

Improving Emergency Department
Performance using Discrete-event and Agent-
based Simulation

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Abstract

This thesis investigates the causes of the long wait-time for patients in Emergency department (ED) of Victoria General Hospital, and suggests changes for improvements. Two prominent simulation techniques have been used to replicate the ED in a simulation model. These are Discrete-event simulation (DES) and Agent-based modeling (ABM). While DES provides the basic modeling framework ABM has been used to incorporate human behaviour in the ED. The patient flow in the ED has been divided into 3 phases: input, throughput, and output.

Model results show that there could be multiple interventions to reduce time taken to be seen by the doctor for the first time (also called WTBS) either in the output phase or in the input phase. The model is able to predict that a reduction in the output phase would cause reduction in the WTBS but it is not equipped to suggest how this reduction can be achieved.

To reduce WTBS by making interventions in the input phase this research proposes a strategy called fast-track treatment (FTT). This strategy helps the model to dynamically re-allocate resources if needed to alleviate high WTBS. Results show that FTT can reduce WTBS times by up-to 40%.

Glossary

ED	Emergency Department
VGH-ED	Victoria General hospital-Emergency department
WTBS	Patient status when he/she is waiting to be seen by a doctor
LOS	Patient length of stay in the ED
VGH-EDsim model	Simulation model of the VGH-ED
SD	System Dynamics simulation
DES	Discrete-event simulation
ABS	Agent-based simulation
Monitored beds	Beds that have the capacity to continuously monitor patient's vital signs
Non – monitored beds	Normal ED beds that do not have monitors.
Monitor – area	Bed area that consists of 15 monitored beds.
Treatment – area	Bed area that consists of 4 non- monitored beds.
MTA – area	Minor treatment area, that consists of 5 non- monitored beds reserved for least acuity patients.
Input phase	Time period between patient arrival till bed allotment.
Throughput phase	The time period between bed allotment till the end of treatment.
Output phase	The time period between end of treatment till patient discharge.
Admits	Patients that are admitted to the hospital upon discharge from

	ED.
Non-admits	Patients that are discharged back into the community.
CTAS	Canadian Triage and Acuity Scale
Initial nurse assessment	The first nurse assessment after patient is allotted a bed
Initial doctor assessment	The first assessment by a doctor. Point where WTBS status ends.
TIP	Patient status when treatment is in progress.
Output status	Patient's status when he/she is in output phase.
ERH	Patient's status when he/she is held in the ED for further monitoring.
TBADM	Patient's status when he/she is waiting for a bed in the main hospital
PD	Patient's status when he/she is waiting on an ED bed for miscellaneous reasons.
W_{BED}	Component of WTBS where patient is waiting for a bed
W_{NURSE}	Component of WTBS where patient is waiting a nurse for an initial nurse assessment.
W_{DOCTOR}	Component of WTBS where patient is waiting a doctor for an initial doctor assessment.
DBA strategy	Dynamic bed-allotment strategy. Agent based strategy to model human factor involved in bed-allotment decision.
Desired treatment location	Patient's desired treatment location based on patient's attributes.
Actual treatment location	Patient's actual treatment location based on patient's desired treatment location and bed availability.
FTT strategy	Fast track treatment strategy. Proposed strategy to improve ED wait-times.

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Dedication

To my parents who have made me what I am. To my wife who was always been there in my journey of doing this research. To my friends who have been with me through thick and thin.

Contents

1. Introduction.....	19
1.1. Background	19
1.2. Research Objectives	21
1.3. Overview of the research-methodology	22
2. Literature review	25
2.1. ED overcrowding problem - An overview	25
2.2. Different approaches of simulating an ED.....	26
2.2.1. System Dynamics (SD).....	26
2.2.2. Discrete-event simulation (DES)	27
2.2.3. Agent-based simulation (ABS).....	28
2.2.4. Why choose DES over SD?	29
2.3. Discrete-event simulation in ED	30
2.3.1. Variable change scenarios.....	31
2.3.2. Process change scenarios	33
2.3.3. Miscellaneous scenarios.....	36

2.4.	Discussion of literature.....	37
3.	Research methodology.....	39
3.1.	Phases of research	39
3.1.1.	Phase-1: Understanding the real ED.....	41
3.1.2.	Phase-2: Data collection and building the VGH-EDsim model	41
3.1.3.	Phase 3: Model analysis and design of solutions.....	42
3.2.	Thesis organization	42
4.	Victoria General Hospital-ED patient flow	44
4.1.	Structure of the ED.....	44
4.2.	VGH-ED patient flow: the Input-Throughput-Output approach.....	46
4.2.1.	Input phase	46
4.2.2.	Throughput phase.....	49
4.2.3.	Output phase	52
4.3.	Problem formulation and underlying assumptions.....	54
4.3.1.	Prima-facie solution	56
5.	Data collection for VGH-EDsim model	57
5.1.	Data collection for VGH-EDsim model.....	57
5.2.	Transforming VGH-ED data into model input data.....	59
5.2.1.	Arrival data	60

5.2.2.	Patient attribute data	65
5.2.3.	Process time data.....	69
6.	The Simulation model.....	71
6.1.	Introduction to Flexsim 3D simulation software.....	71
6.2.	Steps to build a DES model for VGH-ED.....	73
6.2.1.	Step1: Deciding the scope of the model	75
6.2.2.	Step 2: Designing simulation model logic	75
6.2.3.	Step 3: Writing the simulation model logic in FlexSim	83
6.2.4.	Step 4: Verification of the model.....	84
6.2.5.	Step 5: Validation of the model	86
6.3.	Stages of building VGH-EDsim model.....	90
6.3.1.	Stage 1: Building model with bed resource only	91
6.3.2.	Stage 2: Building model with bed and nurse resource.....	92
6.3.3.	Stage 3: Building the model with all three resources.	93
6.3.4.	Analysis of results.....	96
7.	Agent-based simulation	99
7.1.	Need for Agent-based simulation.....	99
7.1.1.	Shortcomings of DES	99
7.1.2.	Agent and agent-based simulation	100

7.1.3.	Modeling of an Agent	102
7.1.4.	Need for integration of DES and ABS.....	103
7.2.	Model validation using Agent-based modeling	104
7.2.1.	Understanding the cause of outliers	104
7.2.2.	Dynamic bed-allotment strategy	105
8.	Model analysis and solution design for ED improvement.....	117
8.1.	Model analysis.....	117
8.1.1.	Analysis of Output phase of ED	117
8.1.2.	Analysis of Input phase of ED	120
8.2.	Fast track treatment (FTT) strategy.....	122
8.2.1.	Simulation model logic for FTT strategy.....	124
8.2.2.	Coding for FTT strategy	128
8.2.3.	Results from Fast track treatment strategy.....	129
8.2.4.	Conclusion of FTT strategy	133
9.	Conclusions and future work	136
9.1.	Research Summary.....	136
9.2.	Research contributions	136
9.2.1.	Patient treatment captured in detail.....	137
9.2.2.	Integration of DES and ABS for a statistically validated model	137

9.2.3. Flexible process change alternative	138
9.3. Recommendations for the VGH-ED improvement.....	138
9.4. Future work	139
REFERENCES	141
A. User Manual.....	149
A.1. Model view and control buttons.....	150
A.2. Model Input window	151
A.2.1. Experiment 1: Change parameters of DBA strategy.....	151
A.2.2. Experiment 2: Study the effect of reducing TBADM and ERH times	152
A.2.3. Experiment 3: Run model with Fast track treatment enabled.....	152
A.3. Model Output window	153
A.4. Collecting data from the model.....	154
B. Distribution Data.....	157
B.1. Arrival distributions	157
B.2. Treatment time distributions	158
B.3. Output phase process-time distributions	159

List of Tables

Table 5-1 ED resource data.....	57
Table 5-2 Hour by Day table (number of patients in an hour of a day).....	61
Table 5-3 Hour by Weekday occurrence table (number of patients in an hour of a day).	62
Table 5-4 Hour by Weekday table (average number of patients in an hour of a weekday)	62
Table 5-5 Inter-arrival time table (in minutes)	63
Table 5-6 Age group based on arrival mode.....	66
Table 5-7 Percentages of CTAS based on arrival mode and age.....	67
Table 5-8 Treatment location percentages based on CTAS.....	68
Table 5-9 Discharge disposition probability percentages based on Age	69
Table 6-1 Comparison of average wait-times and length of stay (time in minutes).....	93
Table 6-2 Normality test results for all data samples	94
Table 6-3 Mann-Whitney U test results for VGH-EDsim model built using DES only ..	95
Table 7-1 Actual and desired treatment location percentages	104
Table 7-2 Possible values of all state variables for database agent	107
Table 7-3 Treatment location percentages (Nurse Dilemma = 30%-40%).....	114

Table 7-4 Comparison of average wait-times, processing times and length of stay (Nurse dilemma = 30%-40%)..... 114

Table 7-5 Mann Whitney u test results for VGH-EDsim model built using DBA strategy 115

Table 8-1 Percentage reduction in WTBS (local best at each T)..... 134

List of Figures

Figure 1-1 Overview of research Methodology [13]	24
Figure 3-1 Research Methodology.....	40
Figure 4-1 VGH-ED layout	45
Figure 4-2 Input Phase of patient flow in VGH ED	48
Figure 4-3 Throughput phase of patient flow in VGH-ED.....	50
Figure 4-4 Output phase of patient flow in VGH-ED.....	53
Figure 4-5 Activities and wait-times in the VGH-ED	55
Figure 5-1 Arrival rate for walk-in and ambulance patients.....	64
Figure 6-1 Model building process-flowchart	74
Figure 6-2 Snapshot of VGH-EDsim model.....	76
Figure 6-3 Input phase of simulation model logic	77
Figure 6-4 Throughput phase of simulation model logic.....	79
Figure 6-5 Output phase of simulation model logic	81
Figure 6-6 Activity flow within treatment phase	82
Figure 6-7 Steady state analysis for a typical VGH-EDsim model run.....	90
Figure 6-8 Frequency distribution histogram to compare model output data with model validation data (DES model).....	97

Figure 7-1 Example of a Moore machine [63].....	103
Figure 7-2 Simulation model for Dynamic bed-allotment strategy	111
Figure 7-3 Frequency distribution histogram to compare model output data with model validation data (Model with DBA strategy).....	116
Figure 8-1 Percentage reduction in WTBS at different levels of reduction in ERH and TBADM times	118
Figure 8-2 Breaking down WTBS into its components.....	120
Figure 8-3 Model output: W_{BED} time broken into time intervals for all CTAS types	121
Figure 8-4 TIP times for CTAS 4 and 5 broken into time intervals	122
Figure 8-5 Simulation logic for Fast track treatment strategy part 1	125
Figure 8-6 Simulation logic for Fast track treatment strategy part 2.....	126
Figure 8-7 Average WTBS time and LOS time plot versus ceiling value (at threshold= 50)	130
Figure 8-8 Percentage of time fast track treatment strategy is implemented versus ceiling limit value (at threshold = 50).....	130
Figure 8-9 Average WTBS time versus ceiling value (at threshold = 50,100,150,200). 132	
Figure 8-10 Average LOS time versus ceiling value (at threshold = 50,100,150,200) ..	133
Figure 8-11 Range of ceiling in which threshold has maximum impact on WTBS	134
Figure 8-12 Model output using fast track treatment strategy: WTBS time broken into time intervals for all CTAS types	Error! Bookmark not defined.
Figure A-1 Model control GUI.....	149
Figure A-2 Model view.....	150
Figure A-3 Model control buttons	150

Figure A-4 Model Input window	151
Figure A-5 Change nurse dilemma values to change the parameters of DBA strategy .	152
Figure A-6 Enter reduction values to see their effect on WTBS and LOS.....	152
Figure A-7 Change FTT parameters	153
Figure A-8 Model output window	153
Figure A-9 Controls to record model data	154
Figure A-10 Model Output data table.....	155
Figure A-11 FlexSim's debugging window.....	156

List of Algorithms

Algorithm 7-1. Charge nurse/decision agent working on the entry trigger of guide-queue
.....**Error! Bookmark not defined.**

Algorithm 7-2. Decision agent working on the message trigger of Hold-queue **Error!**
Bookmark not defined.

Algorithm 8-1 Database agent evaluating to turn the FTT trigger ON/OFF **Error!**
Bookmark not defined.

Algorithm 8-2 Hold queue evaluating which patients to release to the fast track area
.....**Error! Bookmark not defined.**

List of Appendices

Appendix B-1 Arrival Distributions based on time of day **Error! Bookmark not defined.**

Appendix B-2 Treatment distributions based on age and arrival mode..**Error! Bookmark not defined.**

Appendix B-3 Output phase process time distributions**Error! Bookmark not defined.**

1.Introduction

1.1. Background

Health care expenditure accounts for a major part of Canada's GDP. Canadian Institute for health information (CIHI) reported that health care accounts for 11.9% of the total GDP in 2010 which is an all-time high [1]. In the last decade, total health expenditure in Canada doubled from close to \$100 billion to just over \$200 billion [2]. In Manitoba alone health care costs have increased by over 90% from 2001 to 2011 [3] for only a 9% increase in the population. This continuous growth trend in health care costs is a worrying factor for the government and for the society. The problem is complicated by the fact that the high expenditure has not necessarily led to a better health care system. High wait-times are a common phenomenon in our health care system and waiting for care is still the number one barrier in access to health care [4].

Reducing wait-times was identified as a priority by the First ministers in 2004 in the 10-year plan for strengthening the health care system [5]. In recent years wait-times have improved or remained steady in many areas but CIHI admits that long wait-times in emergency department (ED) still remain a challenge to our health care system [6].

When studying wait-times in EDs, a commonly used term is ED overcrowding which has been defined by Canadian Association of Emergency Medicine as:

“ED overcrowding is defined as a situation in which demand for service exceeds the ability to provide care within a reasonable time, causing physicians and nurses to be unable to provide quality care [7].”

This definition helps to sum up all the different wait-times in ED, which may be waiting to see a doctor, time to be seen by a consultant or waiting to get an inpatient bed [7]. In a nutshell it can be said that if any of these wait-times are longer than usual the ED is overcrowded.

Simulation has been used previously in many areas of health care. In the case of ED, simulation provides a technique to build a replica of the real system, such that the model is reasonably close to reality and can be used to study the effect of different process alternatives. It is particularly useful for decision makers to test any prospective alternatives on the model instead of the actual system.

Another major benefit of using simulation is that it can help identify the bottlenecks in a system. Different EDs serve to different kinds of populations and have different amounts of resources and staffing. Working protocols may also differ and hence there are no universal solutions or process alternatives to solve the ED overcrowding problem. For this research we consider the ED of the Victoria General Hospital (VGH), a community hospital located in south Winnipeg, Canada. The Emergency Department at the Victoria general hospital (VGH-ED/ED) provides comprehensive emergency services 24 hours a

day and is equipped to treat injuries and illnesses in all age groups. More than 100 patients present to the Emergency Department each day. The ED was renovated in 1982 and was initially designed to treatment 15,000 patients per year, however, that number has more than doubled by 2013 [8]. This has led to increased pressure on the existing facility and is leading to long wait- times.

1.2. Research Objectives

The broader objective of this research is to improve the performance of VGH-ED.

Waiting to be seen (WTBS) by a doctor and length of stay (LOS) in the ED are used as the two performance measures.

An ED is not an isolated entity in the health-care system. Its performance is directly impacted by the upstream and downstream elements. However in this study the focus is specifically on the ED itself. This research looks at a micro-level of the isolated ED. The goal is to find operational level alternatives within the ED and not macro level policy alternatives.

An ED can be viewed as a discontinuous system, i.e. the system moves from one event to the next and the system state changes only at these events [9]. For example, when a patient arrives in the ED, it increases the number of patients in the waiting room causing a change in the system. However no further change occurs until the registration process starts. Thus arrival and registration are two discrete events and the system does not change between these two events.

