MODELING AND SIMULATION OF EMERGENCY RADIOLOGY UNIT

AT ST. PAUL'S HOSPITAL

by

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Abstract

Increased demand for healthcare services and limited medical resources result in long patient waiting time. This problem is a worldwide concern due to the increasing population and costs. Owing to the key role of the emergency department in a hospital, this study is on this department in St. Paul's Hospital. The objectives are to reduce the patient waiting time and to balance resource utilisation. Discrete event simulation methodology is used to model the patient flow through the emergency radiology units. In this thesis, Arena simulation software is used for modeling, determining the waiting time, and identifying the bottlenecks in the system. These bottlenecks are alleviated using what-if analysis, which enables the radiology department managers make operational decisions based on the alternative scenarios examined. It was concluded that adding one physician and one X-Ray technologist for one shift per day improved the performance in the emergency radiology unit.

Analysis of variance and the Tukey test were used to evaluate the effective decision factors. The results showed that the number of physicians followed by the number of X-Ray technologist had the most noticeable effect on the waiting time. The results obtained from the Tukey test also confirmed those of the Arena simulations.

Lay Summary

The long patient waiting time to access healthcare services deteriorates patient satisfaction and reduce the quality of services. In this thesis the emergency radiology unit of St. Paul's Hospital is simulated, and the results are analysed. This approach provides several alternative scenarios for evaluating the system condition in each case. This enables hospital managers and administrators to have better insight into the system performance and predict the near-future state to make service improvement.

Preface

This thesis entitled "**MODELING AND SIMULATION OF EMERGENCY RADIOLOGY UNIT AT ST. PAUL'S HOSPITAL**" presents original research conducted by Hamideh Torabigoudarzi under the supervision of Prof. Sassani. The proposed methodology in this manuscript is original, unpublished and independent work by the author.

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List of Abbreviations (Acronyms)

Canadian Association of Emergency Physicians (CAEP)

Canadian Association of Radiologists (CAR)

Canadian Institute for Health Information (CIHI)

Canadian Triage and Acuity Scale (CTAS)

Discharge Abstract Database Metadata (DAD)

Discrete Event Simulation (DES)

Emergency Department (ED)

Length Of Stay (LOS)

Mixed Integer Linear Programming (MILP)

Magnetic Resonance Imaging (MRI)

National Ambulatory Care Reporting System (NACRS)

Radiology Information System (RIS)

St. Paul’s Hospital (SPH)

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My sweet son, Parsa for being such a good baby that past seven months, who has given me the extra strength and motivation to complete what I started.

Dedication

To my beloved parents - Fatemeh and Hashem

To my lovely husband - Vahid

To my adorable son - Parsa

Chapter 1: Introduction

1.1 Context and Motivation

Nowadays, improvement in healthcare services has drawn significant attention since it affects practically everyone; caregivers, administrators, and of course the patients. This improvement will lead to increasing healthcare efficiency in light of increasing population and costs. The growing use of emergency department (ED) makes it an increasingly important element in the healthcare system. ED serves as a first choice for the life-threatening injuries and patients who are severely ill and the only choice for those who do not have access to other medical services. According to an international survey on five countries (Australia, Canada, New Zealand, the UK, and the U.S.) which is done by Schoen et al. (2004), Canada had the highest use of ED between 2001 and 2003 and the waiting time before being treated was two hours or more, as shown in Table 1.1.

Table 1.1: ED use and waiting time in five countries (Schoen et al. 2004)

	Australia (No. = 1,400) %	Canada (No. = 1,410) %	New Zealand (No. = 1,400) %	UK (No. = 3,061) %	U.S. (No. = 1,401) %
Went to the ED in the last 2 years	29*	38	27*	29*	34*
Reported waiting >2 hours before being treated	29*	48	27*	36*	34*
Went to the ED, but felt they could have been treated by regular doctor if available	9*	18	7*	6*	16
Regular doctor informed and updated about the plan for follow-up after the hospitalization	74*	70	68	70	77*

Based on the Canadian Institute for Health Information (CIHI), the majority of patients admitted to a hospital were admitted via ED accounting for nearly all of the growth in hospital admissions. All the above points reveal the importance of the ED in measuring the quality of healthcare systems.

One way of enhancing the quality of medical services is reducing the patient waiting time, which is regarded as one of the most important elements in the patient satisfaction level as observed by Bahadori et al. (2017). Table 1.1 shows that Canada had the highest percentage of adults who have waited more than two hours for treatment in the ED. Generally, waiting time arises because of the difference in supply and demand. When healthcare demand exceeds supply, the healthcare supply cannot be instantaneous, and patients have to wait to access healthcare services. Overcrowding in the ED is deemed a national concern for healthcare systems, which can be measured through monitoring the patient waiting time. In the overcrowding situation, the demand for medical services is higher than the ability to provide those services in a reasonable time. Increased patient waiting time can also result in medical error threatening human life (Sun et al. 2013; George and Evridiki 2015).

Table 1.2, which is reported by CIHI presents the recommended and actual times from triage to initial physician assessment, by Canadian Triage and Acuity Scale (CTAS) level. Although patients at CTAS level V (low acuity cases) met the target time, the patient waiting time was longer than recommended response time in the other CTAS levels resulting in the ED crowding.

Table 1.2: Recommended and actual times from triage to physician initial assessment, by CTAS level. (Highlights of 2010-2011 Inpatient Hospitalisation and ED Visits, 2012).

Acuity	CTAS Level	Time to Physician Initial Assessment		
		Ideal Response Time*	Actual (Median)	Actual (90th Percentile)
	I (Resuscitation)	Immediate (<5 minutes)	11 minutes	47 minutes
	II (Emergent)	15 minutes or less	54 minutes	190 minutes
	III (Urgent)	30 minutes or less	79 minutes	229 minutes
	IV (Less Urgent)	60 minutes or less	66 minutes	188 minutes
	V (Non-Urgent)	120 minutes or less	53 minutes	165 minutes

Patients enter the ED with a stochastic pattern, and this randomness affects the system performance in the ED and departments related to it (Joshi and Rys 2011). Among different departments in a hospital, the focus of this study is on the emergency radiology unit. Radiology is a keystone of any hospital allowing doctors to diagnose and treat diseases by detailed images and information of various parts of the body. An efficient radiology unit improves the patient care and patient throughput followed by enhancing the hospital's bottom line.

Enhancing access to imaging equipment is regarded as one of the best approaches to have efficient imaging services. According to a CIHI report in 2015 (How Canada Compares. 2016), nearly 2 in 5 Canadian primary care doctors had reported that their patients had difficulty in accessing specialised diagnostic imaging tests. The international average of accessing imaging equipment was 1 in 5, that is two times more than Canada. Also, CIHI report which is prepared by most provinces in Canada (Wait Times for Priority Procedures, 2017) shows that waiting times for both the MRI and CT Scan have increased since 2012 (Figure 1.1).

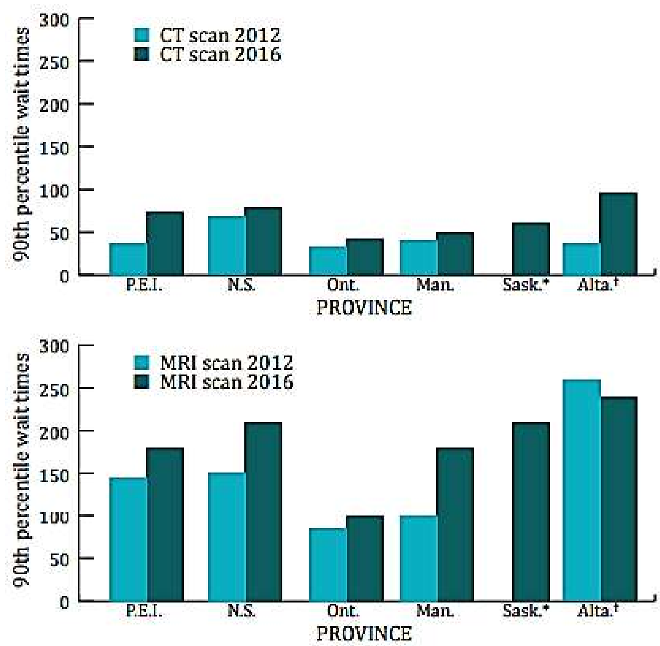


Figure 1.1: Provincial wait time in days for MRI and CT Scan, 2012 and 2016 (waiting times were not available for Newfoundland, Labrador, New Brunswick, Quebec, and British Columbia.

1.2 Problem Description

Since St. Paul's Hospital will move to a new location in eight years, managers are looking for a way to improve their services. The number of patients who are served at SPH has exceeded from 502,516 patients in 2013/14 to 634,384 in 2016/2017 (Table 1.3).

The number of patients who visit the ED is growing, and consequently, the Length Of Stay (LOS) is on the rise. Based on the data submitted to the National Ambulatory Care Reporting System (NACRS) (ED data tables, 2018), the number of ED visits and ED LOS have ascending trend as is shown in Table 1.4 and Figure 1.2. This data covers all the EDs in Alberta, Ontario and Yukon, 29 in B.C., 10 in Saskatchewan, 8 in Manitoba, 11 in Nova Scotia and 1 in P.E.I.

Table 1.3: The number of patients served at SPH in different years.

Year	Patient Served
2013/2014	502,516
2014/2015	564,097
2015/2016	631,771
2016/2017	634,384

Table 1.4: Five-year trend for the number of ED visits and ED Length Of Stay (LOS).

Fiscal year	Number of ED visits	ED LOS (90% spent less, in hours)
2012–2013	983,188	28.3
2013–2014	1,041,271	28.4
2014–2015	1,084,061	30.5
2015–2016	1,103,243	29.3
2016–2017	1,117,538	32.6

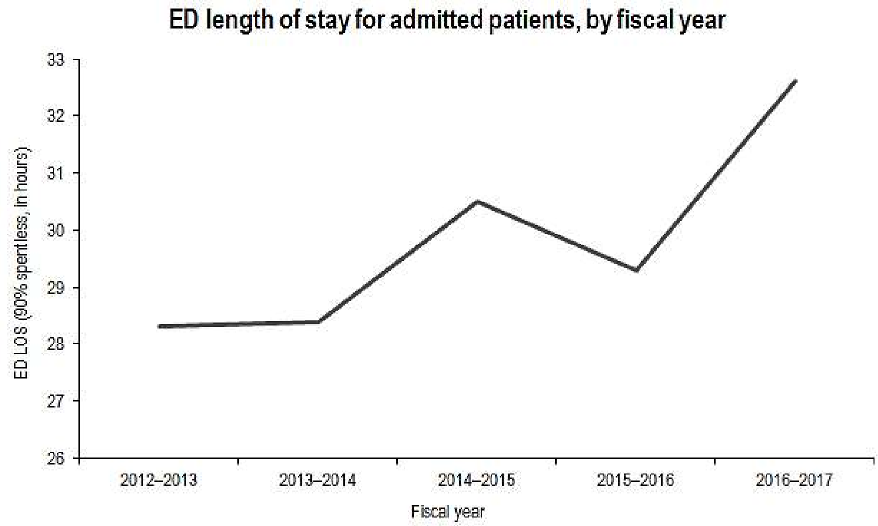


Figure 1.2: Five-year trend, total time spent in the ED for admitted patients (ED data tables, 2018).

Therefore, the problem is overcrowding in emergency radiology unit at SPH, and it was selected to be a representative of a typical hospital with long patient waiting time.

1.3 Research Objectives

The objectives of this study are defined as follows:

1. Improve the services provided by the emergency radiology unit by reducing the patient waiting time.
2. Increase in patient throughput and staff utilisation.
3. Provide means for decision-making.

1.4 Research Methodology

Healthcare services comprise many exceptions, system interactions and emergency cases, which cannot be precisely modeled through common mathematical methods. Popular mathematical methods, like linear programming, provide fixed final results, so, the emergency changes and exceptions cannot be readily examined. According to He et al. (2016), it is not feasible to use mathematical modeling due to the randomness and uncertainty in the ED.

Three main methodologies are used in the healthcare domain; sequencing algorithms, queuing methods, and discrete event simulation method. These three methods are discussed in the following sections.

1.5 Sequencing Algorithms

The objective in the sequencing problems is minimising the completion time, which is the span between the beginning of work on the first task on the first process, and the time when the last task is completed on the last process (Sassani 2017). Sequencing algorithms are usually used for static situations such as manufacturing processes rather than dynamic cases such as a hospital. Unlike the static models, time plays a key role in the dynamic models, and there are time-varying relationships between processes.

1.6 Queuing Theory

Queuing method is a classical operations research methodology, which uses mathematical models for calculating average metrics such as the average waiting time or the average queue length. Since queuing methods need fewer input data compared to a discrete event simulation method and can be implemented via a spreadsheet model that is easier, many researchers have benefited from this methodology in their research. This methodology is appropriate for general services applications rather than healthcare, especially the ED that is complex with many details and variables (Hu et al. 2018). One of the challenges associated with the queuing method is handling different patients with different level of illness. However, in a hospital; different patients with different level of sickness severity should be treated. The ED is more complex to be modeled owing to the following reasons:

- Patient arrival pattern is variable based on time; either weekdays/weekends or day/night hours.
- Patients have different priority according to the level of sickness severity and should be treated accordingly.
- There are different service times based on the patient condition and patient throughput at a given time, so, the steady-state analysis is inappropriate.

- The ED has interactions with other units and departments in a hospital. Its performance is affected by the upstream and downstream elements. Thus, the performance of other units will affect the ED performance.

The above points reveal that queuing theory is not an appropriate method for modeling of systems in the healthcare area.

1.7 Discrete Event Simulation

Among different existing methods, Discrete Event Simulation (DES) is more flexible and provides healthcare services with promising results in facilitating operational decision making (Hu et al. 2018). In DES many details and exceptions can be taken into account, and system operation is modeled as a discrete sequence of well-defined and ordered events in time. Moreover, in the DES, the patient arrival time and service time are stochastic rather than fixed. As discussed, rather than being deterministic, different parameters in the healthcare domain are random. In deterministic models, the parameters are related based on mathematical equations. Thus, no random number can be generated in these kinds of models.

