (*vide section 2.1.3*) a mentality of constant improvement and adapting seems to be very important in reducing waiting times (*vide section 8.1*).

8.3 Limitations

The model created in SIMUL8 was constructed from researching previous papers on the subject rather than observation of ED functioning, meaning that it uses solely secondary data (*vide section 4.1.1*). Hence, the data available to construct the model was severely limited to what was made available on those papers. Therefore, a list of limitations can be enumerated:

- The inability to predict changes in the outcomes of patients when reducing or increasing waiting times. Which also led to an inability to test scenarios which revolved around this rather than average waiting times (e.g. introducing changes to MTS levels after a set period of time waiting).
- Testing was assumed to always require a nurse when, in reality, it is also dependent on machine availability, along with the fact that not all tests require a nurse to be present for the entire duration (e.g. blood and urine analysis).
- Even though some studies mention how age and gender can be relevant to the likelihood of under and over triage (Steiner et al., 2016; Brouns et al., 2019), and others give us data on the likelihood of every urgency level at different ages (Moreira, 2010), due to the lack of available data showing the correlation between age, gender and urgency levels, these are two variables that will not be introduced into the model.
- Despite some assumptions on these subjects being made: not all ambulance arrivals are “red” patients; doctors and nurses are not all equally efficient; staff scheduling issues are a common problem; patients often leave unseen if waiting times are too high (*vide section 5.5.4*)
- Due to lack of available information, the costs and revenues of the ED were not considered.
- Results in simulation are not necessarily equal to real life situations as simulation modelling remains a representation of the reality (Vilas-boas et al., 2015). Implementing the scenarios could yield different results

8.4 Recommendations for Future Studies

As an inductive analysis of case studies one of the objectives of this thesis was to develop hypotheses to be tested in future studies. This is a list of the hypotheses developed:

H1. Increasing the resource available for an activity will reduce average waiting times in that activity (as long as the average waiting time is higher than zero), even if it may not reduce average total waiting times in the system (*vide section45 7.3*).

H2. Decreasing the service times for an activity will reduce average waiting times in that activity (as long as the average waiting time is higher than zero), even if it may not reduce average total waiting times in the system (*vide section 8.1*).

H3. Creating a separate queue for lower priority patients (MTS level 4 and 5) does not reduce average waiting times (*vide section 7.5.6*).

Besides the creation of these hypotheses, there are also other recommendations that have emerged from this thesis:

- This model could be used as a framework for future studies, values from a specific ED would only need to be introduced into the model. In ED specific models, introducing staff scheduling conflicts and different staff efficiencies could be relevant;
- The following set of recommendations are ways to improve upon the created model:
    - Introduce cost analysis: SIMUL8 has the tools necessary to do so, one would only need to gather the required data to introduce them into the model;
    - Use the number of arrivals at EDs since the beginning of the COVID-19 pandemic to develop a model capable of dealing with the increased demand in times of pandemics;
    - Determining the relation between changes to waiting times and patient outcomes and including them in the model, therefore allowing for suggestions based on improving outcomes rather than just waiting times;
    - Determine different likelihood for each MTS level depending on the patient's issue and introduce it into the model;
- Utilize quality improvement methods like Lean and six sigma to improve ED functioning (*vide section 2.1.3.1*);
- Simulate different 5-level triage methods like Australasian Triangle scale, Emergency Severity Index, South African Triage Scale and Canadian Triage and Acuity Scale with the same amount of resources and compare the results.

8.5 Contributions

In general, the development of this thesis contributes for different areas.

From a theoretical standpoint this thesis contributes to healthcare operations management by suggesting hypothesis to be studied by future researchers.

From the practitioners' point of view this thesis may contribute with the creation of a general simulation model that can be adapted to fit a specific ED, therefore allowing for estimating the benefits of different policies before implementation. Moreover, suggestions are provided on practices that, if adopted, could reduce waiting times for patients (*vide section 8.2*).

Finally, this thesis may also contribute do social welfare if its suggestions are adopted and proven to be useful when reducing patient waiting times in EDs and, consequently, improving patient outcomes.