An ED is also a very complex system. These complexities arise due random arrivals, uncertain service times in providing care and randomness in decision- making due to the involvement of humans. For example, some doctors are confident to make decisions on a patient's treatment based on their own judgment while others might want to order multiple lab tests and consult specialists for making major decisions.

The precise aim of this research is as follows:

1. To develop an accurate simulation model that is as close to reality as possible with dynamic human decision-making factors.
2. To utilize this model to study bottlenecks in the current patient flow.
3. To design and test alternatives around these bottlenecks, to help in reducing WTBS and LOS times.

1.3. Overview of the research-methodology

Discrete-event simulation (DES) is a tool which can be used to model discontinuous systems such as the ED. By definition a DES model is one which changes state only at discrete and possibly random events for which probabilities are decided while building the model. A DES model consists of entities and resources [10]. For example, in case of ED the entity is patients which require resources such as beds, nurses and doctors to be treated and discharged from the system.

Although DES is a good tool to simulate multiple events happening in the system at the same time [10], the downside is that the behavior of entities and resources is static and does not change as the simulation runs [11]. This makes DES an insufficient tool to

model ever changing human behavior in the ED. In order to model these human-decision making factors, agent-based modeling (ABM) approach can be used.

In general, agent-based modeling and simulation (ABMS) is used to study complex systems that include decision- making entities and resources. In contrast to DES model the behavior of the entities and resources is dynamic and changes according to the state of the system [11]. In an agent-based simulation (ABS) model the system changes the behavior of entities and resources and they in turn cause the system to change as per their behavior [12]. Using the previous example, patients, nurses, beds, doctors etc. are now dynamic and decision-making entities. In an ABS model these dynamic, decision-making entities are called as agents [11].

Figure 1.1 shows an overview of the research methodology adapted from [13]. In the first step of this research, the functioning of the ED needs to be understood. Based on this understanding, a conceptual model is designed. However not every aspect of the ED can be included in the simulation model either because it is too complex or because it is too trivial. Therefore a set of assumptions is made so that the ED can be represented by the simulation model. The conceptual model is validated by the ED managers to ensure that it is a sufficiently accurate abstraction of the reality. This process is iterative, i.e. more understanding of the system would be required if the conceptual model is rejected by the ED managers. This conceptual model is then used to build a simulation model using a simulation language or software. In this research, a DES software package called Flexsim is used. It has its own coding language called Flexscript which is quite similar to C++ [14]. The model is verified to ensure that it has been built correctly and that there are no bugs or syntax errors in the code. This model is then validated to ensure that it represents

reality. Similar to conceptual model validation, this too is an iterative process and assumptions that were made earlier are modified until a validated model is obtained. This model can then be used to design and test alternatives which can then be applied to the real-world system.

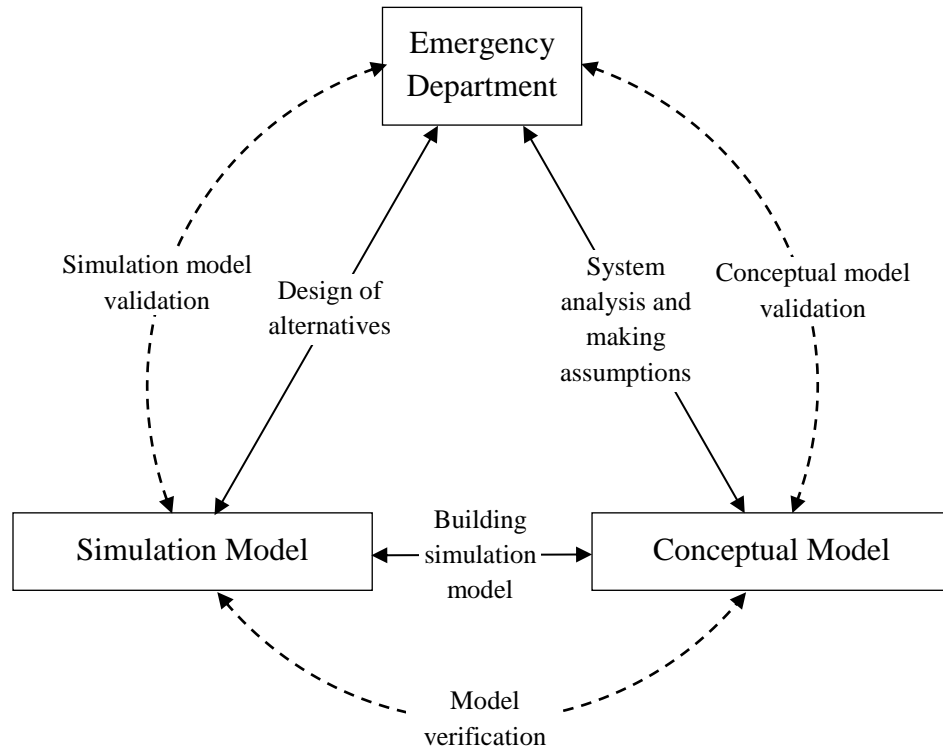


Figure 1-1 Overview of research Methodology [13]

2.Literature review

The first section of this chapter looks into the system-wide nature of the ED overcrowding problem. The second section focuses on the most common simulation methodologies found in literature. The third and fourth sections are dedicated to the literature review of Discrete-event simulation and its discussion, respectively.

2.1. ED overcrowding problem - An overview

The definition of the ED overcrowding discussed in Chapter 1 defines it as a situation when patients in the ED experience long wait-times whether before, during or after treatment [7]. A series of reports was published by the Canadian Agency for Drugs and Technologies in Health (CADTH) which dealt with measuring overcrowding, determining the impact of overcrowding on health standards and the interventions required at a policy level to reduce it [15-18]. In all the reports in this series it has been repeatedly mentioned that ED overcrowding is a system-wide issue with multiple causes and with no simple or immediate solutions [18]. However research only focuses on the ED, its problems and bottlenecks.

2.2. Different approaches of simulating an ED

Simulation is one of the most common operations research (OR) techniques used to model an ED. It is the process of creating a computerized mathematical model of a physical system which can be used to gain insights about it [9]. It is particularly useful for experimentation and for identification of bottlenecks in compressed time. A simulation model comprises of entities flowing/moving from one point to another in the model and they may be discrete or continuous depending upon the nature of the problem and the simulation modeling technique being used [9, 19].

A simple search with the words “Emergency Department” and “simulation” in any of the major databases reveals many papers on this topic. Most common simulation techniques found in literature are system dynamics (SD), Discrete-event simulation (DES) and agent-based simulation (ABS). Before choosing the appropriate strategy to model the VGH-ED it is important to understand these modeling techniques.

2.2.1. System Dynamics (SD)

System dynamics is an analytical modeling methodology to provide a macro level viewpoint of complex problems [20]. The entities in a SD model are continuous and thus the system state changes continuously [19]. It combines the qualitative and quantitative aspects of problem understanding and solving. A qualitative diagram is a causal diagram and its purpose is to demonstrate the positive and negative impacts of a new decision [21]. To generate quantitative results a stock flow diagram is generated and a computer simulation software like STELLA is used to model the system [19].

System dynamics has been used in health care for macroscopic system level research. In a Canadian example, an SD research was carried out by Wong et al [21] in a Toronto hospital to model the effects of altering patient population entering the ED, altering resource allocation and making long-term policy level changes. A detailed study was done by Lane et al to study the effect of reducing bed capacity in hospitals to patient wait-times in accident and emergency (A&E) units across UK's National health systems (NHS) which showed how it can adversely affect wait-times in ED [22]. In another example, a system level research was conducted using SD strategy to study the effect of different proposed policy level changes on healthcare affordability in Singapore [23].

2.2.2. Discrete-event simulation (DES)

A Discrete-event simulation model is visualized as consisting of discrete units of entities that move (flow) through the system [10]. A simulation model consists of one or more source that creates raw entities and one or more sink that destroys processed entities. In this journey from source to sink the entities need to go through one or more number of processes. For this the entities also require resources such as processing stations and operators which process the entities at these stations and move them from one station to another. In a typical simulation model several entities may be processed simultaneously at different stations at any given point of time. If the resources are limited in numbers the entities have to wait in between in queues. Every time an entity interacts with the system or the resources an event occurs. The modeller can write specific codes on any of these events to decide the further course of the entity in the system. Therefore it is said that in a DES model the system state changes only at discrete but possibly random events in time

[9, 10]. For example in a DES model for an ED when a patient (entity) gets triaged (process) it may be triaged (event) as a minor patient or a major patient based on the probability modeled by the modeller. If a bed and nurse (resources) are available, the patient can go to the bed; otherwise he or she has to wait in a waiting room (queue). A DES study begins by the problem formulation and formally agreeing to the number and nature of entities in the target system. This is followed by a conceptual model which is akin to a causal or influence diagram of SD in regards with providing the qualitative analysis [19]. However the conceptual model in DES focuses on the target entities and their flow in the system rather than focusing on the driving influences. More about DES modeling used in the case of VGH ED will be explained in Chapter 3.

2.2.3. Agent-based simulation (ABS)

To understand the concept of agent-based modeling it is necessary to understand the term agent first. In general terms an agent can be described as an autonomous entity which makes decisions based on a set of rules [12]. The agent also communicates with other agents within that system and can adapt and change its behavior based on the outcomes of those interactions. The outcome of a purely ABS model is based on the outcomes of these interactions [24]. An ABS model has three main aspects:

- 1.) Agents, their characteristics and behavior.
- 2.) Relationship between agents, their methods, the probability of their interaction and outcomes of their interactions.
- 3.) Agent's environment. This in some cases can be seen as the manager agent, i.e. the agent that manages all the other agents towards a specific goal.

In this research ABS has been used to enhance the DES model and to study the human factors. The detailed study and literature review will be discussed in Chapter 7 after presenting the DES simulation results in Chapter 6.

2.2.4. Why choose DES over SD?

Before comparing the SD to DES methodologies it is important to notice that DES is purely a simulation methodology and unlike system dynamics that does not have a qualitative aspect. Essentially, it should only be compared with the quantitative aspect of system dynamics. Unlike flow diagrams in SD which view “entities” as a continuous quantity, like a fluid, flowing through a system of reservoirs or tanks connected by pipes, DES considers the system to be made of individual entities which pass through a series of activities or processes and in between these activities where they wait in queues. The state of the system changes at discrete points of time [19].

A number of studies have been carried out comparing SD with DES. The most common argument found in literature is that SD is more useful where a more holistic and broader view of the system is taken and DES suits well where an operational understanding of the system is required [19, 25, 26]. Although some researchers argued that SD models were better because of their transparency [27], this argument seemed to be valid only for qualitative SD models. as quantitative SD models with their complex differential equations, its mathematical models lack the transparency [19]. SD modeling strategy is argued to be more suitable for modeling fuzzy ambiguous systems whereas DES is suitable for clearly detailed systems [28]. In general, it has been established that DES is more suitable where the system is random and changes significantly, in contrast with SD

which is more suitable where the system does not react immediately [29]. In other words, problems that are caused by the system structure are better analyzed by SD, and problems that are caused by the randomness inside the system are better modeled by DES [28].

From the perspective of the problem nature, most researchers are of the view that SD is suitable for strategic problems and DES is more suited to operational and tactical problems [19, 27].

This research focuses on modeling the ED considering it as an isolated system. The system boundaries are from patient arrival to patient discharge and the patient undergoes several discrete processes during this journey. The goal is to find bottlenecks within the ED and solutions proposed will be of operational and tactical level and not policy level. Therefore considering the characteristics of the system under study, DES methodology is chosen over SD as the modeling technique. The next section is for the literature review of DES.

2.3. Discrete-event simulation in ED

Discrete-event simulation is one of the most common methodologies used to model emergency departments. The literature is full of such examples. Jurishica discusses a generic process for developing simulation models for EDs [30]. She presented that alternate scenarios tested on simulation models called as “What-if” scenarios with two categories: variable change scenario and process change scenario. The former deals with finding the optimal resource mix in the ED, for example the number of nurses, physicians

or beds etc. Process changes could either mean replacing processes with alternate processes or changing the entire patient flow according to some new strategy.

The review is divided into three sub-sections. Papers that explore variable change scenarios are discussed in the first subsection, papers that look into process change scenarios are included in the second sub-section. A third sub-section is to present papers that do not fall under of any above two categories but are important research to be discussed.

2.3.1. Variable change scenarios

Many researchers have used DES models to find the optimal resource mix or the optimal staffing schedule [31-37]. While most researchers tried to design the scenarios as suggested by ED managers, a few researchers combined some kind of an optimization technique to find an optimal solution. The variable change scenarios can be further classified as those which tried to find a more robust staffing schedule i.e. reshuffling of existing resources and modeling of the effect of additional resources.

Duguay & Chetouane modeled an ED in New Brunswick, Canada and tested different resource mixes of physicians, nurses and examination rooms [31]. Five alternatives were designed and each of them had one additional nurse and physicians at different times of the day. Two of the alternatives also considered one extra bed; however research showed that adding beds was insignificant to wait-times and simply adding a nurse and a doctor during busy hours can significantly affect wait-times and throughput. The results showed that adding these resources shortened wait-times only by around 10%. Paul & Lin also found out that adding a physician at busy times of the day improves average daily

throughput [32]. Similarly, Shim & Kumar used DES to model the effect of adding another payment station in a Singapore ED [33]. As an example of a major addition of resources (beds in this case), Kolb et al [34] used simulation DES model to test five patient buffer scenarios. The buffers were “bed areas” added for specific kinds of patients. First was “Holding area” for patients that were waiting for inpatient beds, second was an “ED-discharge lounge” for patients waiting to be discharged and third was an “Observation Unit” for keeping patients under observation within the ED. The fourth buffer scenario was a combination of first and second and fifth buffer scenario was the combination of first, second and third. The results showed that ED performance was improved in all of the five scenarios but scenarios 4 and 5 were better than the other 3. Some researchers used optimization techniques such as Genetic algorithm (GA) and balance scorecard (BS) to find the optimal resource schedule or resource mix. Yi & Lin improved the quality of care of an ED using a combination of simulation model and GA [35]. The aim of this research was to find an optimal nurse roster using GA while also looking to minimize wait-times being simulated by the DES model. The GA model selects the feasibility of a nurse roster and the DES model checks it for minimum wait-times. The nurse roster found using this method could reduce wait-times for patients by approximately 43%. Ismail et al used DES integrated with BS method [36], which identified that the ED comprises of several queues and wait-times are distributed across these queues. Three scenarios were tested to balance wait-times across all queues and reduce the total average wait-times while keeping LOS constant or less. In the first scenario a nurse was added at Triage. In the second scenario the capacity of the waiting room was increased. In the third scenario, resources were dynamically distributed in the

ED such that the average wait-times in each of the queues remain equal. The first two scenarios reduced waiting-times at Triage but ended up causing uneven wait-times in the rest of the ED. Moreover since the first two scenarios also meant adding resources (costs), the third alternative of dynamic resource relocation was found out to be the best as it balanced wait-times across the ED and also reduced the rate of patients leaving without being seen. Thus instead of adding permanent resources, a different rule for optimal resource distribution was chosen to improve the performance of the ED.

A special mention should be given to Weng et al as it is one of the very few papers that discuss the cyclic nature of the treatment process [37]. They used the data envelopment technique to calculate the percentage probability of the number of lab and treatment cycles that a patient goes through and also the service time distributions for each cycle. They further used this simulation model to test 32 different combinations of nurses, beds, and doctors, benchmarked them with an efficiency score which was a combination of lower wait-times and higher resource utilization.

2.3.2. Process change scenarios

The second set of DES studies is segregated based on process sequence changes [38-45]. Some changed only the order of specific processes while others completely overhaul the existing process.