The research methodology in this thesis is modeling the radiology unit in the ED through the DES method, and Arena v.14 software is used for this purpose. The modeling is done based on the patient flow, which is presented by the block diagrams in Arena. The animation can be activated while the simulation is running, and numerical results are provided at the end of the simulation. Through what-if analysis, the system bottlenecks can be mitigated to overcome the congestions in the system.

A healthcare system includes many process components, which are used based on the patient flow in the system, as discussed in the following sections.

1.7.1 System Components

In the DES method, a system is modeled as a chronological sequence of events that can be expressed as a function of time and have some uncertainty. DES uses some terminologies as follows:

- Entity: Any object or individual element in the system represented in the model such as people, machines or in the healthcare area can be patients, emergency physicians, or nurses.
- Attributes: The properties of an entity such as patient type, age, or priority.
- State: The collection of variables for describing a system at any time such as the number of patients waiting in a queue or resource utilisation.
- Event: An instantaneous occurrence that changes the state of a system such as the arrival of a new entity.
- Activity: A duration of time with a specified length such as triage nurse assessment, medical imaging examination, physician visit.
- Process: A series of events and activities in a sequential order representing the behavior of an entity in the real system.

1.7.2 Patient Flow

Patient flow data can be obtained through either observing the ED or asking administrators, managers, and staff. Both these approaches are followed in this study.

When a patient arrives in the ED, a triage nurse evaluates the acuity level and sends him/her for assessing the patient's condition by a physician. If patients need imaging, they are sent to the radiology unit for diagnostic imaging. After waiting in the emergency waiting area, the imaging examination is performed, and patients wait for the result. Based on the results, a physician decides whether a patient should be discharged or hospitalised.

1.8 Arena Software

Arena is a computer simulation tool for analysing a system and changing the operational parameters to achieve better system performance. This software is a combination of various modules, blocks, and elements for the modeling of complex systems. Modules represent processes or logic, which are connected by connectors that specify the flow of an entity in the model.

Also, Arena is a DES tool, which was developed by System Modeling. It was acquired by Rockwell Automation in 2000 and uses the SIMAN simulation language. Each module is a combination of SIMAN code which has been pre-packaged without a need for coding (Guneri and Seker 2008).

Arena is the leading healthcare simulation software solution on the market that is currently used in many hospitals in over 20 different countries (Healthcare simulation software, 2018). Healthcare providers around the globe utilise Arena to study patient flow, staffing requirements, optimising the use of facilities, streamlining of the emergency room and admission processes, facilities planning, etc.

Some of the most commonly used modules in Arena are as follows:

- Create: This module represents the arrival time to initiate the simulation process.
- Dispose: Entities are removed from the simulation by this module when the process is completed.
- Process: This module is employed for an activity or a task which is performed by one or more resources during the specified time (service time).
- Assign: It is used to assign an attribute to an entity or a value to a variable.
- Decide: It is used when an entity wants to decide among different possible choices (branches) and only one branch can be taken. This decision can be based on various probabilities or conditions.
- Record: It is used for collecting statistical values such as flow time.

Other than simulation, Arena provides users with several external applications for analysing the input, analysing the process, and optimising the objective function. These are briefly described in the following sections.

1.8.1 Input Analyser

The simulation inputs can be imported to this application through text files. Upon loading the file, a histogram of data can be plotted. The best fit of the histogram is defined by examining different distributions. The fitted distribution is plotted, and the related statistical information is displayed for the selected distribution. A variety of distributions can be compared through statistical information for finding the best one.

1.8.2 Process Analyser

Process analyser gives users the chance of assessing various scenarios via changing parameters in the model. This is called a what-if analysis for evaluating the model under different conditions. Scenarios are defined based on the control and response values. Those parameters that control the performance of a system are namely controls, and those that show the system performance based on control parameters are called responses. After defining control item values in each scenario, all scenarios are run, and responses are displayed. According to the response values, the best alternative can be selected based on the system objective.

1.8.3 OptQuest

Arena allows users to optimise their model through OptQuest package. After defining the controls, responses, constraints and objective function, several possible scenarios will be run based on the controls and responses to satisfy the constraints. Controls are those parameters that can be altered in the system, and system performance changes based on their values, and the responses show the system performance. Constraints are set based on the available number of control parameters. The values of lower and upper bounds should be determined for control parameters (such as resources), and the software selects the best values to optimise the objective function. Finally, the objective function is minimising or maximising the system responses that are specified in OptQuest. In each scenario (iteration), the objective function is calculated and compared with the previous one to determine a new set of combinations for the next iteration. Then according to the objective function, results are ranked from the best to the worst for various scenarios. Generally, Arena OptQuest application optimises the model by running the simulation model successively for several times. This is how optimisation is achieved in a DES.

1.9 Thesis Contributions

The main contributions of this research are as follows:

1. Simulation and modeling a specific radiology unit with a specific condition to assist managers in making operational decisions that would lead to shorter patient waiting time and shorter staff idle time.

2. Determining the optimal shifts for adding new staff (staff scheduling).
3. Identifying effective decision factors.

1.10 Thesis Outline

The study is organised into five chapters. Chapter 1 covers the introduction and provides background about the methodology used in this study. While in Chapter 2, the literature review is conducted for theoretical and empirical studies related to this research. In Chapter 3, two main phases for completing a system modeling using a simulation software (Arena) are discussed. Also, this chapter focuses on the real case study modeling and the simulation criteria. The simulation outputs are presented in Chapter 4. The results are analysed, and different scenarios are highlighted, and more effective decision factors are defined through an analysis of variance. Finally, Chapter 5 covers the conclusions made from the study, states limitations of this thesis, and offers suggestions for future work.

Chapter 2: Literature Review

2.1 Introduction

This chapter provides a review of related literature on patient flow simulation. Accordingly, the pros and cons of the available simulation methods are discussed. Hu et al. (2018) reviewed the application of queuing theory and DES in modeling the ED and observed that more than half of the articles in this area were published after 2011. This trend shows the growing attention in this realm, which is facilitated by improvement in health information systems, analytical software, and computational power (Lakshmi and Iyer 2013).

The important criteria in evaluating the ED performance include patient waiting time, the number of patients waiting in each queue, and resource utilisation. Efficient patient flow in an ED is identified by high patient throughput, short patient waiting time, sufficient resource utilisation rates, and minimum staff idle time (Jun et al. 1999). According to chapter 1, queuing theory and DES methods are widely used in the healthcare domain to analyse the ED performance. However, the sequencing algorithms are mostly used for schedule planning and are reviewed in the next section.

2.2 Sequencing Algorithms

Burdett and Kozan (2018) introduced a sophisticated flexible job-shop scheduling model through Mixed Integer Linear Programming (MILP), which was solved by meta-heuristic algorithms. In this model, patients are considered as jobs and hospital bed units as parallel machines. They assigned patients to beds and scheduled the patient's care activities in the assigned locations. It was concluded that the shorter make-span could be achieved using this approach.

Pham and Klinkert (2008) applied job-shop scheduling for surgical case scheduling problem through MILP with minimising the make-span as the objective function. They considered hypothetical data and solved their model via the CPLEX solver to find an appropriate surgical schedule with minimum completion time. In that work, machines were hospital resources such as surgeons, and jobs consisted of a sequence of operations. Resources were first assigned to each activity of a job, and then activities were scheduled on their assigned resources. They concluded that the main limitation of such an approach is the capability of MILP solvers, which can provide feasible solutions for only small to medium-sized cases.

In the scheduling model presented by Granja et al. (2014), a radiology unit was considered as n-job m-machine problem, where patient schedules were jobs, human resources (physicians, radiology technician, and radiology assistant) and physical resources (waiting room, changing rooms, and exam room) were machines. The objective was to find the workday configuration to increase the patient throughput and decrease the process total completion time and patient total waiting time. In order to optimise the results, a simulated annealing algorithm was used.

A classic job shop scheduling algorithm was used by Othman and Hammadi (2017) to minimise the maximum completion time and reduce the patient waiting time in the Pediatric ED. The n-job m-machine problem was solved by setting up a set of lower bounds characterising criteria limits and mathematical formulation. They considered jobs as treatment tasks and machines as the medical staff. The first stage was assigning the tasks to the resources and then the sequencing of tasks. They used an evolutionary algorithm for solving multi-objective optimisation, and the fuzzy logic was applied to evaluate the final solution. It was shown that the lower-bound method is more reliable in comparison with the fuzzy evolutionary approach. Finally, Java programming language was used for simulating the model illustrating that the quality of medical staff scheduling is improved using the lower-bound method.

Although the above articles did find better scheduling algorithms to increase resource utilisation or reduce the patient waiting time, it should be noted that sequencing algorithms are used for non-dynamic systems (Kadipasaoglu et al. 1997). Above researchers considered the hospital as a static model; however, a hospital represents a dynamic environment.

2.3 Queuing Theory

Sharif et al. (2014) presented an accumulating priority queue modeling, which is a time-dependent and multi-server model. The objective was to identify a selection scheme that can be applied to different acuity-based triage categories with a focus on determining the patient waiting time. Exponential distribution was considered for all the service times and arrival times for different classes of patients. They stated that if those times differ for different patient classes, it will be very challenging to solve the problem analytically. However, the service time and arrival time can have different distribution forms, which cannot be modeled using queuing theory.

The queuing theory was used by Lin et al. (2014) to estimate the average patient waiting time and number of resources (bed capacity) in the ED and the inpatient unit. A fast track (express) line was considered for patients with less severe illness and injury to shorten the patient waiting time. It should be noted that a fast track line worsens the efficiency of the ED and prevents it from providing timely care to patients with high level of illness or injury; moreover, patient conditions could potentially progress to a more serious problem requiring emergency intervention. Also, they considered steady-state and average arrival rates; however, the arrival rate cannot be stationary especially in the ED.

Vass and Szabo (2015) studied the relationship between the number of resources and average patient waiting time using the queuing theory and applied the model to an ED. Poisson distribution was considered for the arrival rate, and exponential distribution was chosen for the service rate. One physician was assigned to each bed. It was proposed that utilising computer simulation is the best approach to find the optimal number of physicians and beds.

The queuing model can be used for determining the nurse staffing and bed occupancy level that affect the ED overcrowding (Yankovic and Green, 2011). Two queuing models were considered in their study: the need for beds and request for nurses. The arrival and service rates had Poisson and exponential distributions, respectively. They used the MATLAB simulation since they clarified that the simulation model conforms to the reality of patient, nurse, and bed dynamics. Other than different distributions for arrival and service time, some other details cannot be handled through queuing theory such as discharging a patient by his/her nurse, bed cleaning time, and different service time for nurses with different levels of skills.

De Véricourt and Jennings (2011) proposed a queuing model to determine the sufficient number of nurses in a medical unit. They assumed an exponential distribution for service time and used simulation to show their results were robust due to some reasons. First, they applied other service time distributions instead of exponential that can be used in the healthcare domain, namely Erlang and hyper-exponential distributions. Second, patients with different levels of acuity were taken into consideration. However, some details such as the variety of patients, randomness in patient arrival rate and workforces with different experience levels cannot be taken into consideration through that modeling.

Xu and Chan (2016) developed a predictive model by utilising future information to predict the patient arrival and reduce the patient waiting time. At first, the waiting area at the ED was considered as a single queue with homogeneous patients while the future information was precisely known. Then, they discussed the unpredicted arrivals and different patient types with two classes of priority. However, different distributions for arrival and service time and prioritising patients based on a variety of acuity level cannot be handled in this kind of modeling.

2.3.1 Queuing Theory and Simulation

As stated, all steps of an operational process in an actual ED could not be covered via queuing modeling. Accordingly, some researchers have benefited from simulation models to verify the queuing model results as follows.

Lin et al. (2014) validated the analytical results by Monte-Carlo simulation and found similar results for the ED resource capacity, patient arrival rate, and the average waiting time for different levels of acuity. Yankovic and Green (2011) took advantage of MATLAB simulation to examine the dynamics between the patients, staffs and physical resources. Moreover, to better understand the queuing dynamic and have a precise arrival rate, Xu and Chan (2016) benefited from the analytical modeling simulation.

Overall, although the queuing theory is a valuable tool for ED modeling and management with minimal data requirement, several assumptions should be made to simplify the real problem in this method. Therefore, for a complex system like an ED, it is difficult to model it through the analytical formulation of queuing theory. On the other hand, in the DES, many details can be taken into consideration. Patient with different attributes can have variable arrival rate and attributes such as age, acuity, priority, etc. Patient flow can be defined based on the location such as an ED or a radiology unit. Patients can use physical resources like a bed or medical equipment with different service times. Besides, they can use human resources with different skills and schedule.

2.4 Discrete Event Simulation

Research articles on DES methodology for modeling are discussed in this section. At first, different simulation software that are used in the healthcare area are presented and compared. Then, literature that used Arena software as a simulation tool is investigated.

2.4.1 Simulation software in Healthcare Domain

The numerical results from DES show a real picture of a system by providing a dynamic analysis. There are many simulation software enabling researchers to model a system. Beside the Arena software, which is widely used in the healthcare area, some researchers used other simulation packages such as SIMIO (Nahhas et al. 2017), Tecnomatix Plant (Johnston et al. 2009), Delmia Quest (Fernández et al. 2017), Witness (Ozcan et al. 2017), or some specific modeling tools such as IDEF0 (Abo-Hamad and Arisha 2013), BPMN (Bahrani et al. 2013), and PartiSim (Monks et al. 2015) for business management simulation.

Nahhas et al. (2017) used SIMIO to design a number of simulation scenarios to identify the required resources such as examination rooms and staffing capacity in an urgent care center. In each scenario, they calculated the Leave Without Being Seen (LWBS) percentage, staffing and operational costs to find the best scenario. Johnston et al. (2009) considered several strategies for increasing the resource utilisation in an ultrasound department using the Tecnomatix Plant simulation tool. However, they both did not verify their model and did not discuss the applicability of their model in reality.

Fernández et al. (2017) used DES to rank a number of alternatives to find the best scheduling scenario for patients who use X-ray and MRI units. The objective was reducing the waiting time and improving the workflow. They used Delmia Quest software for modeling the system. Although the modeling was based on real data and it was validated, it was designed for the scheduled patients who can come based on a predefined schedule. However, in the ED, patient arrival is random, and uncertainty should be taken into consideration.