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Appendix A

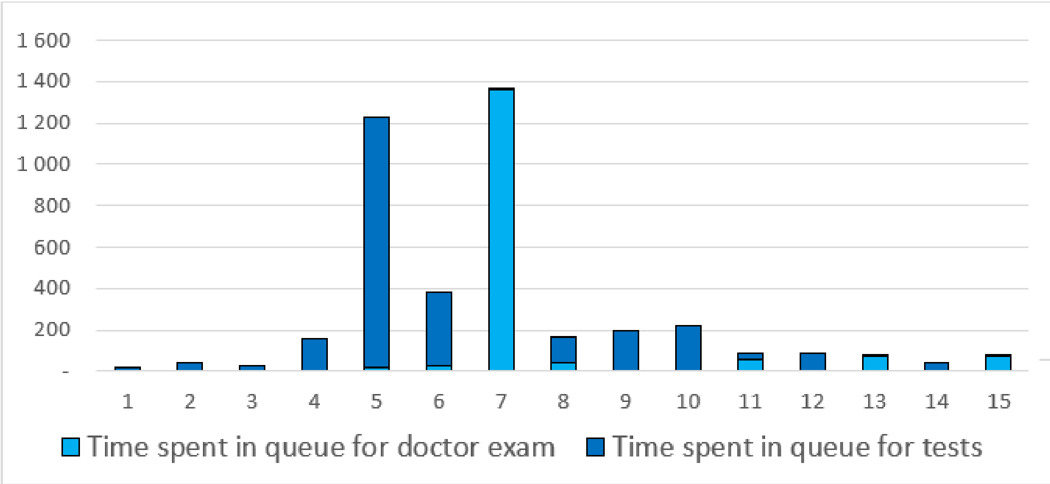

Figure A.1 - Waiting time for MTS level 5 patients (in minutes) per scenario

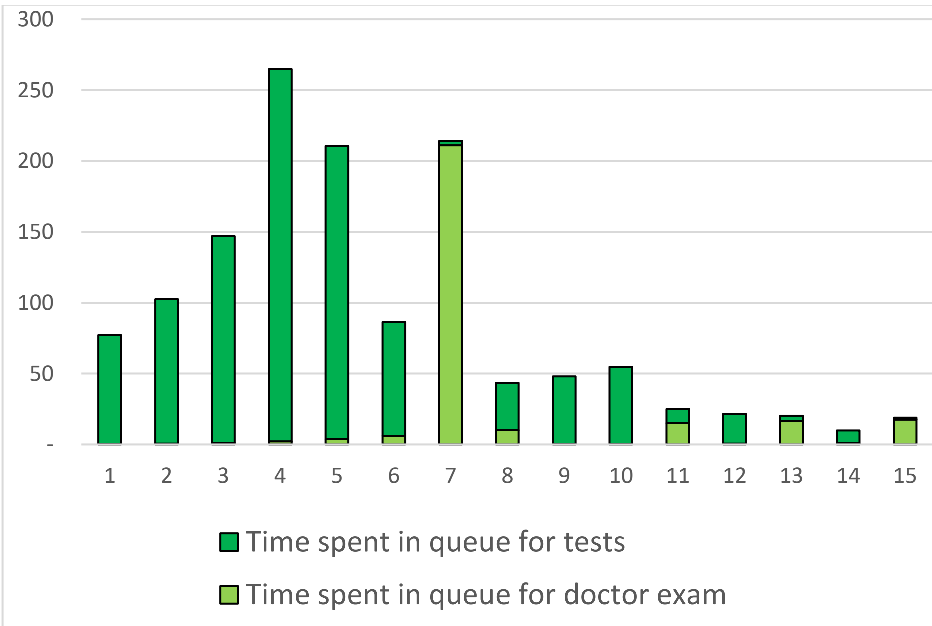

Figure A.2 - Waiting time for MTS level 4 patients (in minutes) per scenario