Five papers are found that alter some specific process in the ED [38-42]. For example, Holm and Dahl studied the effect of using an alternate process sequence in the ED [38]. They studied the effect of physician at triage and found that although it did not have a major impact on wait-times or LOS; it did considerably reduce the time from patient's

arrival to the first meeting with the physician. Thus they argued that a qualitative improvement was achieved without having any ill effects on the average LOS. Similarly Ruohonen and Teittinen carried out a simulation study for studying the effect of a triage process called as the “Triage team method” [39]. The study found that if the triage is done by a team comprising of a physician, a nurse and a receptionist, the average throughput time is decreased by 26% due to the fact that lab tests can be ordered at triage itself. Connelly and Bair built a simulation model and tried the triage concept called acuity ratio triage to solve the problem of high wait-times for low acuity patients [40]. Using this concept, each care provider was assigned a set ratio of high acuity to low acuity patients. Preliminary results demonstrated an overall decrease in service times across all patients.

In another example, Beck et al built a simulation model using DES to study the effect of an alternate process sequence in the ED “Bedside Registration”, where the registration of the patient was done alongside treatment [41]. However, they found that the alternate process worsened the LOS as each patient ended up occupying the bed longer resulting in scarcity of beds. Zeng et al introduced the concept of team nursing to better distribute the nurse resource across the beds [42]. As compared to three beds for one nurse, the responsibility was distributed as per 6 beds for 2 nurses. The result was an improvement of 13-26% in WTBS and reduction of LOS and LWBS.

There are some examples of complete process reengineering. For instance, Hay et al argued that flow in the ED should be process driven instead of being patient driven [43]. The research considered that processes and their sequences can be fixed based on whether the patient is critical or non-critical. These sequences were called “Care

pathways”. The order for patients to enter the care pathways was determined by a dynamic variable called “operating priority” based on the clinical condition of the patient, which was modified by the time when the patient has already waited in the ED. The physician resources were allocated to these pathways and patients based on their “Skill-sets”. The research found that this methodology improved overall patient wait-times and staff utilization.

Konrad et al also modeled the effects of a major overhaul in the process sequence of the ED [44]. The traditional system was a sequential system where patients were seen on the basis of arrival time and acuity. The resources were shared between the major area and the fast track area, thus it was a sequential flow. This patient flow was replaced by a concept called split-flow, where the minor patients are sent to continuous care area and the resources required to treat them are independent of the major area. Thus it turns the ED into a parallel flow. The base case scenario tested for split-flow showed drastic reduction in WTBS times and LOS. The model was further tested for sensitivity to arrival rate and redistribution of patient acuity. In another example of a parallel patient flow, Davies used simulation to demonstrate that non-critical emergent patients (minor patients) should be assessed and discharged by the doctor or a nurse practitioner, and be sent to nurses only for treatment [45]. This system replaced the conventional order of nurse assessment followed by doctor assessment and then treatment. The conventional order was followed for critical patients only. The study demonstrated the average wait-time was reduced up to 3 times following this methodology.

2.3.3. Miscellaneous scenarios

This subsection reviews the literature of DES that could not be assigned to either of the first two sub-sections [46-50]. It is important to discuss them as they show the range of alternatives with a DES model.

An interesting study by Marmor et al used simulation to build a real-time decision support system for the ED [46]. The support system helped interpreting current state to forecast short-term future state of the model. It also assisted ED managers to schedule staff optimally based on the forecasts.

Holm and Dahl simulated the effect of a 45% increase in patient volumes and predicted that with the same number of resources the average LOS will increase by 150% [47]. They also found an optimal mix of resources by a hit and trial method, which would nullify the effect of increase in patient volume on the LOS.

Eskandari et al developed a simulation model for an ED in Iran and tested 14 different scenarios, comprising of variable change scenarios, process change scenarios and one hybrid scenario [48]. TOPSIS weighing technique was used to determine the best scenario and the hybrid scenario was selected as the best.

Gunal and Pidd focused their research on modeling the effect of physician multi-tasking. A physician resource was divided into “M” mini-physicians to model the fact that a physician can take care of more than one patient at a time [49]. The study also modeled the effect of slow and fast doctors on the patient flow.

The study conducted by Ferrand et al was to find an optimal operation room (OR) allocation strategy for elective and emergency surgeries [50]. The choice was between a

flexible strategy where electives and emergent patients had access to all OR beds on first-come-first-serve basis and a focused strategy where a certain number of beds were allocated to emergent patients only while the rest were open for electives. The study found that the focused strategy benefits elective patients but leads to an increase in wait-times for emergency patients.

2.4. Discussion of literature

There are several conclusions that can be drawn from the literature review. Also there are certain gaps in the literature which can be addressed in this study.

Most of the papers have described the treatment process as a single process which is an inaccurate representation (discussed in Chapter 4 in detail). Only Weng et al. [37] have discussed the cyclic nature of the treatment process.

In most of the variable change scenarios, research seems to point to the fact the adding resources does not necessarily improve the performance. Even where human resources need to be added, the proper scheduling has a bigger impact on performance improvement. Thus it can be said that in the majority of cases resource relocation/redistribution should be tried before adding resources permanently to the ED. The process change scenarios show wider variability in results. While in some cases alternate process flows designed on anecdotal evidence improved the ED, in some cases they caused loss of performance. Also researchers argue that a complete overhaul in process sequence is difficult to achieve as it is tough to convince all stakeholders to implement such a major change. The conclusion to be drawn from the review of process

change scenarios is that process reengineering alternatives have different effects on different EDs. Moreover since none of the process change scenarios were Canadian studies, therefore any results no matter how good should be carefully considered in the Canadian context.

Some interesting conclusions can be drawn from some of the miscellaneous papers. For example, one conclusion to be drawn is that simulation models can be used to simulate the short-term [46] and long-term [47] state of the system. Thus DES models may also form the basis of a system level policy change in the long run. The study from Eskandari et al shows that variable changes can also be accompanied with process change scenarios to achieve better results than either of them being used alone [48]. The study from Gunal and Pidd is one of the rare examples for DES used to model the effect of human performance on ED performance [49]. Although its scope was limited, this study can be used as a basis to further look into the role of human factors in the ED.

To conclude, in this research the above mentioned gaps shall be filled. The aim of this research will be to design different solutions to improve the ED, based upon a validated simulation model which considers the cyclic nature of the treatment process and the human factors that affect the patient flow in the ED. Since no two EDs are the same, alternatives will be designed to specifically suit the VGH-ED.

3. Research methodology

This chapter introduces the detailed research methodology. The order of the following chapters is based on the steps mentioned in the research methodology. The concept of research methodology was introduced briefly in Section 1.3 and this chapter is based on that introduction.

3.1. Phases of research

This research can be divided into three phases. First phase deals with identifying and defining the problem and then gaining insight into it. In the second phase, data are collected from the real system and analyzed. These data are used to build a verified and validated simulation model called *the VGH-EDsim model* (or ‘the model’). In the third phase, the results from the model are used for model analysis and solution design. The improvements for VGH-ED are suggested on the basis of these experiments. A detailed flowchart of the different phases is shown in Figure 3.1.

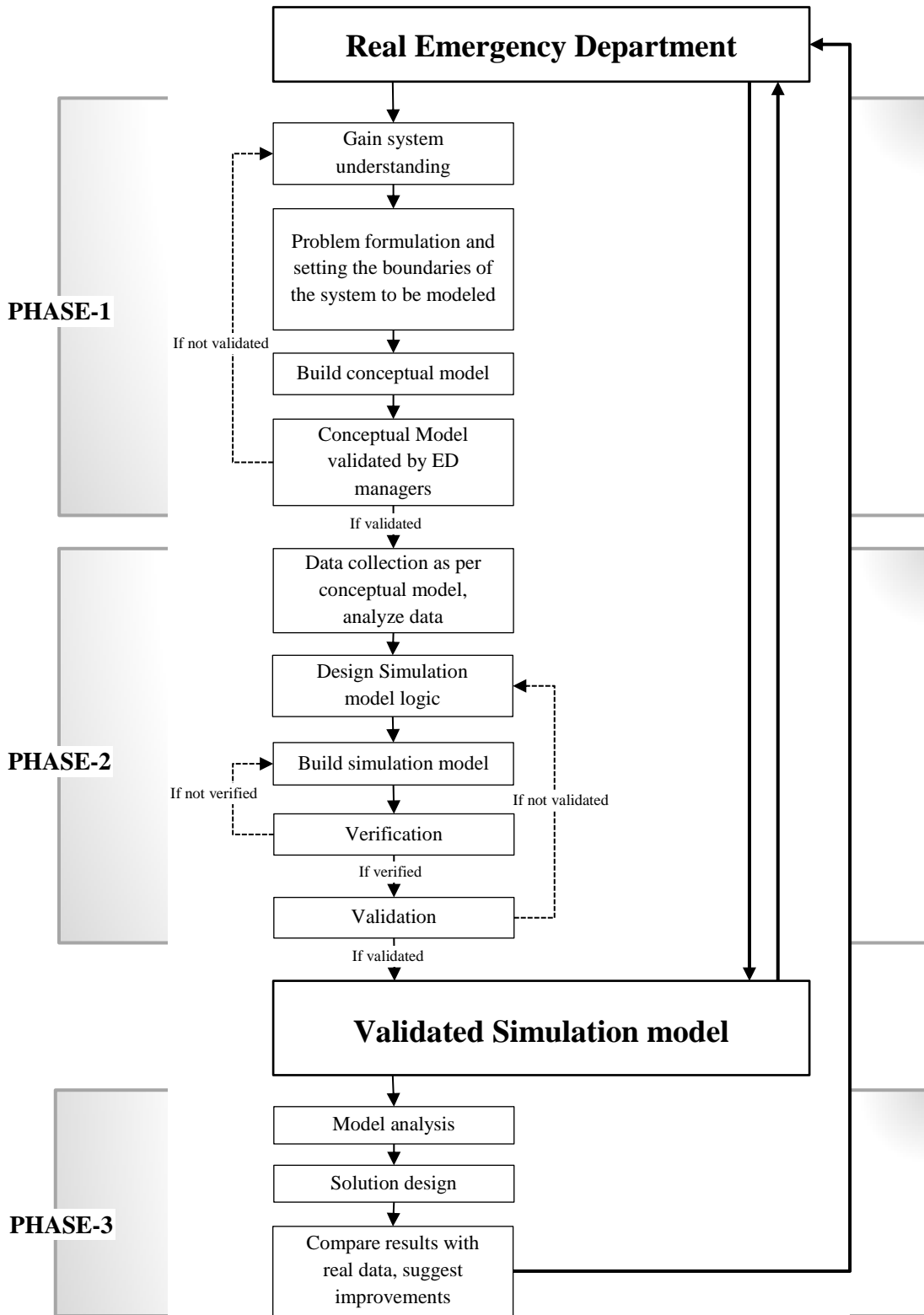


Figure 3-1 Research Methodology

3.1.1. Phase-1: Understanding the real ED.

Phase-1 is done in four steps. The first step is to gain the understanding of the system and get familiar with the ED. In the second step this understanding is put in terms of flowcharts and a rough boundary of the system is determined. The first two steps are iterative in nature. When sufficient understanding has been gained and the flowcharts have been refined, a *conceptual simulation model* is developed using these flowcharts in step 3. The conceptual model is a logical representation of the system and is developed for the objectives of a particular study [13]. Along with the conceptual model the problem statement is also formulated. The conceptual model and the problem statement are validated by the ED managers in step 4 [13]. If there is no consensus then more understanding regarding the system needs to be acquired and steps 1, 2 and 3 are repeated. If conceptual model and problem statement are approved the research moves to phase-2.

3.1.2. Phase-2: Data collection and building the VGH-EDsim model

Phase 2 is done in 3 steps. In step 1 data are collected from the VGH-ED (called VGH-ED data or system's data). The data collection is based on the problem definition and conceptual model. It is important to know what data to collect in order to avoid getting overwhelmed. The system's data are then broken down and analyzed. The data are broken down into stochastic and deterministic forms of information [13]. Arrival distributions, process time distributions and probabilities that determine patient attributes are stochastic forms of data. Structural data like types and number of beds, nurses and doctors are deterministic information.

In step 2 the simulation model is built as per the *simulation model logic*. The simulation model logic is an abstraction of the conceptual model such that it represents all the aspects finalized in the conceptual model [13]. It also describes how the information generated from data collection is used in the simulation model. In this research the model was built using FlexSim which is a discrete-event simulation (DES) software developed by FlexSim Software Products [14]. It uses its own language called Flexscript.

In step 3 the model is verified to ensure that the simulation model logic has been written correctly and that there are no errors in the code. If the verification is successful and no bugs are found in the code, model validation is carried out to ensure that the model represents reality. Model validation can fail if wrong assumptions or over-simplifications were made during conceptual-model building [9]. Until the model is validated it cannot be used to conduct any meaningful research.

3.1.3. Phase 3: Model analysis and design of solutions

When the VGH-EDsim model is validated it can be used to study the system and identify the bottlenecks and possible areas of improvement. Based on this analysis process change solutions are designed for the VGH-ED to improve ED performance.

3.2. Thesis organization

This research is organized into 9 chapters, 3 of which have been already presented. In Chapter 4, phase 1 of the research is covered. Problem definition and VGH ED is discussed and the validated conceptual model is presented in this chapter.

Phase 2 of the research is discussed in Chapters 5, 6 and 7. Chapter 5 is about data collection and analysis. Chapter 6 discusses the entire simulation model, the steps taken to build it, verify and validate it, in extensive detail. Since the initial DES model could not be validated, the cause of this failure and the remedy has been discussed in Chapter 7 called 'Agent-based modeling and simulation'. In the first half of the chapter, literature related to the use of ABS in ED modeling is presented. The second half of this chapter deals with how ABS is applied to VGH-EDsim model in order to validate it. Validation results from DES and ABS methodologies are compared to demonstrate the superiority of ABS.

Phase 3 of the research is covered in Chapters 8. The first half of the chapter focuses on the bottleneck analysis. It details the methods used for the analysis and the results. The second half is dedicated to the fast-track treatment strategy which is an attempt to improve the performance of the ED. Chapter 9 concludes the thesis and presents possible future work.

4. Victoria General Hospital-ED patient flow

This chapter introduces phase 1 of the research for the VGH-ED. The first section presents a general overview of the ED. In the second section patient flow in the ED is discussed in detail and flowcharts are presented. In the final section the problem statement formulation is discussed.

4.1. Structure of the ED

To understand the patient flow in the ED, one has to first understand the structure of the ED. The ED comprises of several beds and waiting rooms for patients with different needs. There are three main waiting areas in the ED. The first is the main waiting area which is further divided into two sub-areas based on the color of chairs and their purpose. The orange chairs are for patients that have just arrived in the ED and the purple chairs are for patients waiting for a bed. The second waiting area is reserved for minor treatment area patients (MTA waiting room), those who are with minor medical issues. There is a third, separate waiting area for ambulance patients called the EMS waiting room. The beds in the ED are of two types: monitored and non-monitored. Monitor beds as the name suggests are for patients who need constant monitoring of various bodily functions. Non-monitored beds are for the less acute patients. The beds have been divided into four

bed-areas. First is the *Monitor area* which has 15 monitor beds and is reserved for higher acuity patients. Second is the *Treatment area* which comprises of 4 non-monitored beds for lower acuity patients. There is another bed area adjoining the treatment area called *Minor treatment area (MTA)* and comprises of 5 non-monitored beds specifically reserved for patients with minor clinical issues. Two highly equipped beds are placed very close to entrance and are called as *Resuscitation beds*. Although all these beds are supposed to be reserved for specific kinds of patients, the ED managers have the discretion to move patients from one bed area to another. The ED layout is shown in Figure 4.1.