Ozcan et al. (2017) used Witness simulation-optimisation software packages for simulating a surgery department of a public hospital to decrease the patient waiting time and optimise the bed utilisation. After simulation, different scenarios were considered to find the best operation aligned to performance objective.

In the present study, Arena software was used as a simulation tool due to its “popularity” in research and academic fields. Dias et al. (2016) prepared an evaluation of different DES software, including 19 commercial simulation tools. The popularity was based on the level of presence on Winter Simulation Conference (WSC; scientific publications), document database-oriented sites (DOCS), web searches with tool name and vendor name (Reviews and social), and the Internet (WWW). The level of presence in each category was scored out of 10 as illustrated in Table 2.1. Among these simulation tools, Arena showed better performance in comparison with the other tools, and it was identified as the most popular DES software. Although more popular tool does not mean a tool with better quality, a positive correlation may exist between them (Dias et al. 2016).

Business management simulation tools were suggested as alternatives to minimise the patient waiting time (Abo-Hamad and Arisha 2013; Bahrani et al. 2013; Monks et al. 2015). Since these simulation tools were not listed at Dias et al. (2016) documentation, it can be said that they are not very popular. Tsironis et al. (2009) stated that creating a simulation model with business management simulation software is more complex in comparison with Arena. Arena simulation software outperforms those tools due to its specialisation for simulation tasks and generating more complete reports for further analysis of the results.

Table 2.1: Final score of simulation tools and Ranking comparison 2006-2011 (Dias et al. 2016).

DES Tools	WSC	DOCS	REVIEWS	SOCIAL	WWW	Growth	tot. (WSC docs social WWW)	Rank 2016
Arena	10	10	10	10	9	10	9,9	1
ProModel	10	9	9	5	9	5	7,6	2
FlexSim	6	7	7	9	8	6	7,2	3
Simul8	6	7	9	7	6	8	7,23	4
WITNESS	8	8	9	7	8	4	7,2	5
ExtendSim	7	8	8	4	5	5	6,2	6
Simio	6	6	4	5	8	9	6,1	7
Plant Simulation	1	6	7	6	7	8	6,1	8
AnyLogic	8	8	8	2	5	7	5,92	9
SIMPROCESS	9	10	4	1	6	4	5,0	10
AutoMod	9	6	7	1	4	4	4,83	11
Micro Saint	4	5	5	0	10	4	4,8	12
QUEST (Delmia)	3	6	4	3	8	4	4,8	13
Enterprise Dynamics	5	4	7	4	4	6	4,8	14
ProcessModel	4	5	1	4	10	3	4,7	15
SimCAD Pro	3	2	5	3	3	5	3,7	16
GPSS World	7	6	2	0	3	4	3,18	17
SLX + Proof 3D	7	3	3	1	3	3	2,9	18
ShowFlow	3	2	5	0	5	0	2,4	19

2.5 Alternative scenarios

After running the simulation and identifying the system bottlenecks, the best solution for removing the bottlenecks can be achieved by considering several alternative scenarios. Mostly, two types of scenarios have been considered in the literature; resource change scenarios and process change scenarios. The first type comprises studies that discuss the effect of changing the resources, while the second type investigates the impact of changing the process and procedures on simulation results to meet the system objectives.

2.5.1 Resource Change Scenarios

Changing resources includes several scenarios about considering the different numbers of physical resources (beds, rooms, diagnostic equipment), human resources (nurses, physicians, technicians), or different staff schedules to achieve better system performance.

Santibáñez et al. (2009) conducted an investigation into the Ambulatory Care Unit (ACU) at the British Columbia Cancer Agency's Vancouver Center to reduce the patient waiting time and improve resource utilisation. They found that these objectives can be obtained through multiple modifications simultaneously, which were redistributed clinic workload, flexible examination room for oncology programs, and re-evaluate physician scheduling. A DES modeling was done by Duguay and Chetouane (2007) in an ED in New Brunswick, Canada. What-if analysis revealed that adding a nurse and a physician during the rush periods will reduce the patient waiting time.

Jamjoom et al. (2014) investigated the appointment scheduling system in the Obstetrics Gynecology department and realised that modifying the scheduling system based on patient type can result in lower patients waiting time. The scenario that served a new patient after serving 3-4 scheduled patients reduced the average waiting time by 26%. Bahadori et al. (2017) found out that the waiting time will be reduced if a Magnetic Resonance Imaging (MRI) machine and a technologist were added to the MRI department. After studying several scenarios, Cochran and Bharti (2006) concluded that reallocating beds from one ward to the other one will lead to 38% more patient flow. Keshtkar et al. (2015) presented several scenarios with a different number of beds, nurses, and physicians. They calculated the necessary budget and patient waiting time for each scenario to help managers in evaluating the system under different conditions and making a decision accordingly. Baril et al. (2014) evaluated the system performance under a different number of consulting rooms and nurses and the variety of appointment scheduling and patient trajectory. Their results showed that adjusting scheduling appointments according to patient trajectory types resulted in a 20% decrease in the total patient waiting time.

2.5.2 Process Change Scenarios

Changing the process includes replacing a process with an alternative one or changing the patient flow in the system to improve the system operation. Holm and Dahl (2009) studied the effect of replacing nurses with physicians in the triage for initial evaluation, which led to the total patient waiting time reduction in an ED. These physicians were referred to triage physicians by authors and their differences with a triage nurse is that the nurses must follow specific guidelines with subsequent precise documentations for acuity evaluation, while this is not necessary for the physicians. Similarly, Ruohonen et al. (2006) proposed a method called the triage-team method.

In this method, instead of being visited by a triage nurse, a team consisting a receptionist, a nurse, and a physician visit the patients, immediately after they enter the ED. In this way, the time should be spent for referring the patient to the lab test or imaging department, which is done by the triage nurse or physician, will be saved and resulted in decreasing the patient waiting time. Davies (2007) compared two methodologies in an ED. In the first methodology, the process of patient assessment combined with the treatment process, and in the second one, those processes were considered separately. The results showed that considering the process of assessment and treatment separately, where the emergency nurse and the doctors behaved the same, resulted in reducing the average waiting time. He et al. (2016) suggested a new registration procedure (patient flow) to optimise resource allocation and reduce the patient waiting time. They added an information desk to the registration area of the ED and reallocated the staffs accordingly due to waiting time reduction.

2.6 Methods Comparison

As discussed in section 2.2, the dynamic and uncertain features of healthcare systems cannot be handled by sequencing algorithms. According to Braubach et al. (2014), many scheduling approaches are not suitable for real-life applications. An efficient mechanism for patient scheduling should be devised due to the inherent characteristics of hospitals, which include unexpected events and unsteady workflow.

Although the queuing theory is a valuable tool for ED modeling, all steps of the operational processes cannot be covered in this methodology. Some simplifying assumptions should be made to adapt the queuing theory to an actual system such as the distribution of arrival time and service time, server types and capacities, room and bed capacities, and queue disciplines. Consequently, it is challenging to model a complex system like an ED that includes many exceptions, variations, uncertainties, priority classes and variable arrival and service times, through the analytical formulation of queuing theory. Hu et al. (2018) found that queuing models tend to oversimplify operations and underestimate congestion levels and obtain less realistic results than comparable simulation models.

However, many details can be taken into consideration in the DES. DES models provide the opportunity to generate results that closely reproduce the observed performance. Among the different simulation tools, Arena software out-stands other ones, as discussed in section 2.4.1.

For analysing the results with the resource change scenarios, it can be concluded that adding more resources cannot guarantee performance improvement; moreover, it is not cost-effective in most cases. Therefore, it is imperative to pay more attention to staff rescheduling, redistribute workload, and reallocate resources before adding additional resources. In the process change scenarios, it can be perceived that changing the process and patient flow cannot readily be done in reality. It is difficult to convince all stakeholders and managers to implement such a significant change. Thus, the resource change scenarios were selected for analysing the results in this thesis. Since different healthcare services have different characteristics and criteria, specific alternative scenarios were considered to deal with long patient waiting time problem in the emergency radiology unit at SPH.

Based on the selected method for analysing the results, Table 2.2 presents a summary of the articles which were discussed in the resource change scenario (section 2.5.1). It contains information about the journals which have published an article, scope of work, objective of that particular article, the method of data collection, and investigates whether that article was verified and validated or not.

Table 2.2: Summary of articles in the resource change area.

Authors	Source	Country	Scope	Actual Hospital	Objective	Data Collection	Verification Validation
Santibáñez et al.	SpringerLink	Canada	ambulatory care unit	Yes	reduce patient wait time-improve resource utilisation	Manually and Data Base	Yes
Duguay and Chetouane	SAGE	Canada	ED	Yes	reduce patient wait time	Manually and Data Base	Validation
Jamjoom et al.	IEEE	Saudi Arabia	Obstetrics Gynecology Department	Yes	reduce patient wait time	Manually and Data Base	Validation
Bahadori et al.	SEMJ	Iran	MRI department	Yes	reduce patient wait time	Manually	No
Cochran and Bharti	SpringerLink	United States	Hospital	Yes	balance bed unit utilisation	Data Base	Yes
Keshtkar et al.	Qscience	Iran	ED	Yes	reduce patient wait time	Manually and Data Base	Yes
Baril et al.	ELSEVIER	Canada	Orthopedic Clinic	Yes	reduce patient wait time	Manually	Validation

2.6.1 Scope and Objectives

All the above researches are on the real hospital showing that the patient waiting time is a national concern. Among them, Duguay and Chetouane (2007) and Keshtkar et al. (2015) have worked on the ED, so, they considered randomness in patient arrival. Other researchers have studied hospital clinics where outpatients usually have a predetermined appointment. However, even clinics should deal with patients who attend late (lateness), no-show patients (absence), and walk-in patients. These researchers have benefited from best-fit distributions for arrival time and service time to consider randomness in their study.

As listed in Table 2.2, reducing patient waiting time was the common objective in all reviewed studies. Only Santibáñez et al. (2009) have considered the resource utilisation rate beside the patient waiting time.

In this work, a real case study was considered like all the above articles. Moreover, the focus was on the emergency radiology unit with random patient arrival rate, so, the time distribution for arrival and service times was used. Based on the importance of the resource utilisation rate, this factor was taken into consideration in this study as well. Thus, the objectives in this research are reducing the patient waiting time and increasing or balancing the resource utilisation similar to what Santibáñez et al. have considered.

2.6.2 Data Collection

Data collection in the healthcare domain is usually done manually, through an electronic database, and inpatient medical record review. Most of the required data in healthcare are not available in electronic medical records and appointments. Therefore, detailed information can be collected manually by observing the patients and interviewing administrators, doctors, nurses, and clerical personnel.

Santibáñez et al. (2009) have used the appointment booking system as a primary data source to know the scheduled appointment information for all patients who visit the clinic. However, this information did not contain detailed data like arrival time or process time for measuring the patient waiting time in the simulation. Thus, they obtained the necessary data through observation of the system and interviews with staffs. Duguay and Chetouane (2007) have collected data using the hospital log sheets (historical data), interviews, and on-site observations. Jamjoom et al. (2014) have considered treatment-related data that consists of the patient type and service time and appointment-related data which includes physician schedules, patient appointment time, and no-show data. Since they could not acquire all the needed data in the electronic database, they used a manual data collection method by observing patients, interviewing administrators, doctors, nurses, and clerical personnel. Keshtkar et al. (2015) have used two methods for gathering data: the triage database and interviewing department staff. Finally, Baril et al. (2014) have considered empirical data in their modeling and that data was collected manually at the clinic.

In this study, the data was acquired through an electronic database, and detailed data were collected manually.

2.6.3 Verification and Validation

Model verification shows that whether the model works as expected or not. Among discussed articles, only Santibáñez et al. (2009) have verified their modeling by tracing entities through the processes to ensure the model logic was correct. They tested extreme conditions to realise that their modeling performed as intended. Due to verifying the model in this study, the input parameters were changed by considering different conditions and confirmed that the output results were as expected.

All the above researchers have validated their modeling by comparing the simulated output with collected data. Among them, Santibáñez et al. (2009) and Keshtkar et al. (2015) have used face validation by interviewing staff as well. Like these two works, this study is validated through interviews with the senior managers who are knowledgeable and have good insight into the system.

2.7 Comparison

Table 2.3 shows the common features between this study and other related works in Table 2.2. "Yes" indicates that the feature is the same as in this study.

Table 2.3: Comparison of this study with related works.

Authors	Scope	Objective	Data Collection Method	Verification Validation
Santibáñez et al.	No	Yes	Yes	Yes
Duguay and Chetouane	Yes	Yes	Yes	No
Jamjoom et al.	No	Yes	Yes	No
Bahadori et al.	No	Yes	No	No
Cochran and Bharti	No	No	No	Yes
Keshtkar et al.	Yes	Yes	Yes	No
Baril et al.	No	Yes	No	No

Chapter 3: Simulation Model Development

3.1 Introduction

The two phases for completing a system modeling using simulation software are the model creation and execution (Bahrani et al. 2013). Each phase contains some details for building an actual patient flow as follows:

Model creation:

1. Problem definition
2. Conceptual model creation
3. Simulation model creation
4. Data collection
5. Simulation setup
6. Model verification and validation

Model execution:

1. Run base case and what-if scenarios
2. Output analysis
3. Decision making

A modeling diagram can be helpful to better perceive the concept of this chapter. Sargent (2013) proposed a simplified version of the modeling process (Figure 3.1), which is an iterative process to develop a valid simulation model. First, the ED should be studied to know the possible problem to be solved. Due to the ED complexity, some assumptions should be made for generating a conceptual model. The created conceptual model is checked for validity, and this process is repeated until the condition of conceptual model validation is satisfied. Then, the simulation model is created, and the checking is repeated to satisfy the model verification condition. This process is followed by assessing the simulation model validation condition. Sometimes, satisfying the validation condition will result in changing the conceptual model or the simulation model that is followed by related verification and validation. Finally, some alternatives can be designed to evaluate the model performance under several different conditions.