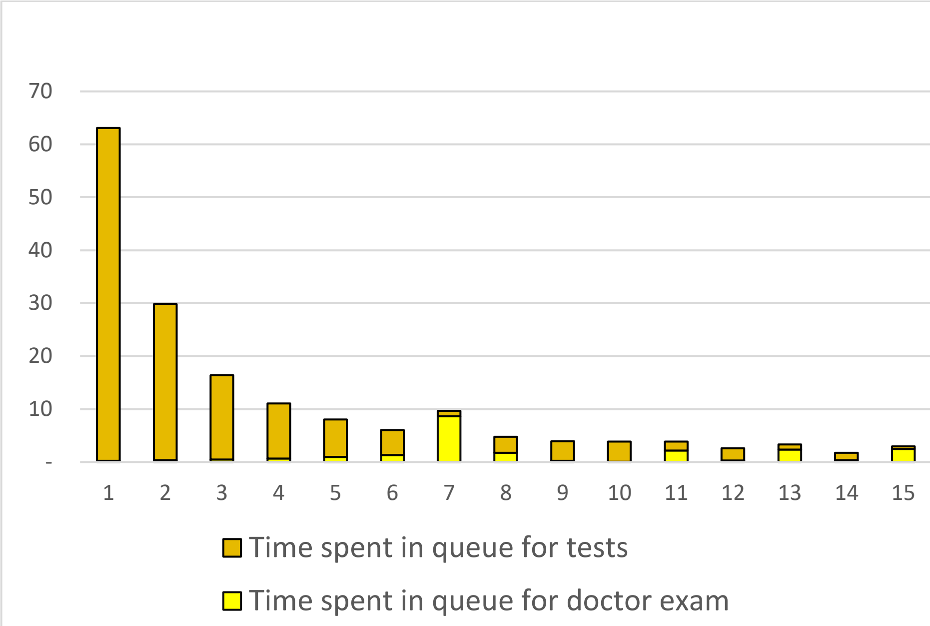

Figure A.3 - Waiting time for MTS level 3 patients(in minutes) per scenario

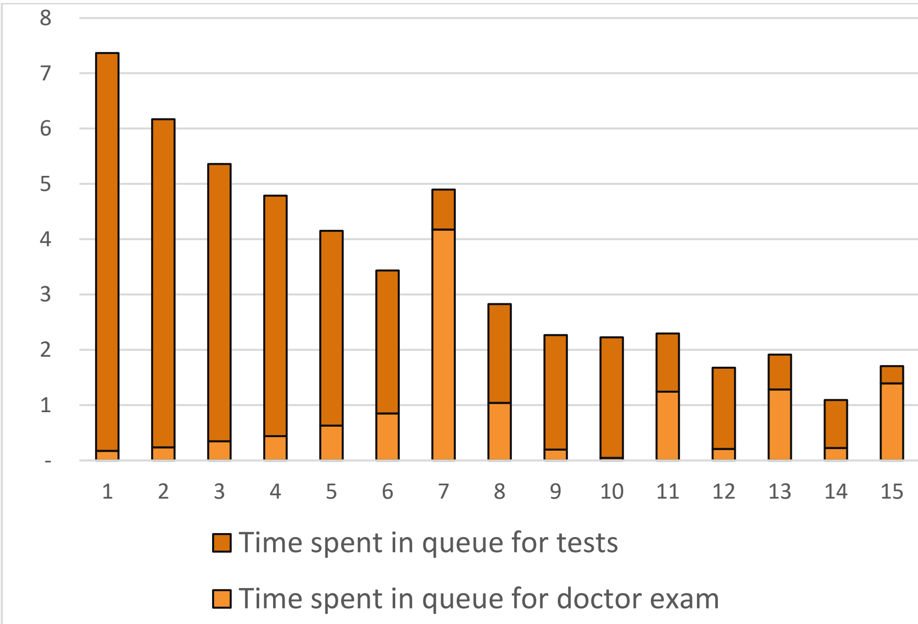

Figure A.4 - Waiting time for MTS level 2 patients (in minutes) per scenario

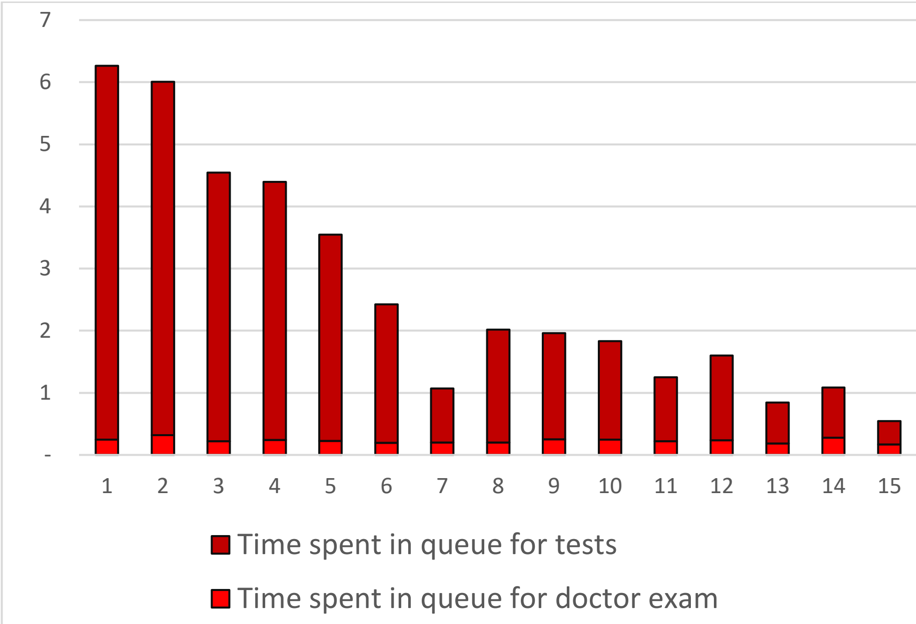