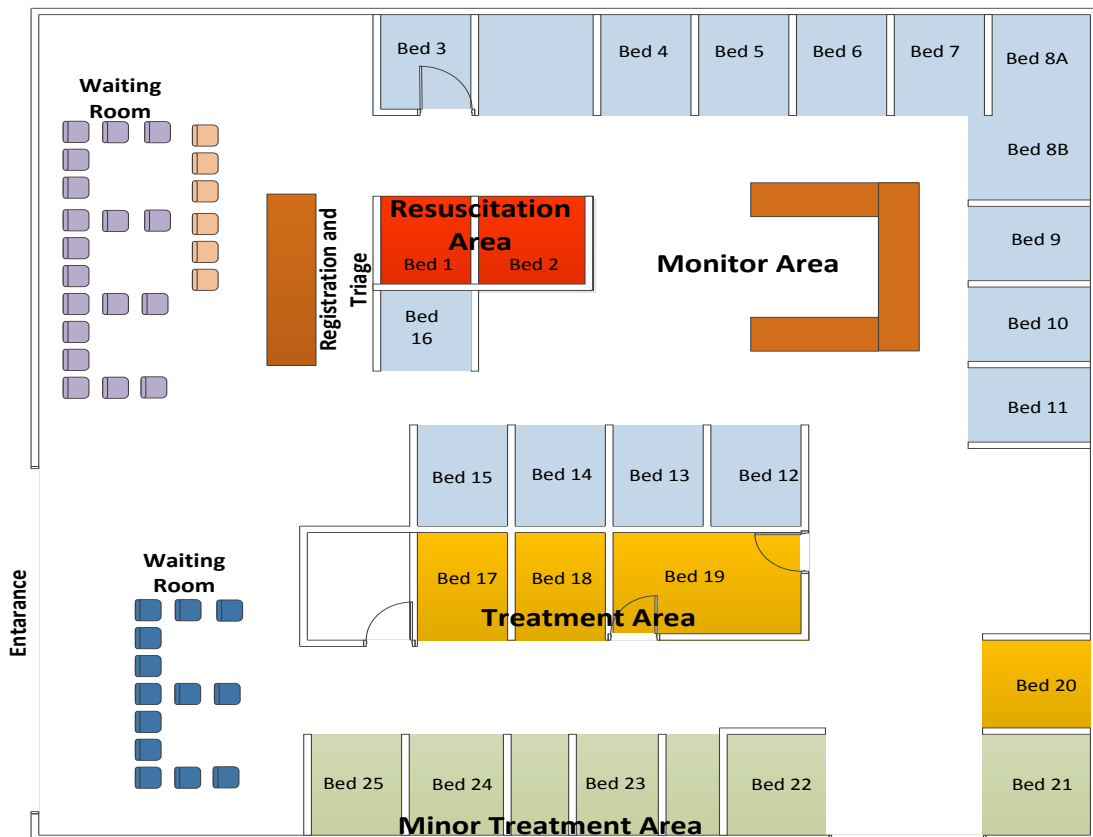


Figure 4-1 VGH-ED layout

4.2. VGH-ED patient flow: the Input-Throughput- Output approach

The patient journey from arrival to discharge/admission can be broken down into three phases; *Input phase*, *Throughput phase* and *Output phase*. The patient's state within these phases is known as *Patient status* (called as status henceforth). The title of each status indicates what is happening with the patient at any given point of time.

Patients are either discharged the same day or are admitted in the hospital. The former kind of patients are called *non-admits* and the ones that get admitted are called as *admits*.

4.2.1. Input phase

Patients come to the ED either via walk-ins or via ambulances. Input phase of the patient's journey in the ED begins at his/her arrival and ends when a bed is assigned to the patient. The input phase is different for critical (also known as *code red/blue*) and non-critical patients. Critical patients bypass the input phase and are placed directly in either of the resuscitation beds. Figure 4.2 shows the schematic for the input phase of patient flow in ED.

The patient's arrival mode also has a big impact on his/her journey in the input phase. If the patient arrives by himself/herself (walk-in patient), he/she goes to the orange chairs in the waiting room. The triage nurse visually assesses the patient and determines if he/she is a critical patient (code red or blue). If not then the triage assistant interviews the patients sitting in the orange chairs and makes a quick assessment in order to prioritize

sicker patients over others. It is in this order that the patients go for the first process of their journey called *Registration*.

In the registration process patient's demographic data such as name, age, contact information, health card number etc. are obtained. As soon as the registration is over the patient status is set to *waiting to be seen by a doctor* (WTBS). After the registration process the next process in a patient's journey is *Triage*. This process happens at either of the two triage desks. Since the triage desks are placed right beside the registration desk, triage mostly takes place right after or alongside registration. In the triage process the patient narrates his/her cause of coming to the ED. The triage nurse records patient's temperature and blood pressure or any other vital sign as per requirement. During triage a number of questions are asked from the patient and on that basis a computer system generates a score called the CTAS score. CTAS is the *Canadian Triage and Acuity Scale* which ranges from 1 to 5; 1 being the most critical and 5 being the least critical. On the basis of patient's medical condition and the CTAS score, triage nurse also determines whether the patient needs a monitored or a non-monitored bed. This decision can also be taken by the charge nurse.

CTAS score is a critical determinant of a patient's remaining journey in the ED. CTAS 1 patients require immediate attention and go to resuscitation beds. CTAS 2 usually also require resuscitation beds but can be also be treated on any other monitor bed. Generally patients with CTAS 3 go to the main waiting room (purple chairs) and patients with CTAS 5 go to the MTA waiting area but there are certain conditions that may apply such as age or any other medical need. CTAS 4 patients go to either of the two waiting rooms based on the discretion of the triage nurse. In the VGH-ED sicker patients (lower CTAS)

are given priority for assignment of bed. Amongst patients with the same CTAS score priority is usually decided by first-come-first-serve basis, but in some cases older patients are given priority.

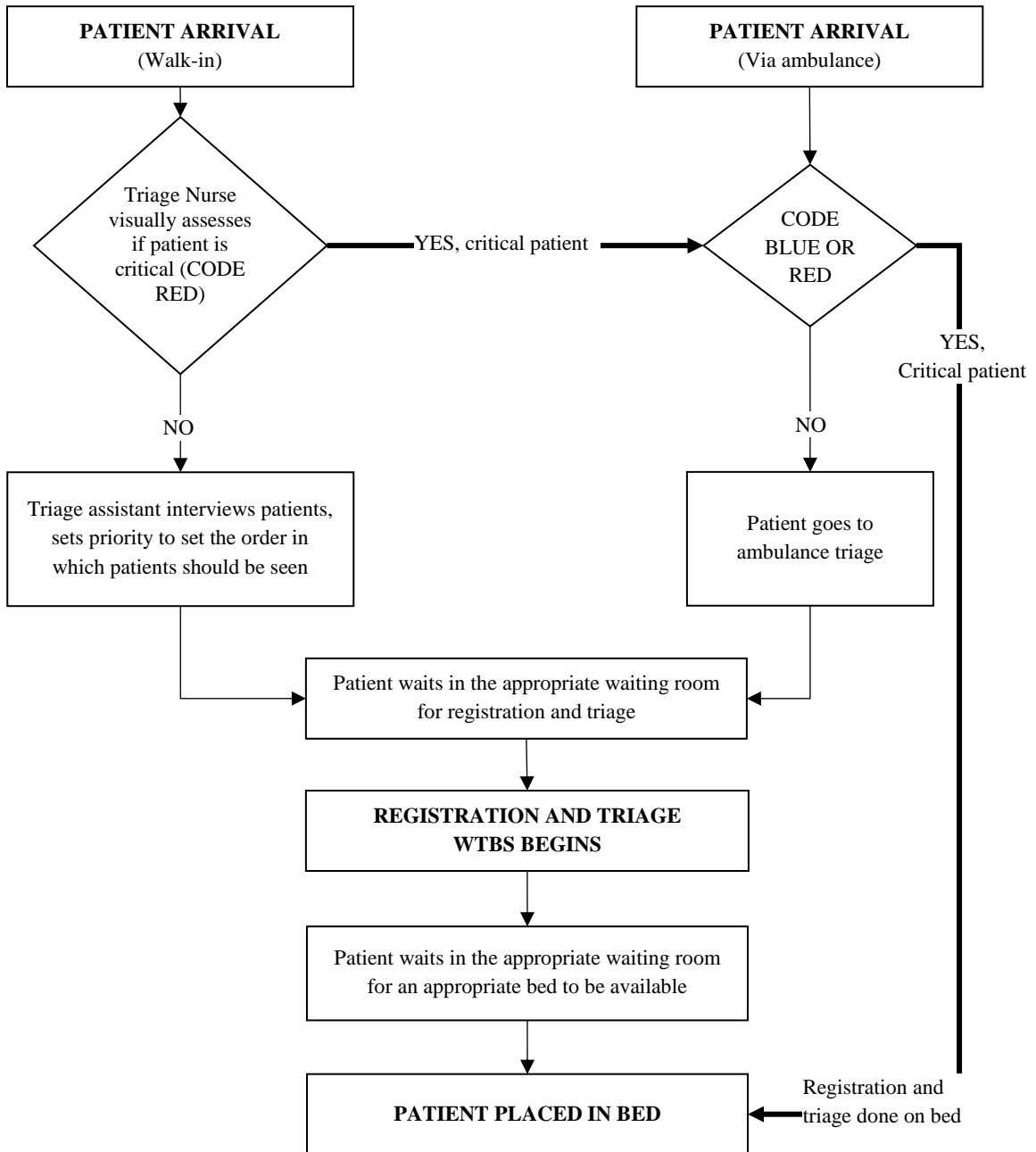


Figure 4-2 Input Phase of patient flow in VGH ED

For patients arriving via ambulance, ED staff members generally have prior knowledge of whether the patient is a critical patient. If the patient is not critical, he/she waits in the EMS waiting room for the process of registration and triage. These processes happen in the same way as for a walk-in patient.

4.2.2. Throughput phase

The throughput phase begins when the patient is assigned a bed and ends when all the treatment that he/she can get in the ED has finished as shown in Figure 4.3. It can also be said that the throughput phase ends when the patient is medically stable and requires no further treatment in the ED.

In this phase the patient utilizes maximum ED resources. A patient requires a bed, nurse and a doctor to get treated. He/she may also require several other resources such as medications, specialist doctor, health care aid but these resources have not been considered in this research.

As per the ED protocol, the first process in this phase is an *initial nurse assessment*. In this process a nurse assesses the patient and records all vital signs. It is a more thorough assessment over the triage assessment. The nurse then records everything he/she has observed about the patient. This record is attached to the patient chart and is accessed by the doctor for treatment. The second process in this phase is the *initial doctor assessment*. The patient status changes to *treatment in progress (TIP)* as soon as the doctor assessment begins.

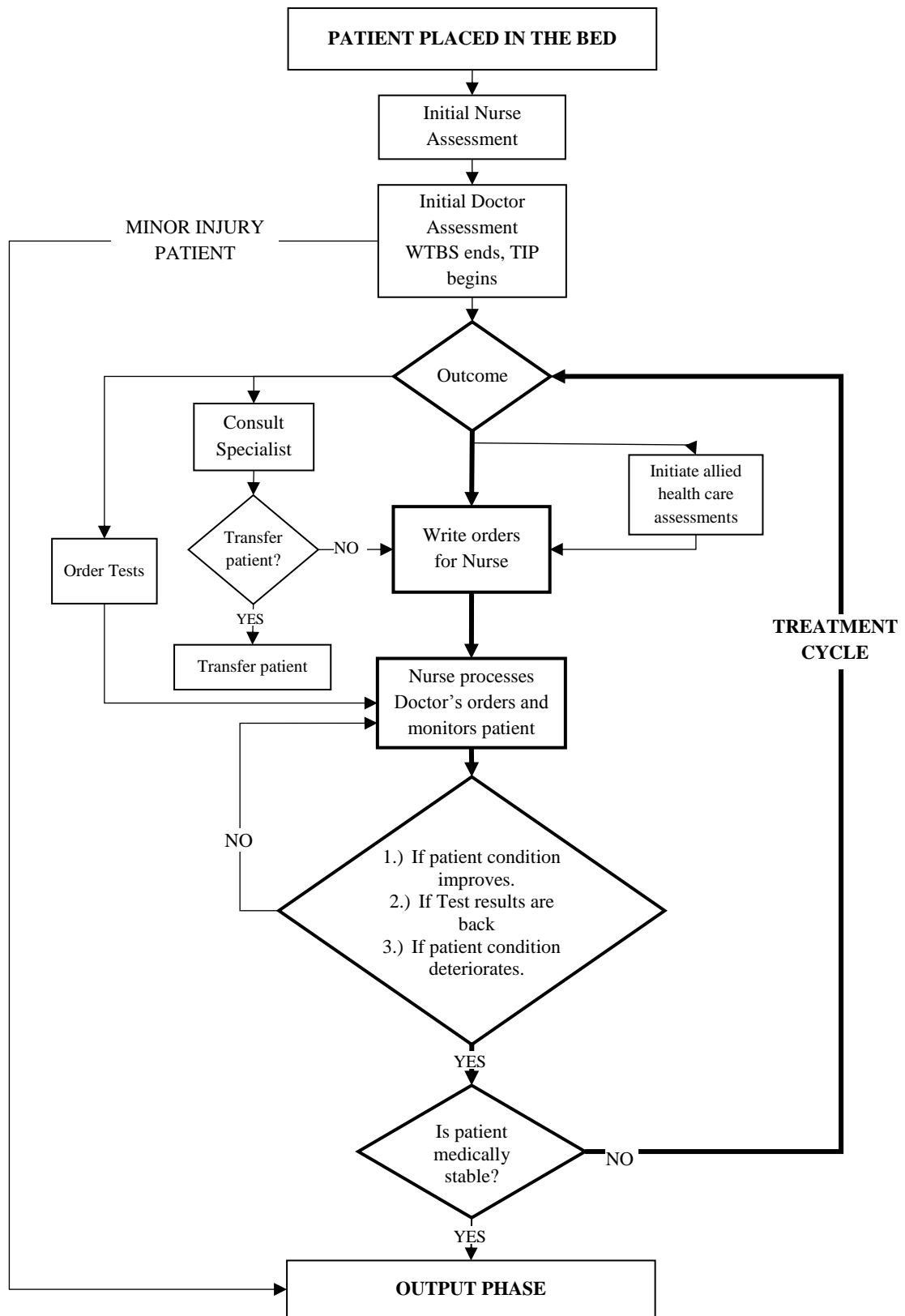


Figure 4-3 Throughput phase of patient flow in VGH-ED

The doctor based on nurse's judgment and his/her own judgment takes a call on the patient. The doctor may take any one of the several possible decisions at this point which include ordering lab tests, asking nurse to perform a procedure, consulting a specialist for an opinion. If the patient is medically stable and is not experiencing significant pain, some allied health care services such as home care, physiotherapy or occupational therapy may also be initiated. In the case of patients with minor medical issues, they could also be discharged after the initial doctor assessment. Thus every patient that comes to the ED goes through the initial nurse assessment and initial doctor assessment.

4.2.2.1. Treatment cycle

Patient treatment is not a singular process but it is a cyclic process. Since the nurses and doctors also treat other patients simultaneously, they repeatedly visit patients in short bursts. After the initial doctor assessment if the patient is not discharged, the nurse processes the doctor's orders. This process is called *nurse process*. The nurse also monitors the patient and the doctor may be called again in any of these three cases:

1. The doctor had ordered lab-tests in the initial doctor assessment and the results are back.
2. The patient is medically stable and the doctor needs to take a call on whether to send the patient home or admit the patient to the hospital.
3. The patient is deemed medically unstable and doctor needs to reassess the patient's condition.

The doctor may decide to keep the patient in the ED if he/she needs more treatment.

More tests or consultations may be required if patient needs more treatment in the ED. If

no further treatment is required, the doctor makes a decision if the patient needs to be admitted or can be discharged from the hospital. This process is defined as *doctor process*. Figure 4.3 explicitly shows the cyclic nature of treatment process. Since the process is cyclic and the doctors and nurses work on multi-tasks, there are some wait-time periods within the treatment process. For the lack of a formal term we can call this as *waiting within treatment* (WWT). This time is undocumented in the data and is a part of the total TIP time.