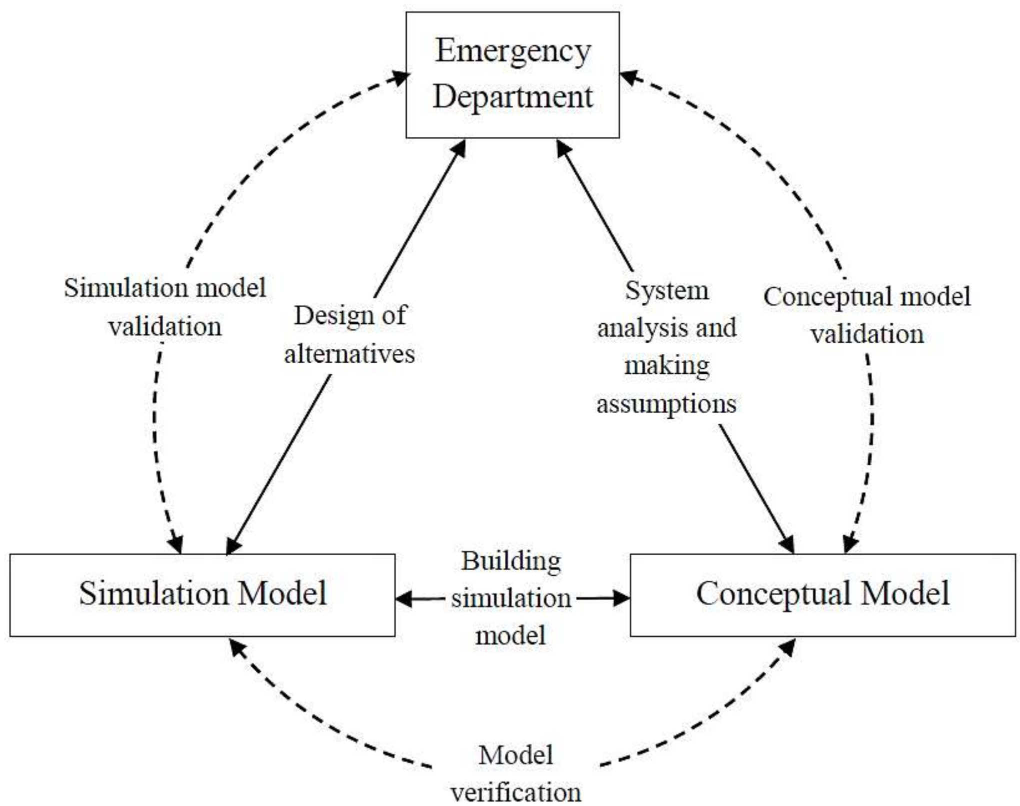


Figure 3.1: Modeling development process (Sargent 2013).

The first phase of a system simulation is creating a model for a system that is under investigation through the listed steps as follows.

3.2 Problem Definition

The first step of creating a model is defining the problem clearly and stating the objectives accordingly.

3.3 Conceptual Model Creation

A conceptual model is an abstraction of ideas to represent a system, and it is developed for the objectives of a study. This model is a combination of concepts making the model easy to understand and simulate. A modeling and simulation research is often carried out by a team of different individuals with different areas of expertise, and the communication among the team members is very important. A conceptual model enables them to have a better assessment of the simulation model. Moreover, it builds a basis that guides all activities in the simulation development and clarifies the scope of the project and the purpose of simulation (Robinson et al. 2015). A conceptual model provides the user with the opportunity to take in or leave out some details in the model, as well as, specify the simulation outputs (Pels and Goossenaerts 2007).

For this case study, a preliminary conceptual model was created; feasibilities and results were discussed with St. Paul's Hospital managers and Providence Health Care experts. This led to removing some details and putting more emphasis specifically on emergency radiology unit. For example, the patient priority changed from Canadian Triage and Acuity Scale (CTAS) levels to radiology-based priority (section 3.5.3), and MRI unit was removed from the department under the study.

3.4 Simulation Model Creation

Once the conceptual model has been created, it is necessary to map it into a model through a simulation tool, which is the Arena software in this study. The purpose of this step is translating the conceptual model into a simulation model. Therefore, all the activities, their sequences, and system components in the scope of the project should be preserved and modeled.

3.5 Data Collection

Data collection is deemed a major challenge in dealing with real problems. Even with available data, data cleaning and deriving the accurate input data that can be appropriately analysed is a demanding process. Developing a simulation model, which reflects the actual system, needs correct and sufficient data.

Usually, there are three methods for collecting data in the healthcare domain. The first is manual data collection from ward-based sources, the second is administrative data from an electronic patient management program, and finally inpatient medical record review. Among these three approaches, the administrative data shows the highest level of completeness (Sarkies et al. 2015). In this study, Providence Health Care provided historical data for the radiology unit of SPH. Historical data is the collected data of past events and activities that their trend can be extended to future activities. In this project, the patient arrival time, the service time for patients in each unit, and the number of equipment and staff are regarded as the input data for the model. Providence Health Care benefits from the Radiology Information System (RIS) database to extract the data needed for the simulation model. The RIS is used for the electronic management of the imaging departments. Since the collected information in the electronic medical database excludes some detailed data on the processes such as time stamps for arrival and staff-patient interaction, and staff idle/waste time, those data were collected manually by observing patients in the emergency department of St. Paul's hospital and by interviewing administrators and managers of this department. Finally, the data has been cross-checked for minimising the data collection errors. Some necessary data should be defined for modeling a system that is discussed in the following sections.

3.5.1 Patient Flow

As discussed in section 1.5.2, a patient is observed from entering the radiology unit to exiting it. This is shown in Figure 3.2 with a red rectangle.

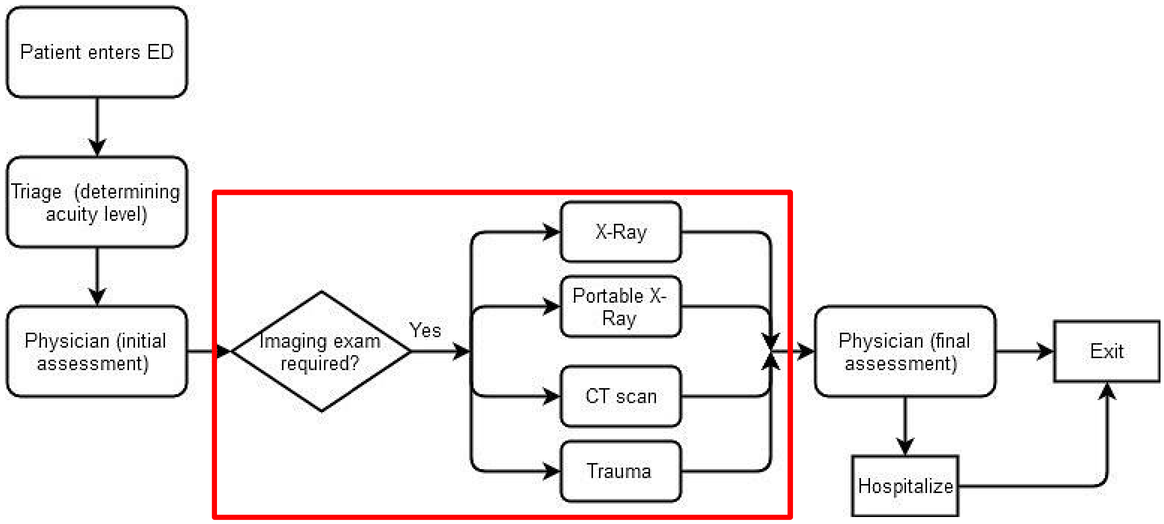


Figure 3.2: Patient flow in the emergency radiology unit.

3.5.2 Patient Arrivals

Patient arrival patterns were obtained using the RIS data in 30-minute window-blocks. Patients arrive in the emergency radiology unit at different rates during day and night. This variation can be introduced to the model by the *create block.*

3.5.3 Patient type

SPH emergency radiology unit has four main sections; emergency X-Ray, CT Scan (CT ER), emergency trauma, and portable X-Ray in the Emergency Room (ER). Patients enter the ED, and if they need imaging, they are sent to the radiology unit. Triage nurses assess the patient's level of severity and categorise them into four groups based on patient priority and isolation case (Table 3.1). Regarding the patient priority, patients are divided into two groups: regular (Reg) and STAT (STAT is from the Latin word *statim,* which means "instantly" or "immediately"). STAT patients have priority over the regular patients, and they have a different service time distribution owing to higher acuity. Regarding isolation case, patients are either regular or isolated (ISOL). ISOL patients have a different service time distribution because of being treated safely[1].

Emergency patients with different level of priority and isolation are sent to one or more sections and use different resources. The total number of used resources is listed in the third row in Table 3.1. It is the number of diagnostic resources used in the emergency radiology unit (CT ER, Emergency X-Ray, Emergency Trauma, and Portable in ER), including repeat uses of resources during the same visit.

Table 3.1: Patient types based on priority, isolation case and total resources to visit.

	Patient Types										
Patient Priority	Reg	Reg	Reg	Reg	Reg	Reg	Reg	STAT	STAT	STAT	STAT
Isolation Case	Reg	Reg	Reg	Reg	ISOL	ISOL	ISOL	Reg	Reg	Reg	ISOL
Total Resources to Visit	1	2	3	4	1	2	3	1	2	3	1

Each patient type has a specific journey for using resources in the ED with different duration distribution. This journey is assigned to each patient in the Arena software through the *Sequence* module. In this module, the sequence of patient flow through the emergency radiology unit is defined, which is the ordered list of units that a patient must visit. Figure 3.3 shows the sequence steps for a patient who uses portable X-Ray and CT Scan, respectively and then exits the ED.

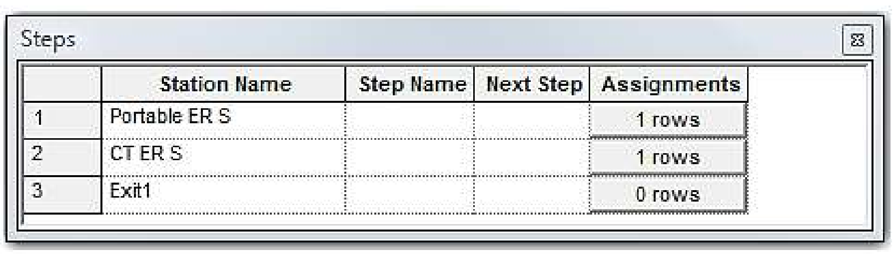
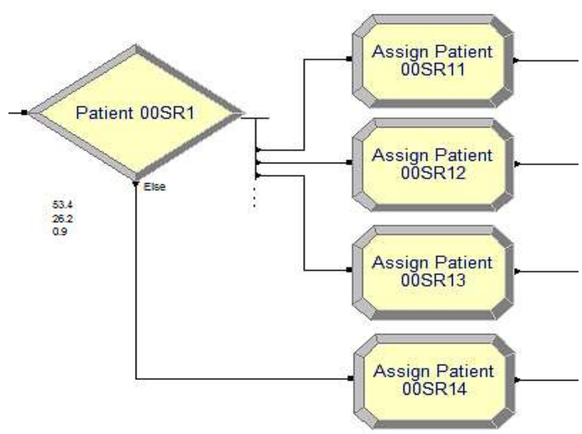


Figure 3.3: Sequence steps for a patient in Arena based on the resources he/she visits successively.

[1] In the healthcare field, isolation is a transmission-based precaution for preventing contagious diseases from being spread from one patient to other patients, healthcare workers, and visitors, or from outsiders to a particular patient to stop germs from spreading across the healthcare setting.

In this case study, patients are specified based on the patient arrival time, patient priority, isolation case, the number of resources to visit, and various patterns for using those resources. In this way, there are 396 different patient types in a day (Appendix A). For example, Patient 00RR32 comprises five attributes 00, R, R, 3, and 2, which stands for a patient who arrives during *00-04* with *Regular* priority, *Regular* isolation case and uses *three* resources in the *second* pattern or Patient 12SI11 (12, S, I, 1, 1) means a patient who arrives at *12-16* with *STAT* priority, *Isolated* isolation case and uses *one* resource in the *first* pattern. The Providence Health Care provided this data.

For distinguishing the priority of STAT patients over the regular patients, this priority can be assigned as an attribute to the STAT patients through the *Assign block* in Arena. For example, in Figure 3.4, a patient type 00SR1 is selected, which contains patients with STAT priority and Regular isolation case that uses one resource. There are four patterns for using the radiology resources, which is the last number of patient type. The first *Assign block* belongs to a patient with four assignments; Entity Type: P00SR11, Entity Sequence: S P00SR11, Entity Priority, and Entity Picture. The *Entity Priority* shows the preference for STAT patients over the regular ones. The *Entity Picture* identifies a patient type in the Arena animation (section 4.3).



Assignments

	Type	Attribute Name	Entity Type	Entity Picture	New Value
1	Entity Type	Attribute 1	P 00SR11	Picture.Report	1
2	Attribute	Entity.Sequence	Entity 1	Picture.Report	S P00RR11
3	Attribute	Priority	Entity 1	Picture.Report	15
4	Entity Picture	Attribute 4	Entity 1	Picture.SR	1

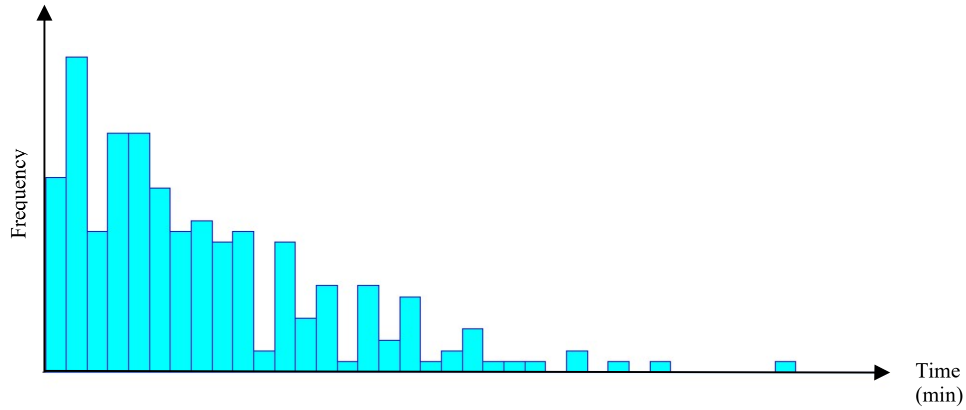
Figure 3.4: Attribute assignments (Entity type, sequence, priority, and Entity picture) to a patient in Arena.