Figure A.5 - Waiting time for MTS level 1 patients (in minutes) per scenario

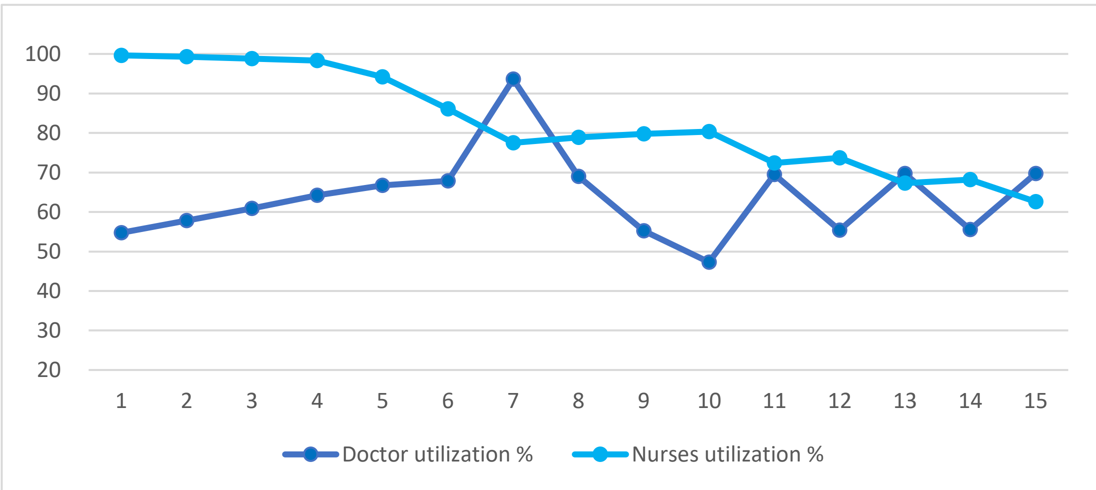

Figure A.6 - Resource utilization percentages per scenario

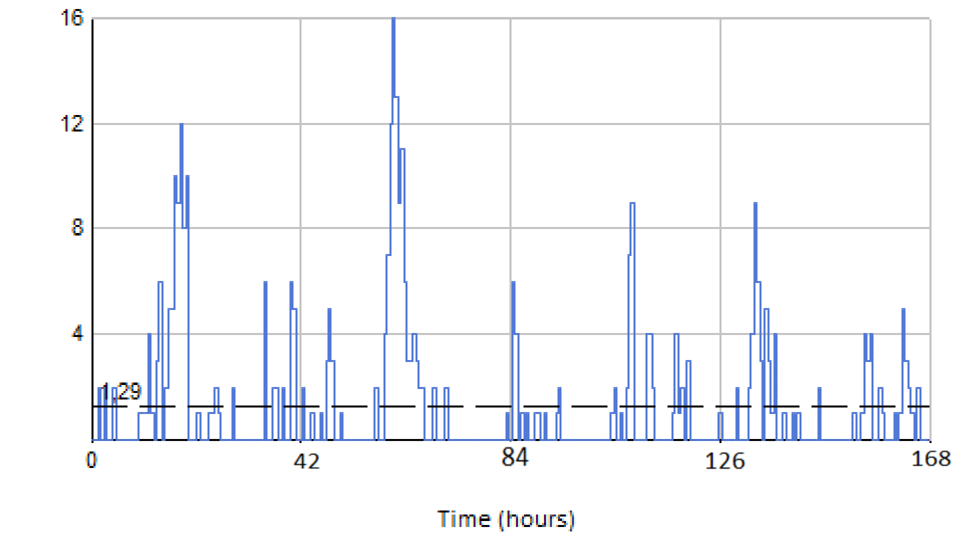

Figure A.7 - Patients in the queue for triage depending on the hour (scenario17)