4.2.3. Output phase

Once the treatment is complete the patient moves to the output phase of his/her journey in the ED and the TIP status ends. A patient can either be sent home or be admitted in the hospital. In both cases the patient has to wait for the final destination to become available. The flow is shown in Figure 4.4.

Patients that need to be admitted to the hospital have to wait for a bed in the hospital. The patient waiting for a bed is in *to be admitted* (TBADM) status. While they are waiting in the ED, they occupy the bed resource and ED nurses and doctors have to periodically monitor their condition.

If the patient is supposed to be discharged, sometimes he/she may not be able to go on his/her own. In such a case the patient requires a ride home or some family member to take him/her home. Whatever may be the case, the patient has to wait in the ED even when treatment in the ED is done. The status of the patient during this wait-time is called *pending discharge* (PD) status. The patient sometimes keeps occupying a bed during this wait-time.

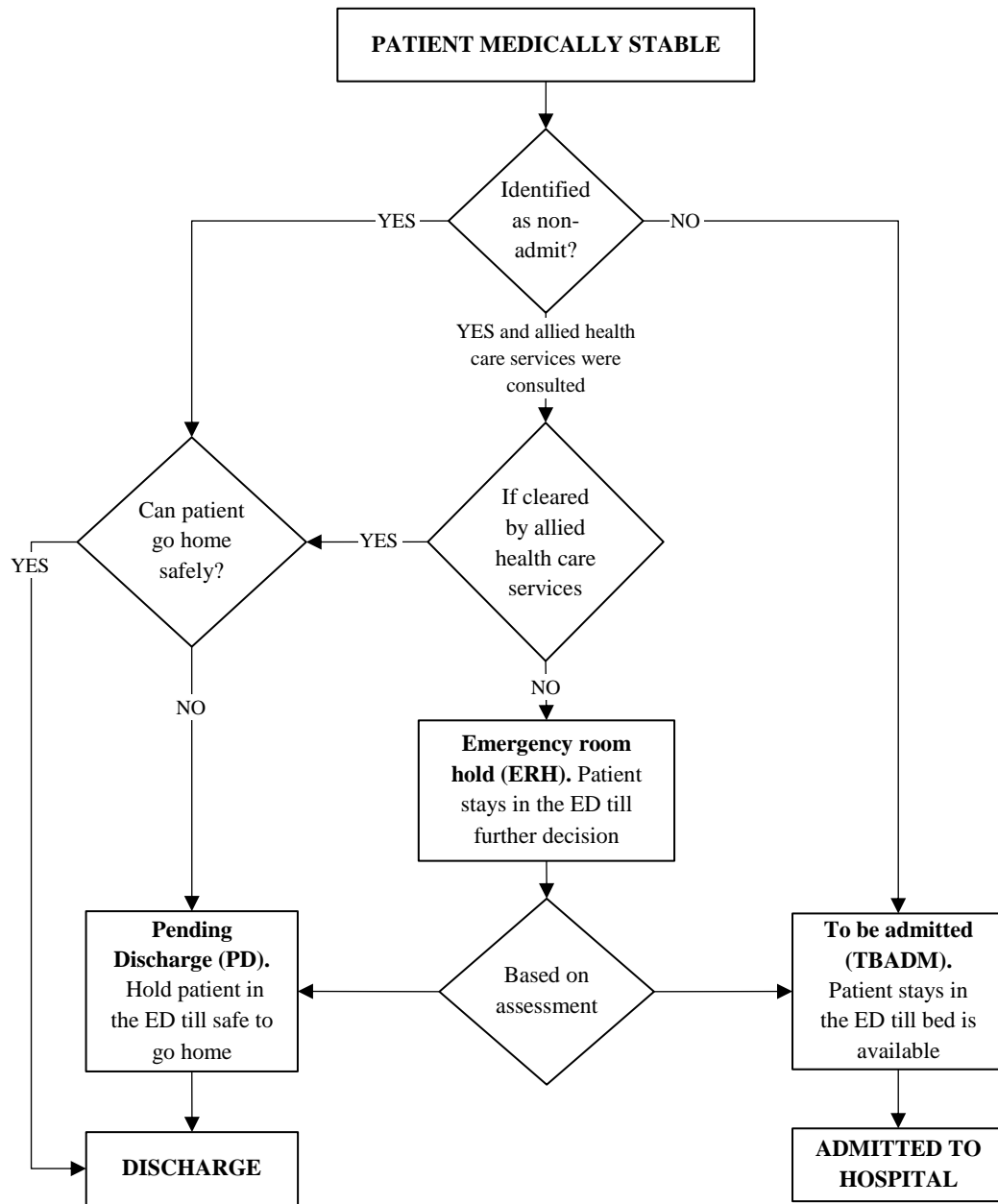


Figure 4-4 Output phase of patient flow in VGH-ED

In some cases even when the patient is medically stable and needs to be admitted/ discharged, there may be some non-acute medical condition due to which the patient may not be immediately admitted/discharged. For example an elderly patient who came to the

ED with fever has been treated. However the ED needs to ensure that the patient will be able to take care of himself at home. In such cases addition allied health care teams determine if the patient is fit to go home. The patient is held in the ED until all necessary assessments are complete and the patient status during the time he/she is held in ER is called *emergency room hold* (ERH) status. It is also necessarily a wait-time as the patient is waiting for a final decision on whether he/she stays in the hospital or is discharged.

4.3. Problem formulation and underlying assumptions

Based on the understanding gained about the ED a precise problem statement is formulated so as to broadly define the constraints and assumptions. A basic assumption in this research is that we cannot alter the clinical component of care. That means that the process times cannot be altered. The goal of this research is to reduce average waiting to be seen time (WTBS), keeping length of stay (LOS) either constant or less, preferably without adding resources. The problem can be defined as:

“Patients arrive in the ED from the community due to some medical condition. After treatment the patients are discharged back into the community, or they are admitted in the hospital for further care. During treatment the patient goes through several *process times* such as registration, triage and treatment and *wait-times* such as waiting for a bed, waiting to be seen by a doctor, waiting to be admitted (TBADM status) or waiting to be discharged (usually called as pending discharge (PD) status) etc. While process times are necessary for the treatment of the patient, wait-times are generated due to scarcity of resources such as beds, nurses and doctors etc. and unavailability of

the final destination. In other words process-times are the constants. Patients need resources to complete these process times and a destination to go to. Since resources are constrained and the destination is not always available it leads to inefficiencies like wait-times”.

Figure 4.5 shows the activity flow in the ED. The treatment process and output wait-times are shown as colored boxes to represent that the patient requires all three resources within these activities. The WTBS is broken into three parts waiting for bed (W_{BED}), waiting for nurse (W_{NURSE}) and waiting for doctor (W_{DOCTOR}).

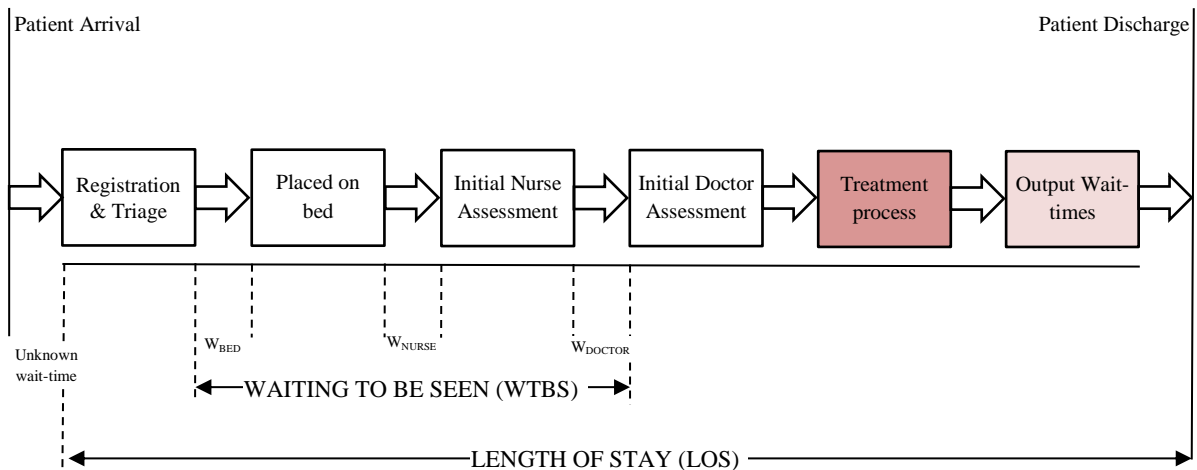


Figure 4-5 Activities and wait-times in the VGH-ED

The reason for defining the patient flow as an *Input-Throughput-Output model* can now be explained. The wait times in the ED are due to different reasons and these can also be associated with the phase they belong to. WTBS wait-time can be associated with the input phase. WWT can be attributed to the throughput phase. TBADM, PD and ERH are associated with the output phase.

4.3.1. Prima-facie solution

The wait-times belonging to different phases are co-related. To reduce WTBS, direct and indirect causes that effect WTBS should be understood.

The direct solution to reduce the W_{BED} , W_{NURSE} and W_{DOCTOR} times is to add more of these resources that cause this wait-time. Such a scenario, where resources are increased, falls under the category of variable change scenarios.

The indirect solution is to free up existing resources from the throughput and output phase so that they can be re-located to the input phase. This re-location can be done either by finding ways to reduce output wait-times; causes of which lie outside of the ED or by distributing resources more evenly between input and throughput phases. Either of these scenarios will fall under the category of process change scenarios.

As argued in Chapter 2 (Section 2.4), variable change scenarios tend to be of a permanent nature. Hence in this research, the aim will be to reduce WTBS, without increasing LOS and without adding more resources.

Using the flowcharts (4.1, 4.2 and 4.3) as a conceptual model, *simulation model logic* is developed in Chapter 6. However before the model is built data need to be collected and analyzed which is discussed in Chapter 5.

5.Data collection for VGH-EDsim model

This chapter focuses on data collection from ED and how the data can be transformed for using in the VGH-ED simulation model (VGH-EDsim model). This chapter has 2 sections dedicated to each of these aspects.

5.1. Data collection for VGH-EDsim model

The ED consists of several resources such as beds, nurses doctors etc. This data is collected directly from visiting the ED and is given in Table 5.1.

Table 5-1 ED resource data

Beds	
Monitor area	15 Monitored beds
Treatment area	4 Non-monitored beds
Minor treatment area	5 Non-monitored beds
Resuscitation area	2 Highly equipped monitored beds
Waiting areas	
Main waiting area	35 chairs (including 8 orange chairs for patients waiting for registration)
Minor treatment waiting area	15 chairs
Nurses	
Monitor area	4 nurses
Treatment area	1 nurse
Minor treatment area	1 nurse
Doctors	
VGH-ED	2 Doctors during day 1 at night

Two methods were used to collect patient data for the VGH-EDsim model; historical data collection and management estimates [9]. A large number of historical data were provided by the hospital authorities, which comes through the Emergency Department Information System (EDIS). Patient identity was deliberately left out to protect their privacy. Some data that were not provided were collected while shadowing staff in the ED and by using estimates by ED management.

Three months of historical data were provided through the Emergency Department Information System (EDIS system) for 7883 patients. The data were provided in the form of an excel sheet. These data include arrival time data, entry and exit time stamps from various locations, start and end times of different statuses, start and end times of various processes such as registration, triage, and basic patient information like age and CTAS score.

The amount of time that a nurse or a doctor spends with a patient in the treatment phase is not recorded in the EDIS data. Therefore the data have to be collected through managerial estimates.

Not all collected data were used to build the model. Instead they were broken down into two groups. The first group is called as *model-building data* and it comprises of the data from the first two months of the total EDIS data. These data are used to build the model. The second set is called as *model-validation data* (also mentioned as real ED data) for the model validation. This technique of breaking down the data sets into two parts is known as *historical data validation technique* [13]. More about validation is discussed in Chapter 6. The model- building data comprise of almost 5200 patient entries for generating credible probabilities and distributions.

5.2. Transforming VGH-ED data into model input data

The historical data available were in the form of absolute arrival times, time stamps and location stamps. However the simulation model requires data in a different format. A simulation model is built using constant values and values that vary over a range of a probability. The constant values are the deterministic data such as number of resources, capacity of waiting-rooms etc. as discussed in VGH-ED structure section (Section 4.1) [9]. The probabilistic data are the ones that vary with a probability range [9]. Arrival-times, process times, patient attributes such as age, CTAS score and treatment location are examples of probabilistic data.

Probabilistic data can be further broken down into two kinds; discrete and continuous data [9]. Examples of discrete data in the case of ED are age, CTAS score and treatment location. These variables can only take limited number of discrete and integral values. Such values are generated using a percentage table. Continuous data on the other hand are required for those variables that can take any positive value. Such data are fit onto distributions. Inter-arrival times and process-times in the ED are a prime example of continuous data.

Three sets of probabilistic data were needed for building the VGH-EDsim model: arrival data, patient attribute data and process-time data. While the first and third are forms of continuous data, patient attributes are discrete.

Before discussing the methodology to generate these data, a few basic things need to be stated. Distributions in this research were generated using a software called ExpertFit [51] which is available as a separate software and is also a part of the Flexsim software

package. The main advantage of ExpertFit is that it can automatically compare up to 40 distributions with a data set and give automated-fitting analysis to the user for the closest possible distribution function and its parameters. It also tells whether the fit of this distribution is good, moderate or bad based on several goodness-of-fit tests. A goodness-of-fit test compares a theoretical distribution with observed data and if the difference between the observed data and the corresponding theoretical distribution is small, then it may be stated with some level of certainty that the observed data could have come from a set of data with the same parameters as the theoretical distribution [9]. Only distributions with good or moderate fits were chosen for the VGH-EDsim model. Wherever the mean of the data is taken as a measure of central tendency, normality tests were conducted in a software from IBM called SPSS [52].

We can now look into the three sub-sections dedicated to different probabilistic data sets. Some managerial estimates regarding unknown process times were also collected. However since there is no methodology used to determine them, they will simply be stated while discussing the simulation model in Chapter 6.

5.2.1. Arrival data

Arrival distributions are one of the most significant data that are required to build a simulation model for an ED. Since the model-building data set is very large, it needs to be broken down into sub-sets since large data sets are usually combinations of different distributions [9]. Therefore the arrival distributions are generated separately for walk-in arrivals and ambulance arrivals. In this section generation of walk-in arrival distributions

has been discussed. The same methodology was used to generate arrival distributions for ambulance patients.

The historical EDIS data has absolute arrival times, whereas a distribution function can only fit onto inter-arrival times; i.e. time interval between the arrivals of two consecutive patients. There are two ways to convert the data into inter-arrival time distributions; direct and in-direct.

In the *direct method*, *inter-arrival times* were calculated for all patient entries in the model-building data set. This is done by subtracting the absolute arrival times of two consecutive patients. However the inter-arrival times generated were very random and no distribution with a good fit could be found.

To model this kind of erratic arrival behavior, an *indirect method* has been used. Rather than fitting the actual inter-arrival times onto distributions, the data is interpreted in terms of *patient arrival rate*.

To identify an arrival-rate, the walk-in data need to be further organized and condensed.

The model-building data set had a single column of absolute arrival time entries for about 3800 walk-in patients over 61 days. These data were broken down into an *hour of day by week day* table in 3 steps.

Table 5-2 Hour by Day table (number of patients in an hour of a day)

		61 Days (1st May-30th June)					
		Day 1	Day 2	Day 3	Day 61
Hours of Day from 1 to 24	Hour 1	3	2	5			2
	Hour 2	1	1	1			1
	Hour 3	0	0	1			2
	...						
	Hour 24	2	1	2			2

In step 1, the column data were transformed into a table with 24 rows and 61 columns. This table can be called as an *hour by day number* table, as each row represented the 24 hours in a day and each column represented one of the 61 days. A snapshot of this table is shown in Table 5.2. Each element of the table equals to the number of patients arriving in hour h (row) of day d (column). Thus more than 3800 (walk-in patients) entries were redistributed into 1464 (61×24) entries of patients arriving per hour.