3.5.4 Service time

In the radiology unit, some resources are used more than the others, and some of them are used more based on different hours in a day or night. The data in the emergency radiology was collected from the RIS database between January 2014 and March 2017. The raw data was heavily processed and cleaned up by Province Health Care.

Different patient types have various service times leading to a variety of distributions. These different service times were plotted in histograms to define the distributions. Text files including the service times were imported, and their related histograms were plotted in *Input Analyser*. Then, different distributions were checked to find the best fit for the data.

Chi-Square Test is a statistical method for evaluating the goodness of fit. It is an appropriate test when the variable under the study is categorical, and the sampling method is simple random sampling like what is observed in this study. The null hypothesis is that the data are consistent with the specified distribution. For example, there are 235 data points for the Emergency Trauma resource for all days, all time slots, all priorities, and isolation cases. After importing the data and plotting the histogram, the data details including sample mean and standard deviation are calculated automatically by the software as it is illustrated in Figure 3.5. The next step is finding the best fit. Checking different distributions showed that the best fit for this case is a Weibull distribution with Squared Error of 0.005126. The Chi-Square Test had the corresponding p-value of 0.545 indicating that the null hypothesis is accepted, and this distribution is the best fit for this data (Figure 3.6). Distributions for different patient types were determined and listed in Table 3.2. The columns in this table contains the name of equipment, the day of using an equipment (weekday or weekend), the time slots (800 indicates 8 am while 2000 shows 8 pm), the type of priority and isolation case, the number of data points, type of service time distribution, expression for the distribution, and the squared error for evaluating the goodness of fit.



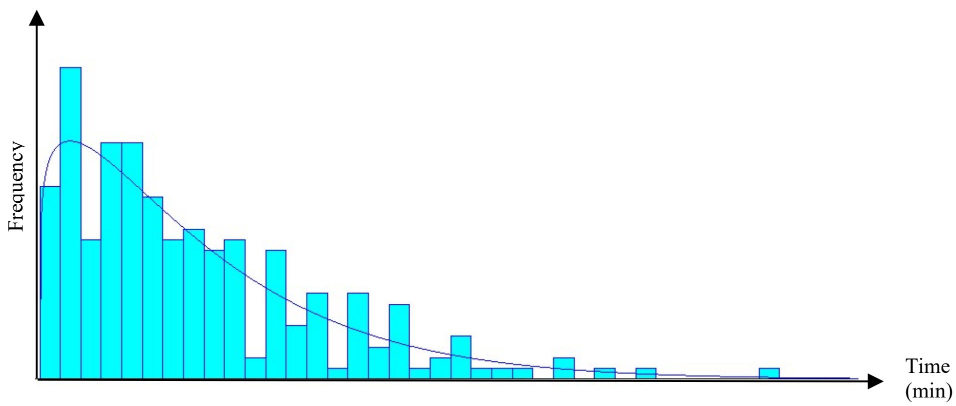
Data Summary

Number of Data Points	= 235	
Min Data Value	= 3	minute
Max Data Value	= 61	minute
Sample Mean	= 10.2	minute
Sample Std Dev	= 7.08	

Histogram Summary

Histogram Range	= 2.5 to 61.5
Number of Intervals	= 59

Figure 3.5: Service time histogram for the Emergency Trauma resource.



Distribution Summary

Distribution:	Weibull
Expression:	2.5 + WEIB(8.16, 1.16)
Square Error:	0.005126

Chi Square Test

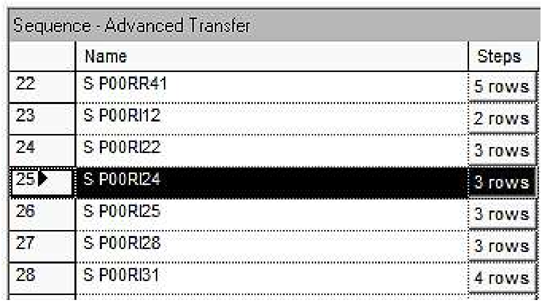
Number of intervals	= 15
Degrees of freedom	= 12
Test Statistic	= 10.8
Corresponding p-value	= 0.545

Figure 3.6: Service time distribution for the Emergency Trauma resource.

Table 3.2: Service time distribution and expression for different patient types (Priority and Isolation) at different time slots in weekday or weekends (Count shows the number of data points).

Resource	Day	Slots	Priority	Isolation	Count	Distribution	Expression	Squared Error
CT ER	Weekday Weekend	All 800	Reg Reg	Reg Reg	8142	Exponential	EXPO(8.95)	0.0187
CT ER	All	All	All	All	11903	Exponential	EXPO(12)	0.0203
X-Ray	All	All	STAT	All	545	Weibull	WEIB(10.3, 1.31)	0.0024
X-Ray	Weekday	All	Reg	ISOL	2862	Lognormal	LOGN(14.7, 18.2)	0.0043
X-Ray	Weekend	All	Reg	ISOL	1065	Lognormal	LOGN(16.1, 20.3)	0.0045
X-Ray	Weekday	0	Reg	Reg	1932	Exponential	EXPO(12.5)	0.0112
X-Ray	Weekday	400	Reg	Reg	851	Exponential	EXPO(15.5)	0.0031
X-Ray	Weekday	800	Reg	Reg	3837	Lognormal	LOGN(11.9, 16.9)	0.003
X-Ray	Weekday	1600	Reg	Reg	5532	Lognormal	LOGN(9.11, 13.6)	0.0029
X-Ray	Weekday	1200-2000	Reg	Reg	9731	Lognormal	LOGN(10.2, 15.3)	0.0026
X-Ray	Weekend	0000-0400	Reg	Reg	1274	Lognormal	LOGN(15.7, 19.7)	0.0036
X-Ray	Weekend	800	Reg	Reg	1238	Exponential	EXPO(10.7)	0.0028
X-Ray	Weekend	1200-2000	Reg	Reg	5377	Lognormal	LOGN(10.2, 15.2)	0.002
Portable X-Ray	All	All	All	All	83	Weibull	WEIB(8.25, 1.53)	0.0064
Trauma	All	All	All	All	235	Weibull	WEIB(8.16, 1.16)	0.0051

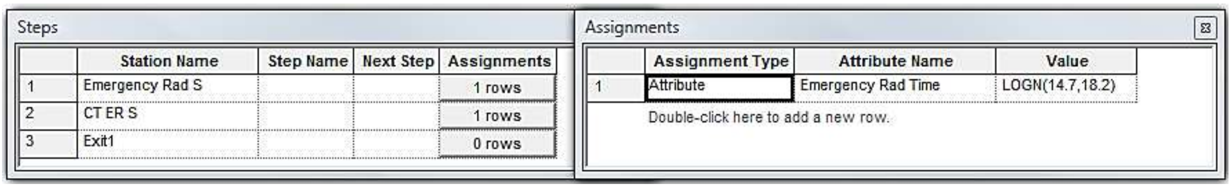
According to the different patient type with a different sequence, the above distributions (in Table 3.2, expression column) were assigned to patients. In Figure 3.7a, the 25th patient type is selected for explaining the modeling process in the Arena software. S P00RI24 means the sequence for a patient who arrives during 00-04 with the regular priority, isolated isolation case and uses two resources in the fourth pattern. The fourth pattern uses emergency X-Ray and CT Scan, respectively, that can be defined as different steps (Figure 3.7b). According to the fourth row of Table 3.2, a patient who uses X-Ray unit in weekdays and all time slots, with regular and isolated condition, follows the distribution of LOGN(14.7, 18.2) and this distribution is assigned as an attribute to this patient in Arena (Figure 3.7c). The same assignment was done for all the 396 different patient types in this case study.



Sequence - Advanced Transfer

	Name	Steps
22	S P00RR41	5 rows
23	S P00RI12	2 rows
24	S P00RI22	3 rows
25	S P00RI24	3 rows
26	S P00RI25	3 rows
27	S P00RI28	3 rows
28	S P00RI31	4 rows

(a) Selecting 25th patient type sequence



Steps

	Station Name	Step Name	Next Step	Assignments
1	Emergency Rad S			1 rows
2	CT ER S			1 rows
3	Exit1			0 rows

Assignments

	Assignment Type	Attribute Name	Value
1	Attribute	Emergency Rad Time	LOGN(14.7,18.2)

Double-click here to add a new row.

(b) Resource sequence for the patient type (c) assigning the service time to a resource

Figure 3.7: Resource sequence for a patient type with related service time.

3.5.5 Travel Time and Waste-Time

Technologists have to spend considerable time finding patients in the waiting area, take them to the examination room and prepare them for the radiology examination. This time is called the travel time or the preparation time. In the radiology database, the service time is recorded from the time that a patient is tagged for examination to finishing it without considering the preparation time. According to the interview with the manager of the radiology department, there are several reasons that prolong the travel time as follows:

- Waiting for patients who come back for multiple examinations
- Waiting for patients who need to be escorted by security
- Watching risk of violence (code white)
- Patients waiting to speak with a doctor
- Patients who refuse to have a radiology examination

- Patients not ready at the time of the request
- Searching for a wheelchair
- Unable to find the nursing staff to help transferring patient
- Cleaning that is necessary before and after isolated patients

Besides the time spent on preparing a patient for an examination, there is the time wasted by technologists during their shifts. For example, they have to answer the patient's question or their colleague's question. So, the travel time and waste-time are the hidden times that should be considered in the modeling. These times were applied to the model by *Delay block.*

There is a records sheet that should be filled each day for listing the reasons for delays in performing examinations and recording the time, which is wasted due to these reasons. The sheet was provided by the manager of the radiology department, and an approximation for the delay time in the emergency radiology unit was estimated accordingly. The *Delay block* provides the user with the opportunity to consider a constant or random distribution for the delay time during a process as it was done in this simulation modeling.

3.5.6 Service Stations

After assigning the type, sequence, and service time to all patients, the resources should be used. Different resources were modeled through *Station block*. As discussed, there are four different resources in the emergency radiology unit; Emergency X-Ray (Emergency Rad), CT Scan (CT ER), Emergency Trauma and Portable X-Ray in ER. Therefore, there are four stations plus one station for exiting the system as shown in Figure 3.8 with pink blocks. Patients use these resources based on their sequence (section 3.5.3).

Technologists serve patients in each unit, and they were included in the simulation model as human resources. The resource(s) and the time an entity spends in a unit can be defined in the *Process block,* which is shown in yellow color in Figure 3.8.

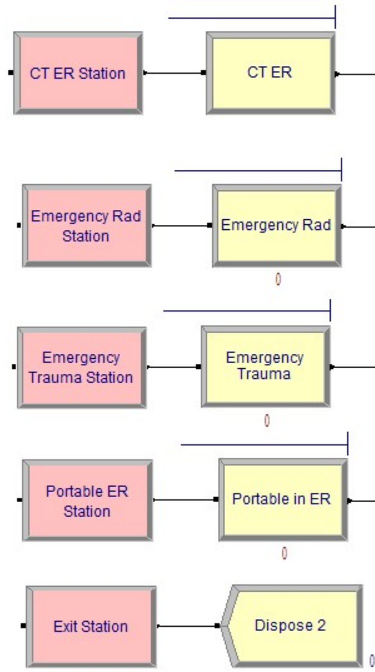


Figure 3.8: Arena blocks for the stations and processes in the emergency radiology unit.

3.5.7 Resource Schedule

Medical staff scheduling is deemed a challenging issue in the healthcare systems. It is necessary to make sure that there are enough human resources to serve patients, human resources are not overloaded, and the healthcare system is not over-staffed.

According to the data provided by the Providence Health Care, technologists at SPH have an eight-hour shift per day including two 15-minutes and one 30-minute breaks. In the X-Ray unit, these breaks are fully covered by float technologists from the main department for day and evening shifts. For the night shift, CT Scan technologists cover X-Ray breaks and come to X-Ray when there are no CTs to be done. In CT Scan unit, two CT technologists work together and cover each other for breaks except for the night shift (23:45-07:45), where there is one CT technologist in this unit due to less demand for CT during the night. Based on the above points, the following staff scheduling was considered in the modeling:

- One X-Ray technologist for 24 hours and three shifts (00-08, 08-16, 16-00)
- One CT technologist for 24 hours and one CT technologist for 16 hours excluding night shift and their shifts are 2345-0745, 08-16, 09-17, 15-23, and 16-00.

In Arena software, these schedules can be assigned to the human resources via the *Schedule* module. Through this module, staff schedule is assigned to them and in section 4.2 is investigated how changing the staff schedule affects the entire system.

3.6 Setup Simulation

A simulation needs setup before running to have reliable results including some parameters such as warm-up period and run length. "Warm-up period" is a transient period at the start of any simulation run since the output values in the transient state are incompatible with the steady-state one. Because a system is not empty at the beginning of observation, it is necessary to consider this time period. Warm-up period is an interval that dedicates enough time to a stochastic process to reach a steady state. Figure 3.9 shows a transient condition at the beginning of the simulation run where there is no entity in the system. The horizontal axis represents time, and the vertical axis shows how the average output values vary during a transient or steady state. Since a system is not empty in reality, using a warm-up period eliminates the idle stage.

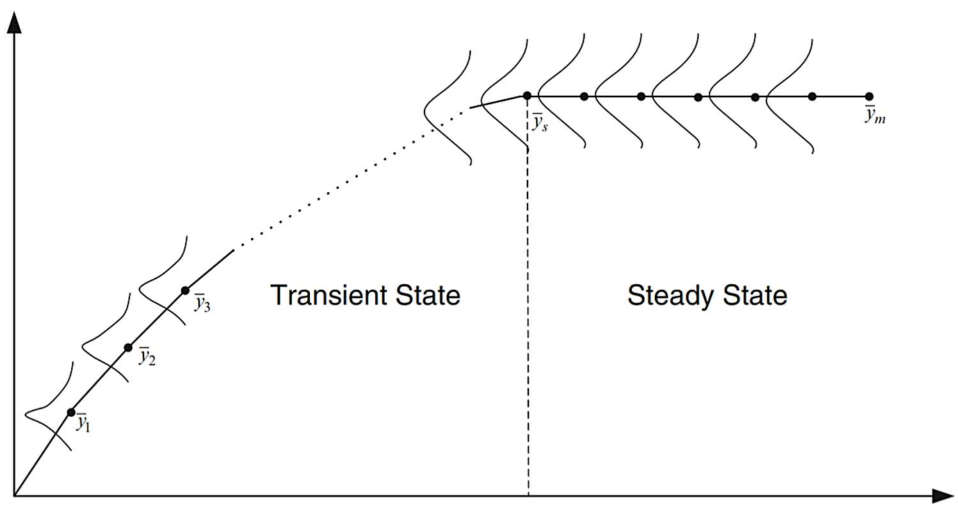


Figure 3.9: Warm-up period for moving from transient to steady state condition (Birta et al. 2007).