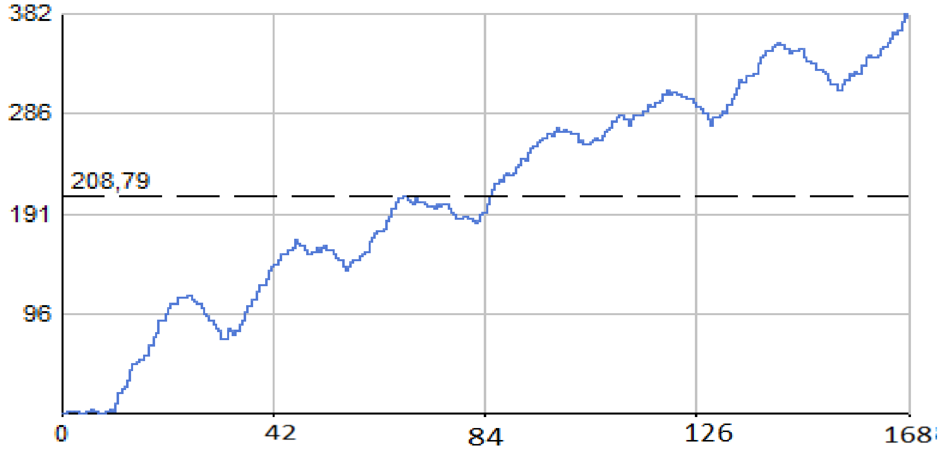

Figure A. 8 - Patients in the queue for triage depending on the hour (scenario18)

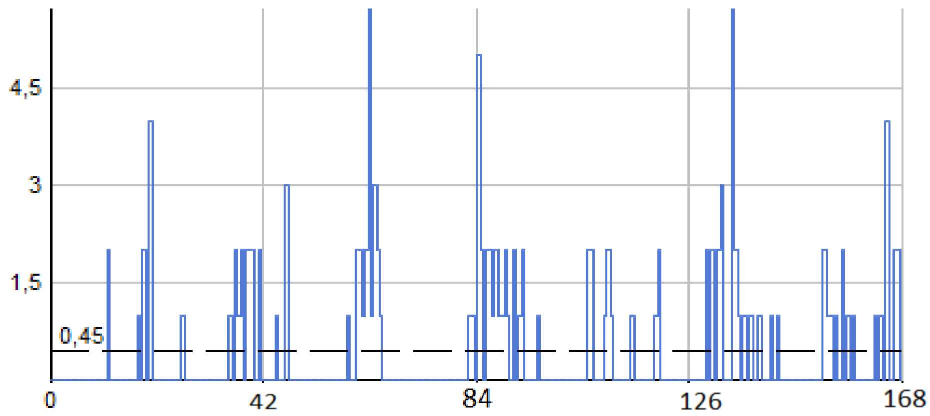

Figure A.9 - Patients in the queue for triage depending on the hour (scenario19)

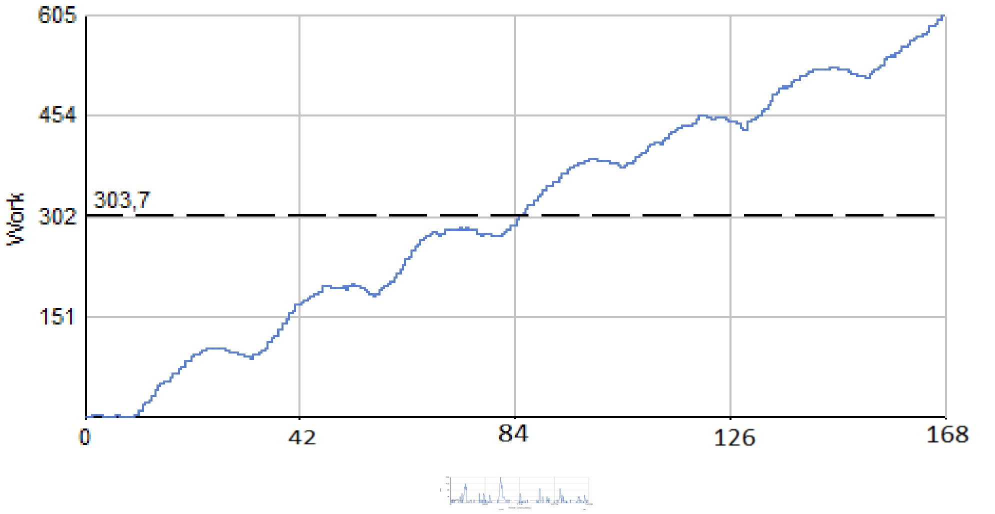

Figure A.10 - Patients in the queue for triage depending on the hour (scenario20)