Table 5-3 Hour by Weekday occurrence table (number of patients in an hour of a day)

Hours of Day from 1 to 24	Number of times a Sunday occurs					
	Day 1	Day 8	Day 15	...	Day 50	Day 57
Hour 1	3	3	2		3	2
Hour 2	1	2	0		3	2
Hour 3	0	2	1		1	1
...						
Hour 24	2	3	2		0	1

In step 2, the hour by day table was broken into 7 different tables based on 7 days of the week and can be called as *hour by weekday occurrence* tables. In the data sample each day of week occurs 9 times with the exception of Friday and Saturday which occurred 8 times. This step divides the total data (1464 entries) into seven smaller tables each having approximately 200 entries. A snapshot of such a table for Sunday is shown in Table 5.3.

Table 5-4 Hour by Weekday table (average number of patients in an hour of a weekday)

Hours of Day from 1 to 24	All days in the week						
	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Hour 1	1.69	2.08	1.31	1.92	1.23	1.15	1.62
Hour 2	1.62	1.23	1.15	1.08	1.15	1.23	1.54
Hour 24	2	2.77	2.46	2.08	2.54	1.85	1.92

In the 3rd step average number of patients coming in given hour for a given weekday is calculated. For example values in all rows of Table 5.3 were averaged and a single column table for Sunday was obtained. This was repeated for all 7 *hour by weekday occurrence* tables. The 7 column tables were then merged back into one table as shown in *hour by weekday* table (Table 5.4).

Each of the value in Table 5.4 represents average number of patients arriving in a given hour of the day. These values are used as denominators with numerators as 60 minutes. This gives us the average inter-arrival time in a given hour of a given weekday as shown in Table 5.5.

Table 5-5 Inter-arrival time table (in minutes)

Hours of Day from 1 to 24	All days in the week						
	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Hour 1	35.5	28.85	45.8	31.25	48.78	52.17	37.04
Hour 2	37.04	48.78	52.17	55.56	52.17	48.78	38.96
Hour 3	55.56	48.78	60	55.56	96.77	77.92	38.96
...							
Hour 24	30	21.66	24.39	28.85	23.62	32.43	31.25

This data can be used to identify patient arrival patterns. The values of Table 5.4 are averaged across columns and turned into a single row data. This row is used to make a line graph with error bars as shown in Figure 5.1. Evidently the error is very small and

hence it can be assumed that arrival rates are similar for all weekdays.

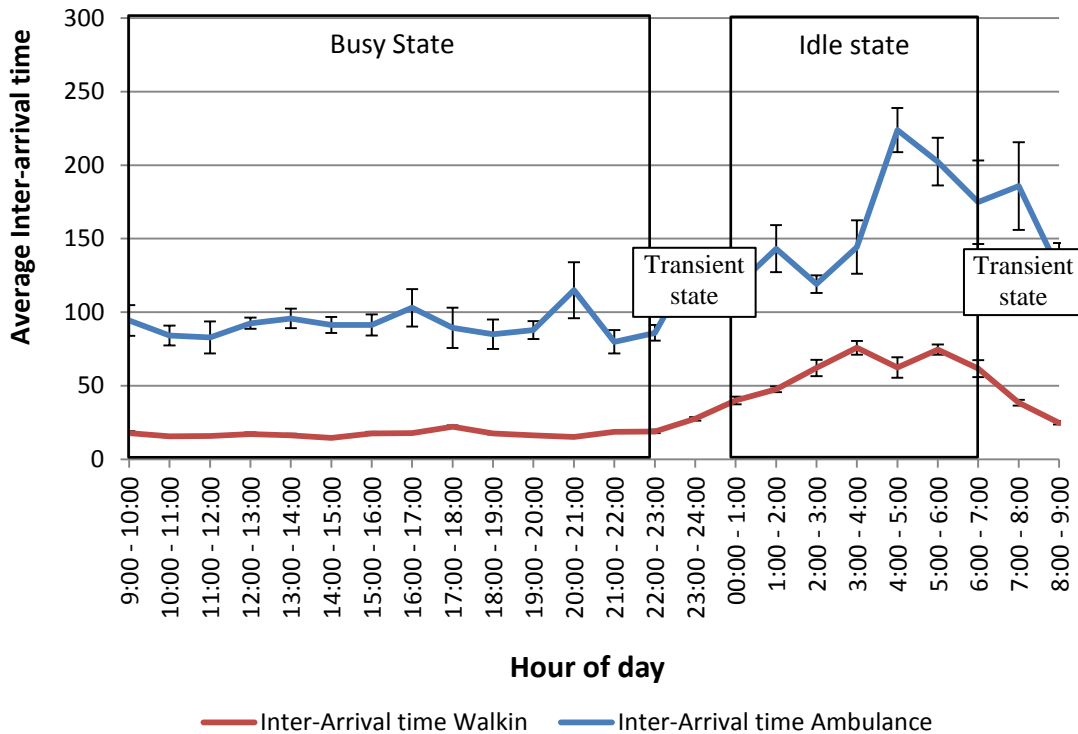


Figure 5-1 Arrival rate for walk-in and ambulance patients

Another pattern found from Figure 5.1 is that from 9am-11:00 pm the ED is in a *busy state* as the inter-arrival time is very small. From 1:00 am to 7:00 am the ED is least busy and this period can be identified as the *idle state* of the ED. Between the busy and idle states, there is another state which is neither busy nor idle. This is identified as the *transient state*. Thus three different distributions can be used for each arrival state of the ED. Values belonging to a particular state are used as input data for ExpertFit which gives the best possible distribution function that fits the particular data set. For example values from row 10-23 were used as input to generate the distribution function for walk-in patient arrival during the busy-state. Distribution functions are listed in **Error!**

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5.2.2. Patient attribute data

Patients journey, the path he/she takes inside the ED and the time the patient spends in the ED is dependent largely upon the patient's attributes such as his/her illness, criticality of illness, age and social background. These attributes need to be replicated in the simulation model in order to represent reality. The patient attributes that are replicated in the VGH-EDsim model are the patient's arrival mode, age, CTAS score, treatment location and patient's discharge disposition (admit or non-admit). Since all of these attributes can only take a few discrete integral (considering age as an integer) values, these data have been categorized as discrete probabilistic data.

5.2.2.1. Patient's arrival mode

This attribute is generated with the arrival of the patient in the model and is dependent upon the source which generates the patient. Patient's arrival mode forms the basis of all future probability generations.

5.2.2.2. Patient age data

The age of the patient is the first attribute that is generated using a probability table. In real world scenario the patient's age could be anywhere between 0-120 years (for all practical purposes). However to model an attribute with such large number of possible values is neither feasible nor required. It is not feasible because if we divide the data into 120 possible sub-groups the sample size in each group would become insufficient to generate an accurate probability. It is also not required because if future probabilities have to be based on age, they cannot be based on 120 different values and thus the values

of age will have to be combined in some groups. In this study the patient age data have been divided into three groups, young, adult and old. The patients with an age under 18 are classified as young patients, patients aged over 18 but less than 65 years of age are classified as adults and over 65 years old patients are classified as old. Therefore these data are called *age group data* rather than age data.

Table 5-6 Age group based on arrival mode

Age group	Arrival mode	
	Walk-in Patients	Ambulance patients
1	17.84	5.05
2	55.79	33.72
3	26.37	61.23

Age group probabilities differ on the basis of patient’s arrival mode. For example older patients tend to arrive via ambulance more often than via walk-in. Therefore the probability of being in age group 3 is higher for ambulance patients. The values for age group probability for both arrival modes are given in Table 5.6.

5.2.2.3. Patient’s CTAS score data

In the real world ED, the CTAS score is based on a patient’s medical condition and the severity of the condition. However all possible medical conditions with which patients present to the ED are near impossible to model. Therefore the CTAS score in the model is based on the age and arrival mode of the patient. The data have two sub-tables based on arrival mode and each sub-table is shown in Table 5.7.

Table 5-7 Percentages of CTAS based on arrival mode and age

Arrivals via Walk-ins				Arrivals via Ambulance			
	Age group 1	Age group 2	Age group 3		Age group 1	Age group 2	Age group 3
CTAS 1	0.61	0.92	2.19	CTAS 1	0	5.87	4.57
CTAS 2	5.41	10.67	11.1	CTAS 2	17.57	18.62	18.51
CTAS 3	21.31	29.54	36.98	CTAS 3	31.08	37.25	38.57
CTAS 4	55.63	44.85	38.28	CTAS 4	47.3	35.63	35.23
CTAS 5	17.03	14.02	11.46	CTAS 5	4.05	2.63	3.12

5.2.2.4. Patient's treatment location

Patient's treatment location is based on patient's medical condition and its severity (CTAS). To replicate this in the model, the treatment location is based on the CTAS score of the patient. For example a patient with a low CTAS score of 2 or 3 is more likely to need a monitor bed and patients with CTAS score 4 or 5 are more likely to require non-treatment beds in treatment or minor treatment area.

However generating treatment location data is not that simple. In practice, patients are often transferred from one bed to another during their treatment as per the need of the hour. This behavior is very difficult to model as there can be many possible reasons for bed transfers. Therefore the bed-transfers are ignored while building the simulation model.

The original data file had timestamps for different locations which helped generate the amount of time spent at a particular type of bed. The assumption made for this research is that if the patient spent time in more than one bed areas, the area where he/she spent the maximum time is chosen as the treatment location for model purposes. Based on this assumption 5 probability tables were generated for 5 CTAS scores each having 4 possible

treatment locations: Monitor, Resus, Treatment and Minor treatment area. These data are shown in Table 5.8.

Table 5-8 Treatment location percentages based on CTAS

	CTAS 1	CTAS 2	CTAS 3	CTAS 4	CTAS 5
Resuscitation	20.41	1.88	1.59	0.91	0.86
Monitor	63.27	70.54	48.18	24.87	9.63
Treatment	9.18	14.455	26.42	37.96	43.96
MTA	7.14	13.125	23.82	36.26	45.56

5.2.2.5. Patient’s discharge disposition data

Patient discharge disposition is a binary decision. A patient either gets admitted and if not then he/she is discharged back to the community. If a patient needs to be admitted, he/she will almost always go through the TBADM wait-time. But in the case of non-admits only some patients go through PD wait-time while others may go through an ERH wait-time. No patient goes through more than one wait-time.

Three probabilities are needed to represent this scenario. First probability can be defined as patient’s admission probability. If a patient turns out to be a non-admit then there is a second probability of whether the patient will go through PD wait-time. The third probability is whether the remaining of the non-admit patients that may go through an ERH process.

All of these probabilities were found to be dependent on age. Older patients have a higher chance of going through ERH and also have a higher admission rates than younger patients. Even in the case of non-admitted patients older patients go through PD wait-time more often than younger patients. The probability data are given in Table 5.9.

Table 5-9 Discharge disposition probability percentages based on Age

	TBADM		PD		ERH
Age group 1	0.66	Age group 1	19.52	Age group 1	1.07
Age group 2	3.8	Age group 2	25.82	Age group 2	6.04
Age group 3	17.45	Age group 3	29.85	Age group 3	23.44

5.2.3. Process time data

Process times can take any value and are not limited to a few discrete values. Therefore process time data fall under the category of continuous probabilistic data. The reason for discussing process time data after patient attribute data is because process times are based on patient attributes.

There are four major process time data that could be abstracted from the EDIS data.

These are *treatment in progress* times (TIP), *pending discharge* times (PD), *to be admitted* times (TBADM) and *Emergency room hold times* (ERH). In real ED the last three are wait-times but since the VGH-EDsim model has not been linked to the external world, the model cannot generate these wait-times. However to model their effect on the ED, these have been modeled as process-times.

The length of TIP status can be calculated directly from the model-building data as time stamps for beginning and end of TIP are given. However the whole data should not be fitted onto a single distribution as TIP process time depends largely on the patient condition. The distributions are given in **Error! Reference source not found.** The amount of time a nurse or a doctor is utilized by the patient is calculated by dividing TIP time by nurse factor and doctor factor, which is assumed to be 4 and 20, respectively.

Since a patient's medical condition cannot be modeled, the patient treatment location and arrival mode are chosen as the best possible estimates of a patient's health.

The length of the TBADM and PD time does not depend upon age as these wait-times are dependent on the blockage in the external system rather than condition of the patient.

ERH process times however were seen to be a function of age. It can be inferred that medical conditions of older patients are generally more complex and thus they have to be observed for a longer period of time. The output-phase process time distributions are given in **Error! Reference source not found.**

6. The Simulation model

This chapter is completely dedicated to the VGH-EDsim model. It is divided into three sections. In the first section, FlexSim, the software used to build the model, is briefly introduced. The second section explains the model building methodology. The third section details the different stages in which the VGH-EDsim model was built.

6.1. Introduction to Flexsim 3D simulation software

There are three types of objects in the FlexSim's object library, namely the flowitems, fixed resources and task-executers. Flowitems represent the entity that flows through the system. FlexSim allows the user to choose different kinds of items from an existing flowitem bin or to create a custom flow-item. Processors, multi-processors, queues, sources, sink and dispatchers all fall under the category of fixed resources, since the quantity is fixed in a simulation run. Task-executers represent human or robotic operators/transporters that can process an item at a processing station and/or move items from one fixed-resource to another. Fixed resources and task-executers are connected to each other through their *ports*. The ports are of three kinds; input ports, center ports and output ports. Fixed resources such as processors and queues receive items from input

ports and release them through output ports. Additional resources, such as task-executers required by processors and queues for various activities are connected via a center port. Every object in FlexSim library can have attributes which differentiates it from others of its kind. Fixed-resources have attributes such as process times and capacity. Flowitems have an additional attribute called *itemtype* which can take a positive integral value. The user can decide these attributes and their values and store them in *labels*. Labels can take either a string or number value depending upon the attribute the user wants to decide. Since FlexSim is a simulation software system, the state of the model changes at default events. In the software package these events are also called as *triggers*. The state of the system changes on these triggers.

Since fixed-resources are of many kinds, they can have different kinds of triggers. As a default for every fixed resource, there is an *on entry*, *on exit*, *on message* and an *on flow* trigger to represent Discrete-events. A modeller can write a program inside any of these triggers as per the simulation logic. The modeller can use attributes of flowitems and fixed resources stored in labels to build logic for individual code.

Apart from these, FlexSim also provides ways where objects of the system can communicate. Any object in FlexSim can send coded messages to other objects. Every message has 3 parameters which can take any value therefore there is an infinite number of differently coded messages that can be sent. FlexSim also lives up to its promise of flexibility as it also allows a user to create custom events. An object in FlexSim can also send a delayed message to another object. While the command itself runs inside a default event, it can create an event for future and the default event acts as a reference point.

Another way to create a custom event is to create a *user event*. The first user event time

and the subsequent intervals can be defined. The communication feature and the user event feature are essentially used for agent-based modeling and their usage will be discussed in Chapter 7.

6.2. Steps to build a DES model for VGH-ED

When sufficient knowledge about the patient flow has been achieved (validated conceptual-model), model input data can be abstracted from VGH-ED data. In this section, the steps required to transform this knowledge into a validated simulation model to conduct experimentation are discussed.

Even the simplest simulation model requires a considerable amount of programming, therefore one should avoid building the whole model without debugging [9]. It could be extremely difficult to make such a model error free. Therefore to build the VGH-EDsim model, a divide-and-conquer approach was used [9]. Under this approach the model is built in stages and in each stage a few details are added and the model is checked for errors. The actual stages of VGH-EDsim model building have been discussed in the last section of this chapter.

In every stage/iteration, 5 basic steps are followed. The process of model building ends when all details have been successfully modeled. The first step in this methodology is to decide the level of detail to be included in that iteration. The second step is to decide the simulation model logic to model the chosen level of detail and the third step is to code a simulation model that runs that logic. The model is verified and validated in steps 4 and 5. Verification is the process by which it is determined if the model works as intended

[9,13, 53]. Validation on the other hand is the process by which it is determined if the model represents reality [9,13,53]. In other words it can be said that model verification ensures that the model is built as per simulation model logic and model validation ensures that the simulation model logic represents reality as defined by conceptual-model and data collected from the ED. Figure 6.1 shows the flowchart for model building process. If verification fails one has to go back to step 3. If validation fails then steps 2, 3 and 4 have to be repeated. The following sections discuss these steps and the related concepts in detail.