The next parameter is the "run length", which is the length of a single replication in a specified time unit. This length should not be too small or too large to obtain accurate and reliable results that are suitable for short-term predictions. The objectives and the nature of activities in any simulation model clarify the best run length for the system, and it varies from a model to the other one. In this study, the model was run for one day (run length) with two hours for the warm-up period.

3.7 Model Verification and Validation

Model verification confirms that the simulation modeling and implementation of the conceptual model are correct and ensures that the model works as intended. In the case of discrete-event models, various routines can be changed to produce specific random variables and check whether they provide an output that has the appropriate statistical properties or not (Murray-Smith 2015). Verification gives an opportunity to the model developer to find and fix the modeling errors and match it with any specifications and assumptions (Carson 2002).

Model validation confirms that there is no significant difference between the model and the real system and approves that the model represents the reality to a sufficient level of accuracy. According to Abo-Hamad and Arisha (2013), there are three techniques for validating the results of a simulation: face validation, comparison testing, and hypothesis testing. Face validation is performed by interviewing senior managers and nursing staff, while comparison testing is done by comparing the output of the simulation model with the real data of the system. Hypothesis testing is employed where a random sample from a population was examined. If sample data are not consistent with the statistical hypothesis, the hypothesis is rejected. The first and second approaches are commonly used in the healthcare area (Abo-Hamad and Arisha 2013).

In this study, the input parameters in the model were changed, and the output results were checked to see if they were as expected or not. For example, increasing the arrival rate or service time led to a longer patient waiting time as it was expected and having constant time for arrival time and service time resulted in no queue in the system. Since the data was based on the actual data in reality, the managers who are directly involved with the activities in the system can confirm the model validity. Therefore, the outputs were validated by one of the radiology managers at SPH, and it was confirmed as reflecting the real emergency radiology pathway.

3.8 Model Execution

Once the simulation model is created and validated, the next stage is the model execution. This phase covers running the model, results analysis, future prediction, and making operational decisions.

3.8.1 Run Base Case and What-If Scenarios

After running the model, numerical results are displayed that is called baseline outputs. Base case (baseline) scenario is the first scenario that reflects current or near future condition for the system at hand. The target is solving the defined problem through what-if scenarios. Therefore, what-if scenarios are alternative scenarios to modify the base case model and remove or include new conditions. In other words, we can alter some effective parameters in the system (base case), which acts as control elements. Afterward, the system performance is estimated and evaluated via response elements that are defined by a researcher.

3.8.2 Output Analysis

Output analysis focuses on analysing the simulation results and output statistics. Simulation outputs include information about all events and activities in the model such as entities, resources, and queues. After running the model for different scenarios, Arena provides the output metrics for each scenario, and the next step is a trade-off between these metrics to have a more efficient system.

3.8.3 Decision Making

In this step, the best scenario among the alternative scenarios in what-if analysis should be selected. According to the system objective, the decision-maker would select one of those alternatives, through which, the system behaves efficiently. One method for selecting a solution among a set of solutions is "paired comparison", which compares results in pairs to decide which one is preferred. Paired comparison is widely used in the analytical process and facilitates making a decision in complex systems. It results in ranking alternatives desirably based on the system criteria (Saaty 2008). In some cases, a system contains several criteria to be considered, so, a decision maker faces several options to make a trade-off between them and select the most efficient and applicable one. Once the simulation model is run, outputs of different scenarios are analysed, and the best one is selected, then, the proper action is taken based on the best case.

Chapter 4: Results

4.1 Running the Base Case Scenario

Once the simulation model is created, the next step is the model execution. After running the simulation model, some results that assist in altering the simulation model are as follows:

1. *The patient waiting time and the number of patients in a queue (Table 4.1)*

There are queues in CT Scan, X-Ray, and portable X-Ray units and the average waiting time of these queues are 3, 117.22 and 117.38 minutes, respectively. Moreover, the average number of patients in queues is less than one for the CT Scanner and the portable X-Ray, while this number is about six for stationary X-Ray.

Table 4.1: Average patient waiting time and the number of patients in a queue.

Radiology unit	Average waiting time (minutes)
CT ER	3
Emergency X-Ray	117.22
Emergency Trauma	0
Portable X-Ray in ER	117.38

Radiology unit	Average number of patients in a queue
CT ER	0.13
Emergency X-Ray	6.36
Emergency Trauma	0
Portable X-Ray in ER	0.41

A snapshot of the queue for X-Ray (Emergency Rad) from the Arena animation is shown in Figure 4.1. In this animation, Regular-Regular patients are depicted by people with the blue shirt and blue pants, Regular-Isolation by the blue shirt and yellow pants, STAT-Regular by the red shirt and blue pants, and STAT- Isolation by the red shirt and yellow pants. As illustrated in this figure, the STAT patient has priority over the regular ones, and this patient type is the first one in the queue to be visited.

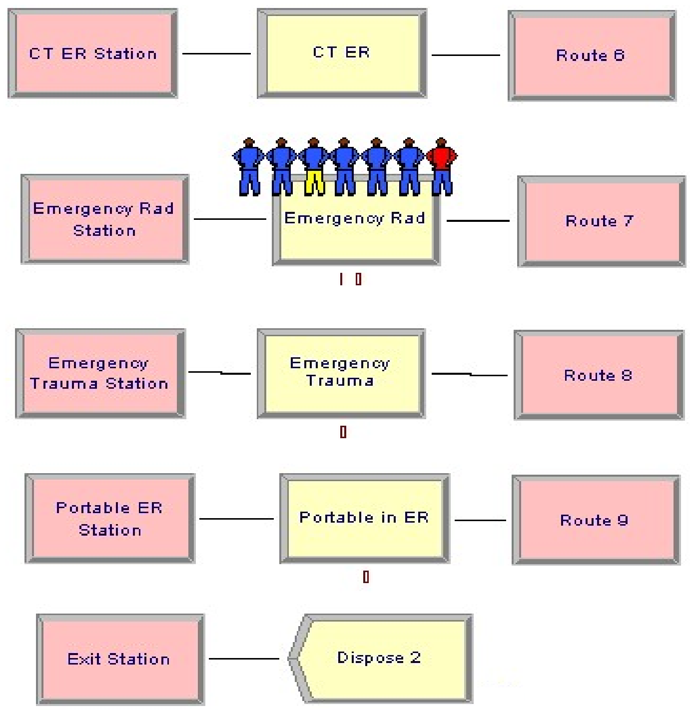


Figure 4.1: Arena animation for showing the queue in the emergency X-Ray.

2. *Resource utilisation (Table 4.2)*

Number Busy item introduces the number of busy units of a resource. The *Number Scheduled* item indicates the resource capacity. *Instantaneous Utilisation* includes utilisation per resource unit and shows the proportion of time that a resource is busy with working in a unit and indicates how well a resource handles the load (Altiok et al. 2007). *Scheduled Utilisation* is the proportion of time that a human resource is busy based on his/her schedule and indicates how overall capacity can handle the overall load. If resource capacity varies among several different positive values, it will be better to use *Scheduled Utilisation* (Kelton et al. 2015). In this model, the X-Ray technologist has the highest utilisation that shows he/she is busier than the CT Scan technologists.

Table 4.2: Resource utilisation for the different staff in the emergency radiology unit.

Radiology technologist	Instantaneous Utilisation	Number Busy	Number Scheduled	Scheduled Utilisation
CT Tech 1	0.37	0.37	1	0.37
CT Tech 2	0.22	0.22	0.67	0.32
Emergency Trauma	0.01	0.01	1	0.01
X-Ray Tech	0.91	0.91	1	0.91

The patient waiting time and the number of patients in a queue show how much a unit is crowded and resource utilisation indicates the staff workload. Accordingly, there is a bottleneck in the emergency X-Ray unit, and this bottleneck should be alleviated through what-if analysis.

4.2 What-If Scenarios

What-if scenarios are alternative scenarios that are used to modify the baseline model and remove or include new conditions to examine the effect of changes on the performance of the system. The objective is to reduce patient waiting time and improve resource utilisation rates to decrease staff idle time.

This bottleneck can be mitigated via adding an X-Ray technologist. While a technologist is busy with positioning a patient, the other one can do the paperwork to have a new patient. Moreover, *Process Analyser* application in Arena software helps to assess a variety of scenarios via changing the number of resources in the model (section 1.6.2), and the result is shown in Table 4.3. The table shows the effect of adding more technologists on the patient waiting time, the number of patients in a queue and resource utilisation. This table also confirms that adding one X-Ray technologist (Scen 1) results in decreasing the patient waiting time, and balances the resource utilisation in the emergency radiology unit. The first column includes the scenario name, the second column contains the control parameters, which are the number of CT Scan and X-Ray technologists, and the last column includes the system responses that show the waiting time in minutes, number of patients in the queue, and resource utilisation for CT Scan and X-Ray units.

Table 4.3: Patient waiting time, the number of patients in a queue, and resource utilisation for CT Scan and X-Ray units based on the different number of technologists in the alternative scenarios (Scen).

Scenarios	Controls		Responses					
Name	XRay Tech	CT Tech	XRay Waiting Time	CT waiting Time	Number in XRay queue	Number in CT queue	XRay Tech Utilisation	CT Tech Utilisation
Baseline	1	2	117.22	3	6.36	0.13	0.91	0.37
Scen 1	2	2	3.33	0.1	0.18	0.03	0.41	0.23
Scen 2	2	3	3.33	0	0.18	0	0.41	0.12
Scen 3	3	2	0.16	0.1	0.01	0.03	0.28	0.22
Scen 4	3	3	0.16	0	0.01	0	0.28	0.11

Now, the question is "when is the best time to add another technologist to meet the system objective?". To answer this question, different schedule times and a different number of technologists are considered for the X-Ray unit as follows:

1. What-If analysis 1 (WI-1): Add one technologist to each of three shifts (00-08, 08-16, 16-00),
2. What-If analysis 2 (WI-2): Add one technologist to each of two shifts (08-16, 16-00),
3. What-If analysis 3 (WI-3): Add one technologist to one shift (08-16),
4. What-If analysis 4 (WI-4): Add one technologist to one shift (12-20),
5. What-If analysis 5 (WI-5): Add one technologist to one shift (16-00),
6. What-If analysis 6 (WI-6): Add one technologist to one long shift (10-22) or one and a half shifts (10-18, 18-22).

The results such as patient waiting time, the number of patients in a queue, and resource utilisation, are shown in Table 4.4. The first column includes the resource name, the second column shows the Arena output, and the rest of the columns contain the results for different alternatives. Although adding three or two technologist results in shorter patient waiting time and less number of patients in a queue, it increases the staff idle time. The best scenario is the fourth or sixth, which is adding one technologist from 12 to 20 or from 10 to 22.

Table 4.4: Arena output for comparing baseline model and what-if scenarios (WI).

Resource	Arena Output	Baseline	WI-1	WI-2	WI-3	WI-4	WI-5	WI-6
			00-00	08-00	8-16	**12-20**	16-00	**10-22**
X-Ray	Waiting Time (min)	117.21	3.34	18.1	34.74	**27.25**	56.55	**23.85**
	Number Waiting	6.36	0.17	0.51	2.12	**1.58**	3.27	**0.92**
CT Tech 1	Resource Utilisation	0.37	0.23	0.38	0.37	**0.38**	0.38	**0.35**
CT Tech 2		0.32	0.16	0.33	0.35	**0.33**	0.3	**0.28**
X-Ray Tech 1		0.91	0.38	0.53	0.79	**0.77**	0.78	**0.58**
X-Ray Tech 2		-	0.39	0.45	0.71	**0.64**	0.8	**0.44**

4.3 Animation

The animation feature is activated while the simulation is running to have a better understanding of the system. The entities, resources, and queues can be depicted through animation. Moreover, the desired plots and histograms can be drawn during the simulation runtime. Animation helps the managers to have a better insight into the modeling and make a decision accordingly.

In this study, patients, different units, technologists and queue for each unit of the emergency radiology are represented in the animation. According to the model objectives, resource utilisations and the number of patients in a queue are shown during the simulation runtime (Figure 4.2). These results are selected from the many results that Arena software provides.

Figure 4.3 shows the plot in the animation during the simulation time which is 24 hours with 2 hours warm-up period (totally 1560 minutes). This plot presents the number of patients in the X-Ray queue and CT Scan queue against the simulation time. As shown, there is a peak between the 800 minutes to 1400 minutes in simulation time, which indicates the busiest time in the X-Ray unit. The best time to add more technologists to the system is when the unit is busy, and there are patients waiting in the queue. Since the warm-up period is 120 minutes, the peak time shows the time from 680 to 1280 minutes, which is from 11:20 to 21:20. Thus, an X-Ray technologist can be added to the system during this period. It confirms what was concluded in the what-if scenarios (section 4.2); which is adding an X-Ray technologist from 12 to 20 or from 10-22, is correct.