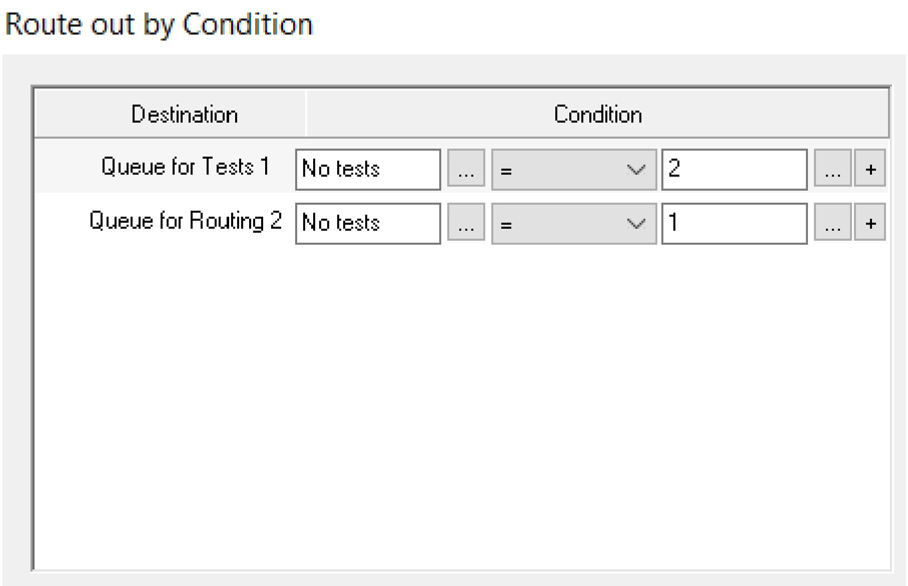

Figure A.11 - Screenshot from SIMUL8 showing the routing out conditions for the Doctor Examination of MTS level 5 patients in scenario 24. "No tests"=1 means the patient will not have to go through any tests

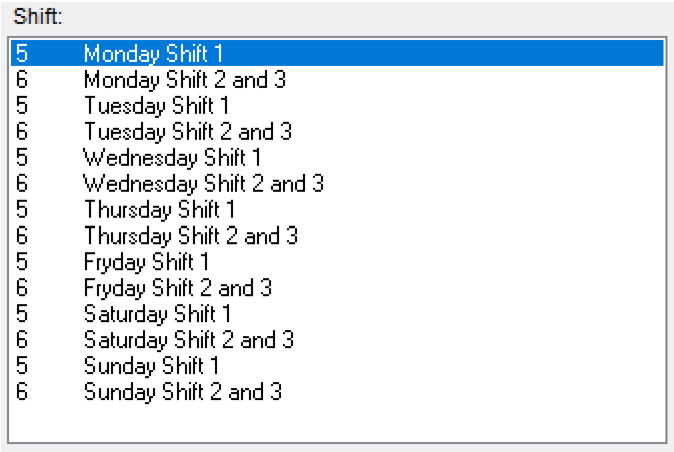

Figure A.12 - Screenshot from SIMUL8 showing the availability of the resource "doctors" in the base model

Table A.1 - Average total waiting times depending on MTS level and on change to interarrival time

			50%	20%	10%	base	-10%	-20%	-50%
Total Waiting time (Including triage queue)	Green	-95%	2,64	12,25	18,07	19,68	24,64	35,85	85,58
		Average	4,62	18,02	28,12	31,24	40,43	55,52	112,63
		95%	6,61	23,79	38,16	42,79	56,22	75,19	139,67
	Yellow	-95%	1,74	4,42	6,26	7,32	9,35	13,53	55,82
		Average	2,59	6,15	8,38	10,44	13,73	19,97	67,25
		95%	3,44	7,88	10,50	13,56	18,11	26,42	78,68
	Orange	-95%	1,50	3,67	4,37	5,49	7,06	9,81	46,62
		Average	2,37	4,91	5,70	6,96	8,88	12,44	54,29
		95%	3,23	6,14	7,04	8,43	10,71	15,07	61,95
	Red	-95%	0	0,23	0,20	0,38	0,48	0,48	0,90
		Average	0,18	1,13	0,59	1,10	0,99	1,09	1,78
		95%	0,37	2,03	0,99	1,83	1,50	1,71	2,66