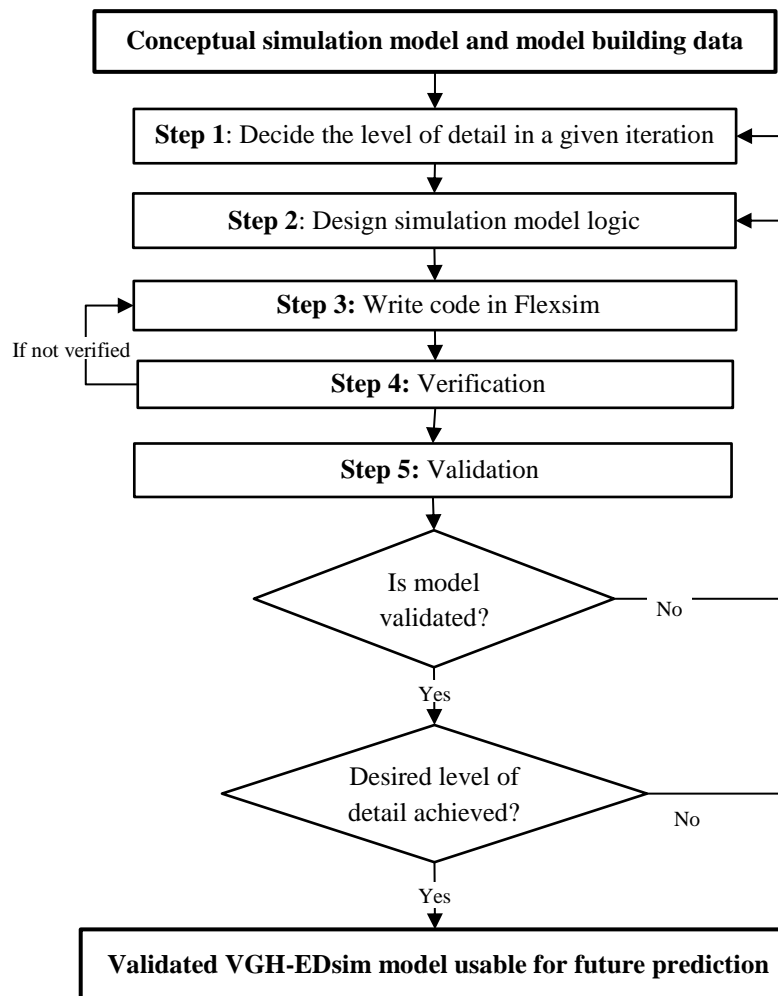


Figure 6-1 Model building process-flowchart

6.2.1. Step1: Deciding the scope of the model

As mentioned earlier, a divide and conquer approach is needed to build the VGH-EDsim model. Different aspects of the model are coded in different iterations. The details are discussed in Section 6.3.

The scope of the VGH-EDsim model includes:

- 1.) Output phase wait-times (ERH, TBADM and PD) built as individual process times.
- 2.) The treatment times captured from the data with smaller process times to capture the cyclic nature of the treatment process.
- 3.) The resources (bed, nurse and doctor), their behaviors and processes in the input phase modeled to generate input waiting-time (WTBS) and total LOS as close to reality as possible.

6.2.2. Step 2: Designing simulation model logic

To transform the conceptual-model and model input data into a simulation model, *simulation model logic* is required. The simulation model is nothing but simulation model logic running in a simulation software package. For ease of explanation the simulation model logic is also presented in an input-throughput-output phase. As FlexSim is primarily a manufacturing-software, the objects in the object library do not relate to patients and resources of the ED. Therefore in the VGH-EDsim model, the processors are used as registration and triage desks, multiprocessors as beds, sources are used to create patients, sink is used to discharge patients and queues represent waiting-rooms. Figure 6.2 show a snapshot of the simulation model. To represent the four bed areas, the VGH-

EDsim model has 4 bed clusters with the same names as the bed areas. Each cluster has a number of multiprocessors and a queue.

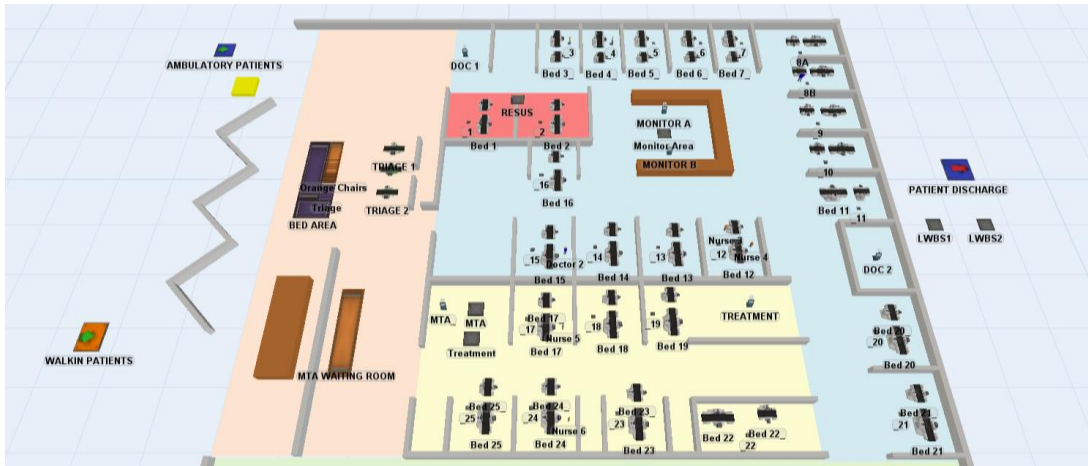


Figure 6-2 Snapshot of VGH-EDsim model

6.2.2.1. Input phase of simulation model logic

The simulation logic for the input phase is given in Figure 6.3. Two sources create patients using the arrival distributions. From there the patient goes to the first queue called *waiting for registration* where he/she waits for the *registration processor* to become available. The entry trigger of registration processor has code written on it to record patient's arrival time and decide patient's age. After registration the patient goes to *waiting for triage* queue where the patient waits for a *triage processor*. The patient's CTAS is decided on entry trigger of the triage processor based on the age and arrival mode. Patient's prospective *treatment location* is decided based on CTAS score of the patient. After triage the patient is sent to one of the 4 *waiting for bed* queues based on the treatment location. These queues distribute the patients amongst available beds in that bed area. This step is called the bed-allotment decision.

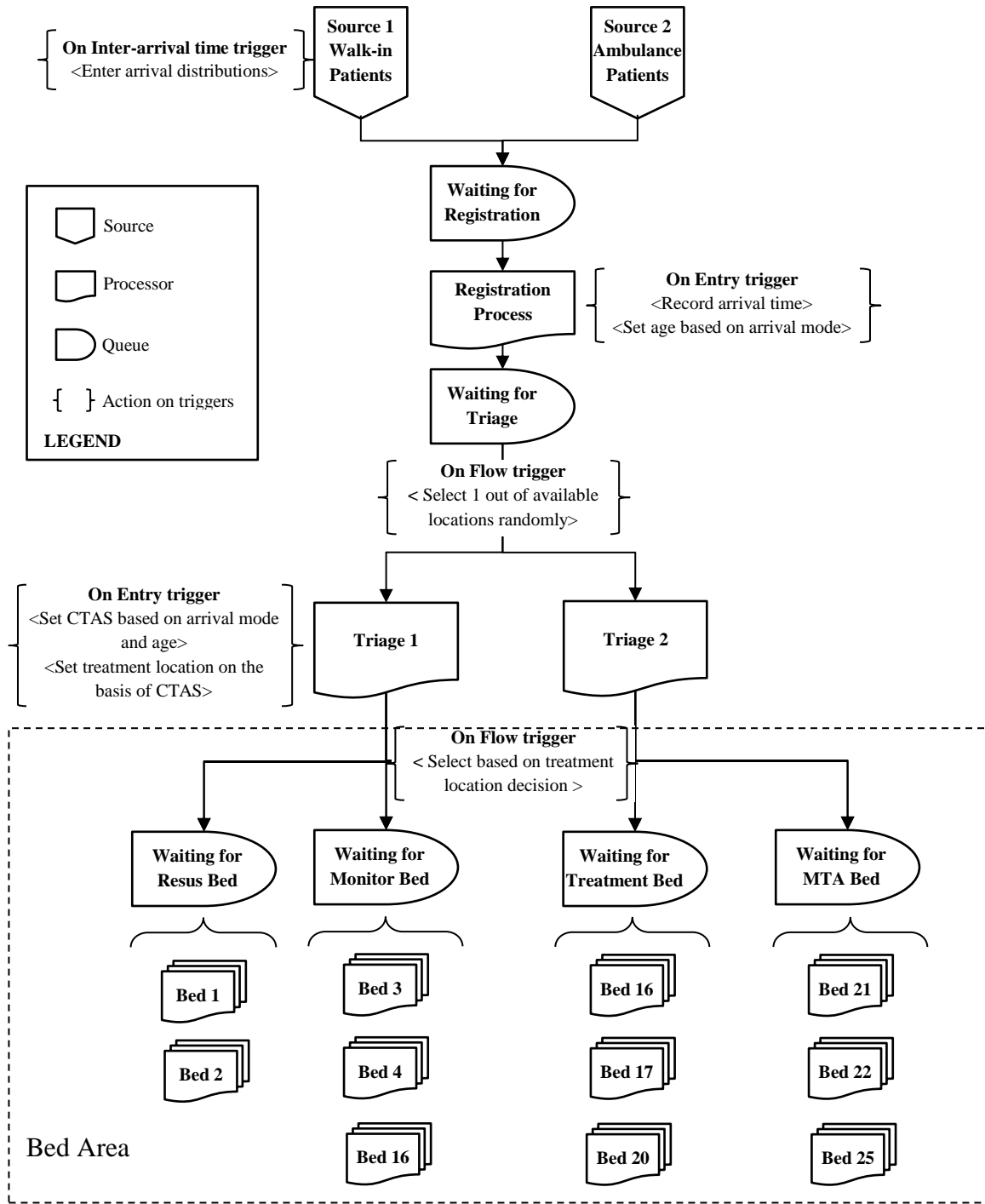


Figure 6-3 Input phase of simulation model logic

6.2.2.2. Throughput phase of simulation model logic

As soon as the patient is able to get a bed as his/her pre-decided treatment location, the throughput phase on patient's journey begins. The simulation logic for the throughput phase is shown in Figure 6.4. The multiprocessor that represents the bed performs many sub-processes. On the entry trigger of the multi-processor, the TIP time is generated and total nurse and total doctor times are decided by dividing the TIP by nurse and doctor factors. The logic is as follows:

Calculate TIP based on arrival mode, age and treatment location;

Total nurse time = TIP/Nurse factor;

Total doctor time = TIP/Doctor factor; // where nurse factor = 4, doctor factor = 20

The first sub- process is called *initial nurse assessment* in which the multi-processor calls the nurse resource followed by *initial doctor assessment* where the doctor resource is called by the multi-processor. Process times for these two processes are fixed and every patient goes through them only once. To represent the various processes such as lab-tests, specialist consults etc. a sub-process called *black-box process 1* is modeled, after the initial doctor assessment. A process can be modeled as a black-box if its actual working is unknown and only the input and output characteristics of the process are of concern [54]. The duration for this process is 20 minutes of TIP time whichever is less. The multiprocessor does not need to call any other resource during this process.

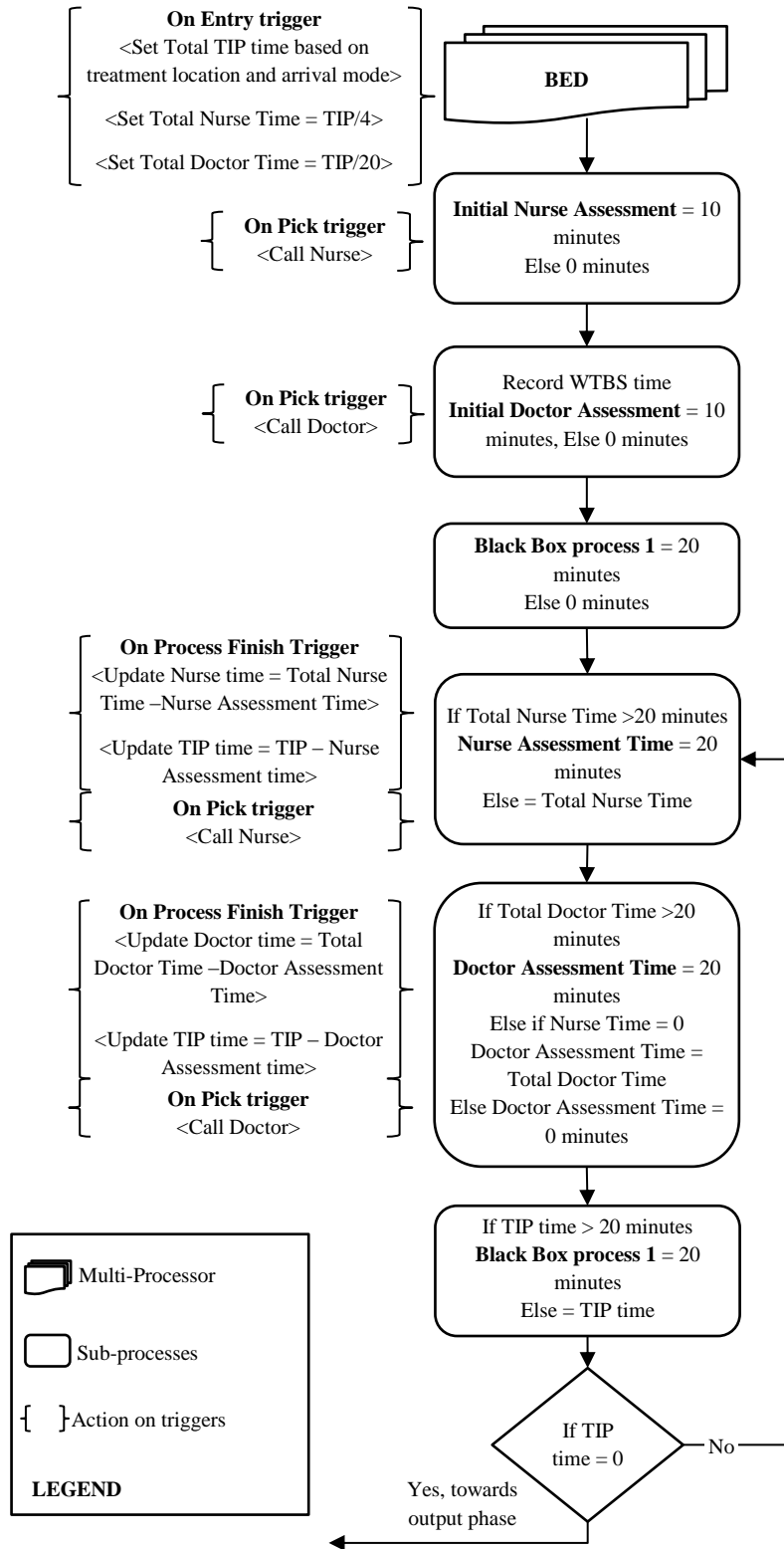


Figure 6-4 Throughput phase of simulation model logic

After this sub-process the cyclic nature of the treatment process begins. Followed by the black box process 1, is the *nurse procedure process*. This represents the process of the ED where the nurse processes doctor's orders and monitors the patient. The time of this monitoring is 10 minutes or total nurse time whichever is less. After this the nurse calls the doctor and the duration of the *doctor reassessment process* is given by the following logic:

If total doctor time > 10 minutes, duration = 10 minutes;
If total doctor time < 10 minutes, check if nurse time = 0;
If nurse time = 0, duration = doctor time, else duration = 0;

The reason behind this logic is that the final doctor process should only occur if all nurse time has been exhausted. In the ED the doctor takes the final decision and that is represented by this logic. Another process called *Black box 2* is followed by the doctor reassessment which is exactly the same as black box 1 process. If all the TIP is exhausted after this process the patient moves to output phase, else the patient goes back to the nurse procedure process.