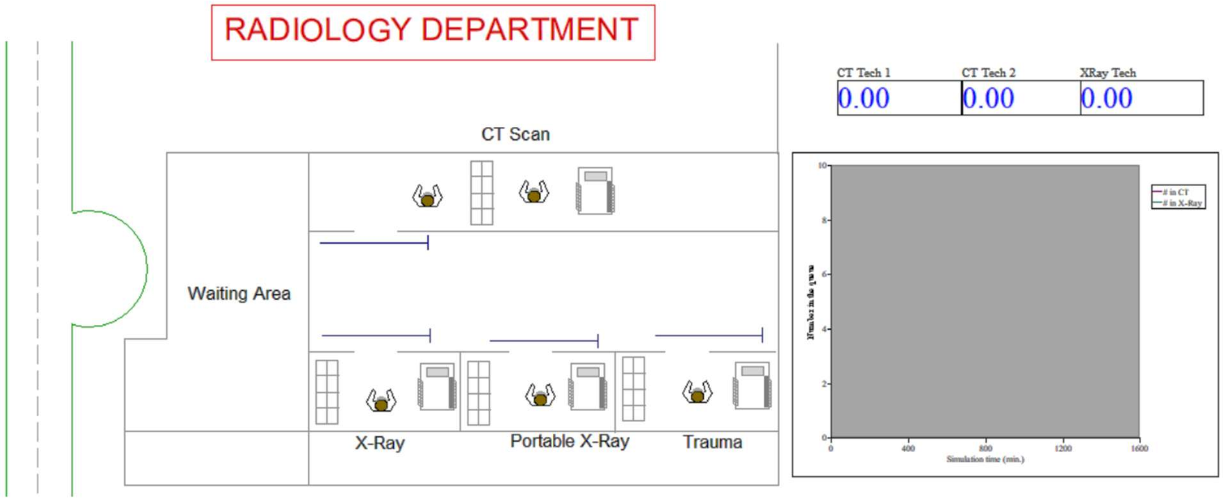


Figure 4.2: Animation area for the emergency radiology unit, plot, and resource utilisation during the simulation run.

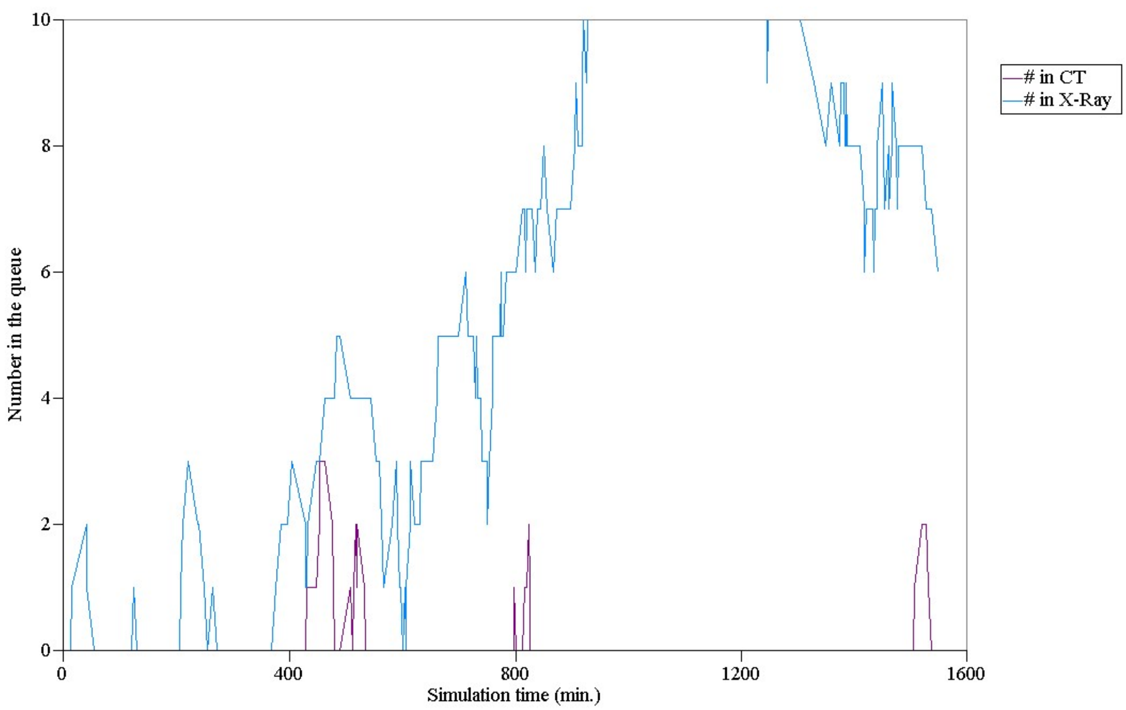


Figure 4.3: Number of patients in the CT Scan and X-Ray queues against simulation time.

4.4 Modeling the Patient Flow from Entering the ED

Since the radiology unit performance is affected by the upstream elements, other units that were shown in Figure 3.2 are considered in the new modeling (Figure 4.4), from the point that patients enter the ED and are sent to the radiology unit until they are discharged. The elements after leaving the emergency radiology unit are ignored since they have no impact on the patient waiting time in this system.

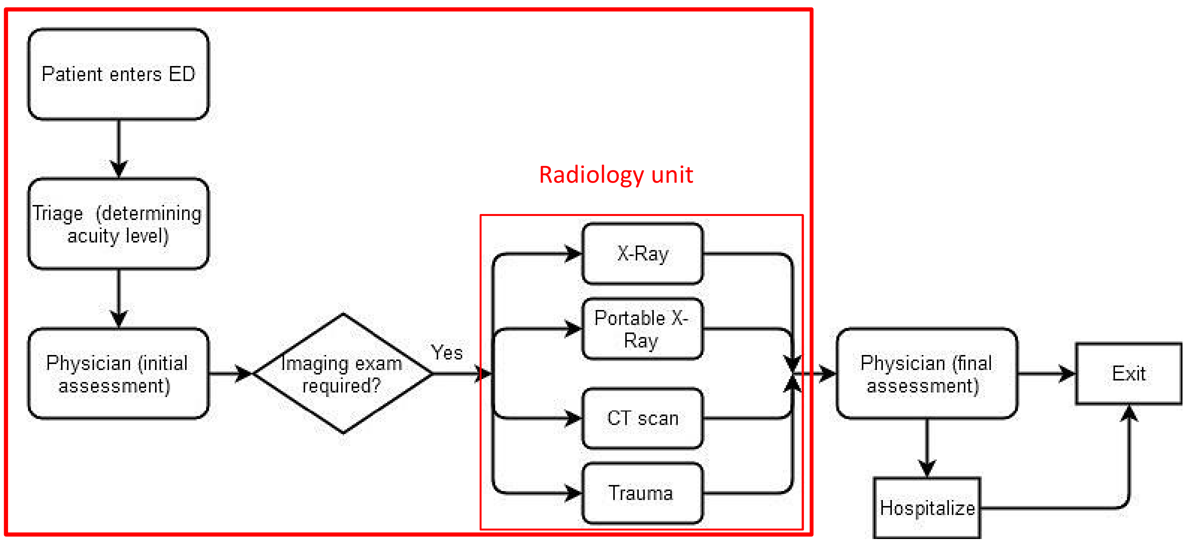


Figure 4.4: Patient flow in the ED.

There are only two additional sections in the new modeling, and the other modeling sections remain unchanged. Two added sections are triage and initial assessment. Necessary data were obtained based on the observation of the system and interviews with the radiology manager. One triage nurse and one physician are involved before the radiology, who are the resources in the Arena. They are responsible for determining the acuity level and initial assessment, which are included in the model using process block as shown in Figure 4.5.

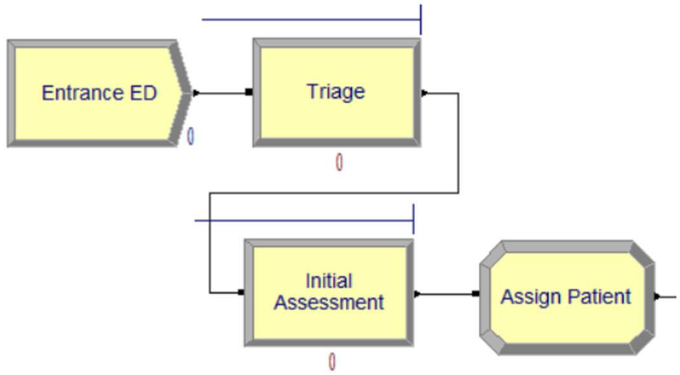


Figure 4.5: Two process blocks (Triage and Initial assessment) before entering the radiology unit.

4.5 Baseline and Alternative Scenarios

After running the simulation model, results show that there are bottlenecks in the initial assessment and X-Ray units since they have the highest average patient waiting time and number of patients in the queue (Table 4.5). The resource utilisation is presented in Table 4.6 illustrating that physician and X-Ray technologist are busier than the other staff. These bottlenecks can be alleviated through adding more human resource either more physicians, or X-Ray technologists, or both.

Table 4.5: Patient waiting time in different sections and the number of patients waiting in the queues.

Radiology units	Average waiting time (minutes)
CT ER	2.59
Emergency X-Ray	41.27
Emergency Trauma	0
Initial Assessment	75.16
Portable X-Ray	42.48
Triage	23.88

Radiology units	Average number of patients in a queue
CT ER	0.1
Emergency X-Ray	2.32
Initial Assessment	6.21
Portable X-Ray	0.15
Triage	1.97

Table 4.6: Resource utilisation in the new modeling.

Radiology technologist	Instantaneous Utilisation	Number Busy	Number Scheduled	Scheduled Utilisation
CT Tech 1	0.25	0.25	1	0.25
CT Tech 2	0.16	0.16	0.67	0.24
Physician	0.84	0.84	1	0.84
Triage Nurse	0.64	0.64	1	0.64
X-Ray Tech	0.78	0.78	1	0.78

4.6 Animation

By using the graphical capabilities of Arena software, the floor plan of the SPH ED (Appendix B) was embedded in the simulation model, and the entire process was animated. Also, the number of patients in the X-Ray and initial assessment queues are plotted during the simulation time. This plot shows what might happen in real time.

To find the best time to add more human resources, one way is using what-if scenarios similar to what was done in section 4.2; another way is to use the plot in the animation as discussed in section 4.3. This plot is presented in Figure 4.6 for the new modeling. Since there is a long queue in the initial assessment and X-Ray sections, these two queues are shown. This plot depicts the number of patients waiting in each queue in 24 hours with 2 hours for simulation warm-up period. The number of patients in the initial assessment queue is shown in red and in the X-Ray queue in blue color. The number of patients increases and peaks and then decreases. Accordingly, the best time to add one physician and one X-Ray technologist is when there is a peak in the number of patients in the queues. The peak for the X-Ray queue is from 750 to 900 minutes and then from 1100 to 1400 minutes, which is during 10:30-13 and 16:20-21:20. The peak time for the physician is from 750 to 1350 minutes, which is 10:30-20:30.

For confirming the accuracy of the animation result, one X-Ray technologist and one physician are added to one shift from 12 to 20. Based on Table 4.7, the results show that the bottleneck is removed from the X-Ray and initial assessment units. Although the average number of patients in the initial assessment queue is 1.36, the average patient waiting time is 15 minutes. Table 4.8 shows that resource utilisation is more balanced compared to the previous condition (Table 4.6).

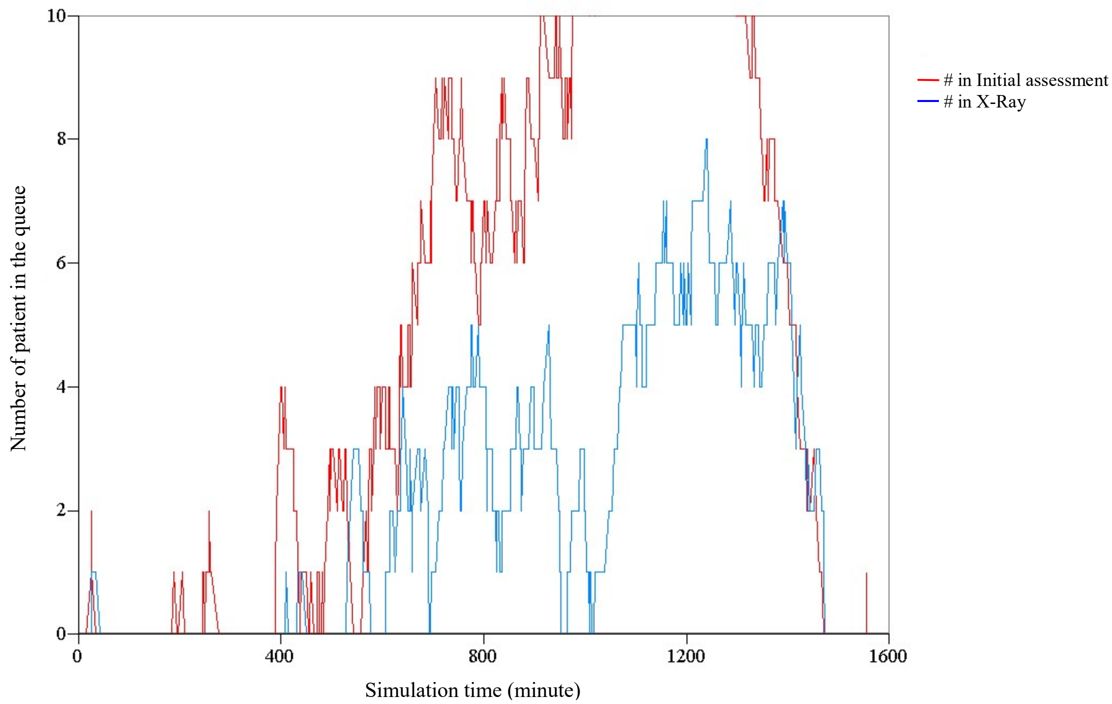


Figure 4.6: The number of patients in the initial assessment and X-Ray queue during the simulation time.

Table 4.7: The effect of adding an X-Ray technologist and a physician on the patient waiting time and the number of patients waiting in each queue.

Radiology units	Average waiting time (minutes)
CT ER	1.98
Emergency X-Ray	13.03
Emergency Trauma	0
Initial Assessment	15.21
Portable X-Ray	12.36
Triage	23.88

Radiology units	Average number of patients in a queue
CT ER	0.08
Emergency X-Ray	0.8
Initial Assessment	1.36
Portable X-Ray	0.04
Triage	1.97

Table 4.8: The effect of adding an X-Ray technologist and a physician on resource utilisation.

Radiology technologist	Instantaneous Utilisation	Number Busy	Number Scheduled	Scheduled Utilisation
CT Tech 1	0.41	0.41	1	0.41
CT Tech 2	0.21	0.21	0.67	0.23
Physician	0.67	0.67	1	0.67
Physician 2	0.25	0.27	0.33	0.75
Triage Nurse	0.64	0.64	1	0.64
X-Ray Tech	0.66	0.66	1	0.66
X-Ray Tech 2	0.25	0.25	0.33	0.75

4.7 Analysis of Variance (ANOVA)

Analysis of variance is appropriate for comparing more than two group means for statistical significance and shows the important decision factors in an analysis. The null hypothesis for an ANOVA is that there are no significant differences among group means in a sample. Therefore, the alternative hypothesis is that there is at least one significant difference between them. Some key assumptions should be tested in an ANOVA as follows:

1. Each group sample is drawn from a normally distributed population.
2. Groups should have approximately equal variance, which is called homogeneity of variance.
3. Each sample is drawn independent of each other and randomly selected. So, there is no pattern in the sample selection.

In this study, the purpose is assessing the difference in the patient waiting time by changing the number of staffs in the various sections in the radiology emergency unit. In other words, it will be investigated whether changing the number of staffs in the various sections has a significant effect on the waiting time or not. ANOVA was done in Minitab 17 software, and the results contain the probability value (p-value) and the F-ratio. The F- ratio or F-statistic is used in combination with the p-value to decide whether the overall results are significant. The null hypothesis is supported with a confidence level of 95% if the p-value is larger than 0.05. The p-value is a probability, while the F-ratio is a test statistic and indicates if the variance between the means of two populations is significantly different or not. (Archdeacon 1994).

The ANOVA is regarded as an omnibus test statistic since it makes a comparison among groups and cannot tell which specific groups are significantly different from each other. Thus, if the null hypothesis is rejected, then, post-hoc tests must be used to know which groups are different from each other. Tukey's honestly significant difference (HSD) post hoc test can be used to complete the ANOVA. Tukey's method creates 95% confidence intervals for all the pairwise differences between factor level means that identifies which mean differences are statistically significant. Therefore, Tukey's method specifies that the entire set of comparisons have a family error rate of 0.05, which is equivalent to a 95% simultaneous confidence level (Pairwise comparisons, 2018).

In this study, the effect of the number of staff and their interactions on the total waiting time is investigated. Therefore, there are four factors: triage nurses, physicians, X-Ray technologists, and CT Scan technologists. There are two levels associated with the number of staff for triage nurse (1 or 2), physician (1 or 2), X-Ray technologist (1 or 2), and CT Scan technologist (2 or 3). In total, there are 16 treatments to be investigated by ANOVA.

Figure 4.7 illustrates that the model meets the above assumptions of the analysis:

1. The assumption of having residuals with a normal distribution is verified by the normal probability plot. Since the residuals follow a straight line, they are normally distributed, and the test results are reliable.
2. The points in the residuals versus fit plot scatter randomly on both sides of 0 and do not have a recognisable pattern. Thus, this plot verifies the assumption that the residuals are distributed randomly and there are not any groups to have substantially different variability, and there are not any outliers.
3. The residuals versus order plot verifies that the residuals are independent. Since there is no pattern or trend in scattering the residual points in time order, and these points fall randomly around the center line. If a pattern or trend appears in this plot, residuals may be correlated, and they are not independent (Pairwise comparisons, 2018).

According to Table 4.9, the null hypothesis is rejected for all four factors and interaction of physician with triage nurse and X-Ray technologist. In other words, these elements have a significant effect on the total patient waiting time. Based on the F-statistic, the effect of the number of physicians followed by the number of X-Ray technologist have the most significant effect on the patient waiting time in comparison with the other elements.

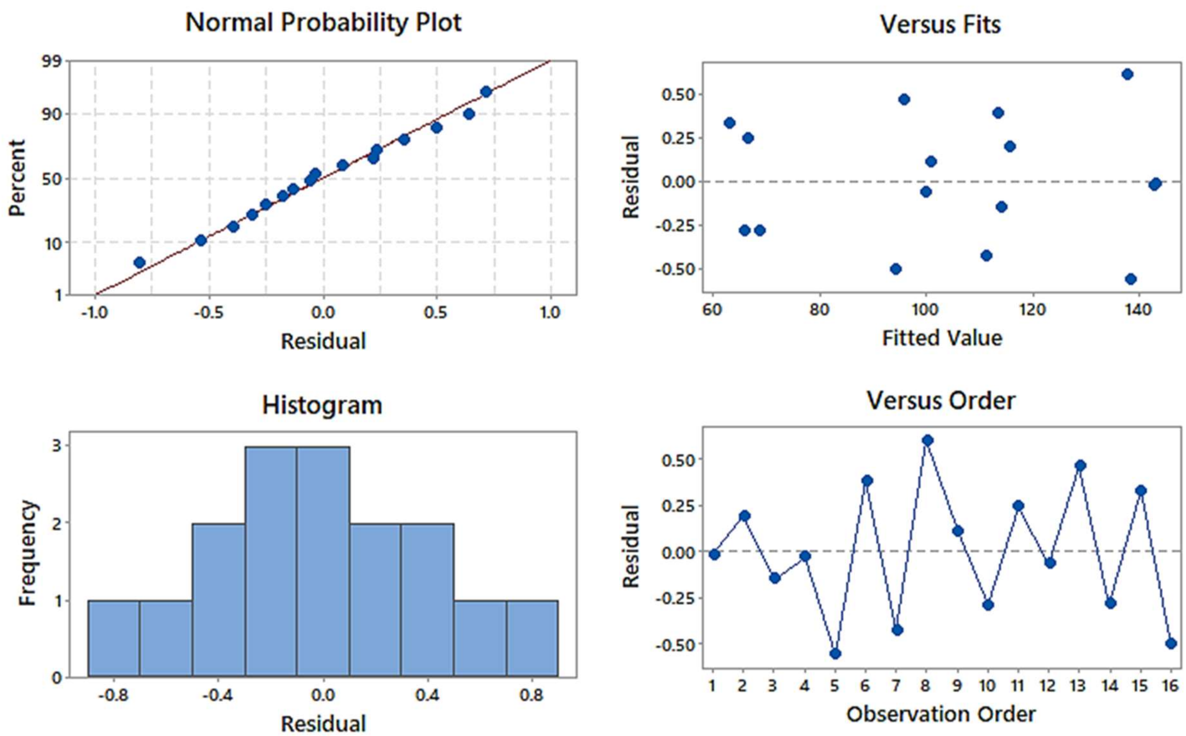


Figure 4.7: Residual plots for total patient waiting time for testing the assumptions to use ANOVA.

Table 4.9: ANOVA result for investigating the effect of the number of staff and their interactions on total patient waiting time.

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Triage Nurse	1	15.6	15.57	28.49	0.003
Physician	1	8939.7	8939.75	16359.17	0
Xray Tech	1	3542.8	3542.78	6483.06	0
CT Tech	1	8.7	8.68	15.88	0.01
Triage Nurse*Physician	1	20.6	20.57	37.64	0.002
Triage Nurse*Xray Tech	1	1.6	1.63	2.99	0.144
Triage Nurse*CT Tech	1	0.2	0.22	0.41	0.55
Physician*Xray Tech	1	34	34.03	62.28	0.001
Physician*CT Tech	1	0.5	0.51	0.93	0.38
Xray Tech*CT Tech	1	1.3	1.34	2.46	0.178

The Tukey test provides a Grouping Information table containing mean and group letters that groups the factor levels. Those groups, which do not share a letter, have a mean difference, and their difference is statistically significant. According to Table 4.10, if the number of staffs (in all four sections) change from one to two, the grouping letter will change, which indicates that there is a significant difference between the mean values. In other words, if the number of triage nurses, physicians, or X-Ray technologists increases from one to two and for CT Scan technologists from two to three, the total waiting time will decrease significantly. However, the mean value of patient waiting time for adding a triage nurse or a CT Scan technologist does not decrease very much comparing to that of physician and X-ray Tech, which and can be ignored. Therefore, the optimal condition is achieved by having 1 triage nurses, 2 physicians, 2 X-Ray technologist, and 2 CT scan technologists. It can be seen that the same conclusion was made from the Arena results (section 4.6), where adding one physician and one X-Ray technologist significantly reduces the patient waiting time. Therefore, the statistical analysis using ANOVA and Tukey test support the simulation results.

Table 4.10: Tukey test for comparing the difference between the mean patient waiting time values when the number of staff changes in each section in the emergency radiology unit.

Section	umber of Staff	Mean	Grouping
Triage Nurse	1	106.270	A
	2	104.297	B
Physician	1	128.921	A
	2	81.646	B
X-Ray Tech	1	120.164	A
	2	90.403	B
CT Tech	2	106.020	A
	3	104.547	B

4.8 Cost Estimation

According to the data provided by Providence Health Care expert, the average salary per year for each staff is as follows:

- Triage nurse: $78k
- Physicians: $230k
- X-Rey technologist: $67k
- CT technologist: $45k

Full-Time Equivalent (FTE) is the ratio of the total number of paid hours during a period by the number of working hours in that period. In other words, one FTE is equivalent to one employee working full-time (Full-Time Equivalent, 2019).

In St. Paul's hospital, a year for one FTE is equal to working for 52 weeks * 37.5 hours per week, which is working 1950 hours in a year. According to the results, patient waiting time will decrease by adding one full time X-Ray technologist and one full-time physician. Therefore, the required budget for recruiting an X-Ray technologist and a physician is $67k and $230k per year, respectively.

In particular, there is an overhead cost associated with these salaries which are referred to as backfilling or relief cost in the medical field. Backfilling is the filling of a position after an employee takes up a new role, goes on a justified leave of absence, or quits their job. Therefore, A new employee with the same skill and qualifications fills the vacancy in the meantime. The average backfill percentage is typically around 15% of wage cost which managers should take it into account when budgeting.

Chapter 5: Conclusions and Closing Remarks

5.1 Conclusions

In this thesis, the attempt was to develop a simulation model to aid St. Paul's hospital's administrators in improving patient care and services. The application of the DES for decision making was investigated, and patient flow from entering the emergency to exiting the radiology unit is modeled by Arena software.

Real data was supplied to the model to reproduce the current operations in the emergency radiology unit and facilitate the near-future state predictions. Arena software provides average performance metrics that help to compare different sections in the ED and find the bottlenecks. The system bottlenecks are alleviated by considering alternative scenarios, which show the impact of any decision on the system performance.

Also, the best scenario can be chosen via a plot which is generated in the animation, while the simulation is running. Alternative scenarios and an animation plot enable the manager to make decisions on various ways to shorten patient waiting time. Such decisions will involve trade-offs between the various performance metrics generated by the Arena, budgetary conditions, and the specific situation at hand. Simulation outputs indicate that certain changes in the number of staff and their schedule leads to a reduction in patient waiting time in the emergency radiology unit.

Also, after considering 16 different scenarios for the model, an ANOVA along with the Tukey test was used to study the relations and interactions between the decision factors. The results indicated those factors that play a key role in improving system performance. Finally, cost estimation is presented to estimate the necessary budget for adding a new human resource.

5.2 Limitation

In this study, the staff travel time and waste-time were taken into account as a delay in the service time (section 3.6.5). However, the staff lateness and absence have not been considered. If a staff member is not present on time (based on the schedule), it leads to a longer waiting time. Also, it is assumed that there is no failure in the X-Ray and CT Scan equipment and transportation between different sections are not needed. If any failure occurs, patients should be transported to the main radiology section (second floor), in this case, the transportation time and the elevator failure should be considered in the simulation model.

The accuracy and reliability of any analysis including simulation studies depend on the quality, relevance, and the age of the input data. The results reported in this research will certainly be affected by the change in such factors as operating protocols, healthcare service procedures, union regulations, technology improvements, budget availability, and passage of time, all of which can affect the numerical value and the nature of data. Although predictions through simulation with a given data can be made for an extended period of time, the results, however, can be considered reliable for a much shorter period of time. Administrators, managers, and analysts should always be on the lookout for new data, and updated simulation models to ensure that output results are current and reliable.

5.3 Future Work

Based on the understanding of the ED and DES method, below works are suggested for future research:

1. Besides the emergency radiology unit, there is a radiology department at SPH for outpatients. In the new modeling, it can be investigated whether using the outpatient radiology department would have a positive impact on reducing patient waiting time of the ED at peak time. In this case, transportation would be taken into consideration.
2. Simulation results can be used for training an artificial neural network (ANN) to predict the patient waiting time based on the patient arrival rate. For this purpose, a large database is needed. More research can be performed on developing a mobile app or a website accordingly. Therefore, patients or ambulances that carry STAT patients can have a reasonable estimation of the waiting time before attending the ED.

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Appendices

Appendix A **: Patient types**

Patient arrival time is divided into 6 time-blocks: 00, 004, 008, 12, 16, and 20.

According to the last row of below table, the total number of exams in a day is 66 exams.

22+19+21+4 = 66

Thus, based on the patient arrival time, their priority, Isolation case, the number of using resources and various pattern for using those resources, there are 396 patient types.

66*6 = 396

Patient Priority	Reg	Reg	Reg	Reg	Reg	Reg	Reg	STAT	STAT	STAT	STAT
Isolation Case	Reg	Reg	Reg	Reg	ISOL	ISOL	ISOL	Reg	Reg	Reg	ISOL
Total Resources to Visit	1	2	3	4	1	2	3	1	2	3	1
Journey (resources to visit, in order shown)	**Pattern type for using those resources**										
CT ER	1				1			1			1
Emergency Rad	2				2			2			2
Emergency Trauma	3				3			3			3
Portable in ER	4				4			4			4
CT ER|CT ER		1				1			1		
CT ER|Emergency Rad		2				2			2		
CT ER|Portable in ER		3				3			3		
Emergency Rad|CT ER		4				4			4		
Emergency Rad|Emergency Rad		5				5			5		
Emergency Trauma|CT ER		6				6			6		
Portable in ER|CT ER		7				7			7		
Portable in ER|Emergency Rad		8				8			8		
Portable in ER|Portable in ER		9				9			9		
CT ER|Emergency Rad|CT ER			1				1			1	
CT ER|Emergency Rad|Emergency Rad			2				2			2	
Emergency Rad|CT ER|CT ER			3				3			3	
Emergency Rad|CT ER|Emergency Rad			4				4			4	
Emergency Rad|Emergency Rad|CT ER			5				5			5	
Emergency Rad|Emergency Rad|Emergency Rad			6				6			6	
Portable in ER|CT ER|Portable in ER			7							7	
Portable in ER|Portable in ER|CT ER			8							8	
Emergency Rad|Emergency Rad|Emergency Rad|CT ER				1							
Total number of exams for different patient types	22				19			21			4

Appendix B **: Floor plan for emergency radiology unit in SPH**