6.2.2.3. Output Phase of simulation logic

The output phase happens on a separate multi-processor connected to the primary multiprocessor where treatment took place, however the main multi-processor does not accept new patients until the current patient has finished the output phase of his/her journey.

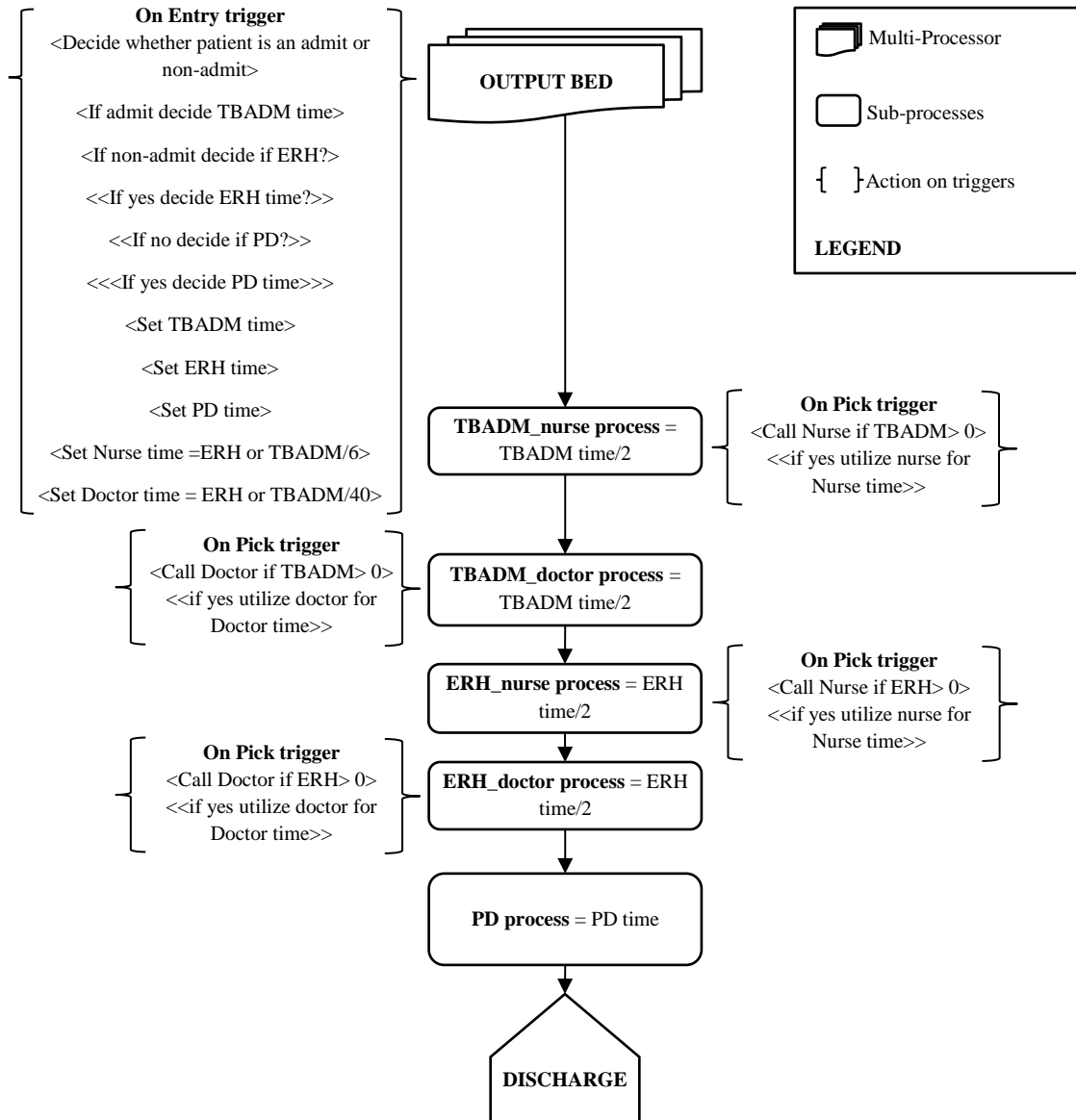


Figure 6-5 Output phase of simulation model logic

On the entry-trigger of the output multi-processor, the decision whether the patient goes through any one of the TBADM, ERH or PD processes is made and the process times are also determined. The order of sub-processes is shown in Figure 6.5. The TBADM and the ERH processes require nurse and doctor resources. The nurse and doctor times are decided as factors of these processes (See Table 5.9). The output phase is not modeled in

a cyclic order because the utilization of nurses and doctors is far less compared to the treatment process.

6.2.2.4. Reduction factor for TIP

A lot of sub-processes shown in Figures 6.4 and 6.5 require a nurse or a doctor resource. Since these resources are scarce there is a wait-time between these sub-processes. In Figure 5.6 the activity flow within the treatment process is given. The activities are shown in boxes and wait-times are represented by arrows. It clearly represents that the actual activity time is less than the total TIP-time. The total TIP can be broken into:

$$Total\ TIP = Actual\ activity\ time + wait_time$$

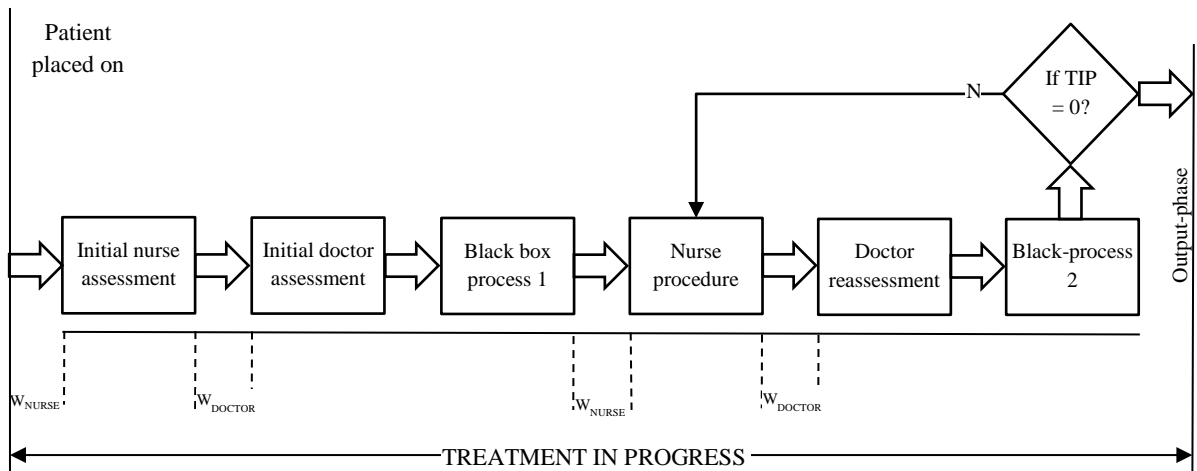


Figure 6-6 Activity flow within treatment phase

The data collected from the VGH-ED do not give details about the waiting time within the treatment phase. Moreover there is no credible way to determine the actual activity time and the wait-time. Therefore a method was needed to extract the actual TIP time from the total TIP time. It is therefore assumed that actual activity time is a fraction of the total TIP time, i.e. the total TIP can also be written as:

$$Total\ TIP = Total\ TIP * (reduction\ factor) + wait_time$$

Where the value of the reduction factor = .75 (found out using hit and trial method)

6.2.3. Step 3: Writing the simulation model logic in FlexSim

The model code is a set of several codes written on different triggers in the model. It is these set of codes that guide the flowitem through the model. To write a basic program in FlexSim one has to learn a few basic concepts of FlexSim.

The model built in FlexSim has a tree structure where every fixed-resource and task-executer exists represents a node. The items are also temporary nodes that flow between the fixed-resource nodes. Each node has certain attributes. For example all fixed resources can have labels on them which represent their attributes.

FlexSim uses its own coding language called Flexscript which consists of about 700 commands. A command can take 3 different types and combinations of inputs; node, number, and string. Depending upon the nature and purpose of the command it could return either a node, or a number or a string. An example of a command that takes node and string as input and gives a number as output is:

```
getlabelnum(current, "Bed type");
getlabelnum(item, "Patient number");
```

In this example the command *getlabelnum* is executed upon node *current* (fixed-resource) for fetching the value of the label named *Bed type* (attribute). The value of this label is the form of a number. It can be said that by default, the node named *current* is the fixed-resource where this code is being executed. In the second line the same command is

being executed upon node named *item* a term used for the flowitem currently at the fixed-resource called *current*.

Flexscript being similar to C++ has *if*, *else*, *for* and *while* commands, for a case where the code needs to be run based on some condition. For example

```
if( getlabelnum(item,"Patient number") == 4)
    {
        return 4;
    }
else return 0;
```

It is noticeable how a conditional logic can be developed. For creating the condition the operation “==” is used for comparing a number variable with a number constant. So *if* this comparison is true the *getlabel* command returns a number which is equal to 4 then the code inside the curled brackets is executed otherwise the code written after the *else* command is executed. The return command is used before declaring values for triggers that are supposed to generate values. For example an *on process time* trigger is supposed to generate a value for process time therefore a return command is used to do so.

The more complicated codes are usually tested on a dummy model before implementing them to the full model. Right after a code is written the next process is verification.

6.2.4. Step 4: Verification of the model

The verification is the process of verifying the code of the model. Every iteration of model building needs to be verified. Since the model in each iteration is built by many smaller codes, each of these codes can be built into a dummy model which can be verified separately. Verification is usually done to identify two types of errors in a code; syntax and logic.

Syntax can be a simple spelling mistake which the software captures very easily. FlexSim has the capability to detect certain errors and it reports them under *system console*. The most common of such errors is the one when the code is called upon/for something that does not exist. Any such behavior is termed as an *exception*. Whenever an exception occurs, FlexSim also gives the user some information about the exact time and source of error. Once the source and cause of error is identified and understood the code is fixed. Syntax errors are very easy to catch as the model automatically detects them.

Verification of syntax does not mean that the model logic is also verified. Sometimes a code is written in a way that it works for a range of values but fails beyond that range. Therefore a modeller needs to verify a code for a range of situations.

Model's logic verification can be tricky as wrong logics are not as easily detectable as wrong syntax is. To help the user, FlexSim has many inbuilt tools. FlexSim can generate an *event log* in which every event, its time and the objects participated in that event are listed. It is particularly helpful if the behavior of a particular fixed-resource such as a bed or queue needs to be verified.

Sometimes if a user is not fully confident of the code written, FlexSim has a tool called *step debugging*. The user can put a red dot on the left side of those lines of code where the user wants to stop and verify the behavior. Once the model is stopped the user can click on the *step into* button to stop the model at the next line of code. Thus instead of trying to identify sources of error or abnormal behavior in a running model the user can start and stop the model at chosen points. This feature has been particularly used to verify the VGH-EDsim model.

Another technique, commonly used to verify a simulation model, is by generating a variable/attribute output file in which data (wait-times, process times attributes etc.) for each patient is recorded [9]. The modeller can then scan the output file for any anomalies.

6.2.5. Step 5: Validation of the model

While verification means to ‘build the model correctly’, validation means to ‘build the correct model’ [9]. There are many possible ways to compare the simulation model with the real system and the validation process is often based on the purpose of the model and research goals [53]. For example if the need of the research is to build a more predictive model, the technique used to validate it must also be foolproof.

Even in a given model certain parts of it are built in more detail than others (section 5.3.2) and the model validated for a particular purpose may not be validated for another as there is no such thing as general validity [53]. For example in the VGH-EDsim model the input and throughput phases of the model are built in more detail so they need to be robustly validated but in other parts such as inter-arrival time and output phase wait-times a lot of assumptions are made and thus these aspects should not be tested with the strictest validation techniques.

As the goal of the research aims to predict improvements in WTBS and LOS, these two are chosen as the main parameters for model validation and will be subjected to more robust tests. Individual process times are used as secondary parameters for generating more confidence for example TIP process time. Activities such as ERH, TBADM and PD were added and a comparison was made between total output-phase wait-times from the data and total output-phase process times from the model. As mentioned in Section 5.1,

the third month's data called the *model validation data* are used as a basis to validate the VGH-EDsim model

6.2.5.1. Model validation techniques: Subjective and Objective

There are two techniques used for model validation; subjective and objective. The subjective techniques are used to ensure that the model, at least on the surface, represents reality [9]. One such technique is *face validity* where it is determined that the model's patient flow is in-line with the patient flow of the conceptual-model [9, 13]. Subjective validation is often confused with model verification. However one should remember that in verification the behavior of the code is tested and in validation the sequence of events is tested against that of conceptual simulation model. The same tools used for verifying the logic of the code such as event log and step debugger, can also be used to validate the sequence of events of the model. This validation technique is also called as *tracing* where behaviors of specific types of entities is analyzed [13]. If the sequence of events is found to be incorrect the modeller may need to repeat the verification process or in some cases may need to revisit the simulation model logic. Apart from sequence of processes the modeller can also test special circumstances and check if the model is in line with the conceptual-model.

Subjective assessments are necessary but are insufficient to validate a model on their own [9]. To validate the model with greater precision an objective assessment, which is based on some type of mathematical procedure, is required [13].

Objective techniques are used to compare data output from the model with collected data. There are two types of objective techniques; qualitative and quantitative. Qualitative

analysis is a combination of subjective and objective assessments and is done to examine if the magnitudes of the output behavior of the model are ‘reasonable’ [13]. For example comparing average values for model and data is a qualitative analysis. Similarly *graphical analysis* is another qualitative technique, as it is a combination of objective and subjective analysis (visual inspection is always subjective). Quantitative analysis, on the other hand, is completely objective and involves some kind of statistical test. The choice of the statistical test is based on whether the data sets are normal or not.

In order to predict accurate WTBS and LOS, the most objective validation technique should be followed, whereas for the remaining aspects of the model the validation technique can be partially objective.

6.2.5.2. Collecting data from the model for validation

In all stages and iterations of model building, validation is done objectively which requires that *model output data set* is compared with the *model validation data set* (data from the third month of EDIS data, 2701 patients). The procedure of collecting model output data depends upon the system that is being modeled.

Simulation models can be of two types; terminating and non-terminating. Terminating systems are the ones that run for a fixed period of time, such that the previous period has no effect on the starting conditions of the next period. In contrast non-terminating systems are those which run for a period of time but at the starting of a new period, entities from the previous period may exist [9].

The VGH-ED is a 24 hours and 7 days facility. The ED virtually never stops and even if it is studied for a particular period, the ED will have patients at the beginning of that

period. In non-terminating systems such as ED, initially the model is empty and therefore the first few patients have very less wait-times and length of stay as all resources are readily available. However after a while as the arrival rate remains faster than patient discharge rates the model fills up. This filling up period is known as *warm-up time* and is also known as *transient state* of the model. After the transient state is over and the model is filled up, it is said to be in *steady state*.

The point where the transient state ends and steady state begins is usually different in every model replication even if all other parameters are same. This point can be calculated using a graph where time is plotted on x-axis and running average of WTBS is plotted on y-axis. Running average of WTBS means the average value of all WTBS values up to that point. For example for patient ‘Pⁿ’ with WTBS as ‘Wⁿ’ running average of WTBS is given by:

$$\text{Running WTBS after nth patient} = \frac{W^1 + W^2 + \dots + W^n}{n}$$

In this plot the user visually determines a steady state line, beyond which the slope of the graph approaches to 0. The data on the right side of the chosen point can be used as a pool to pick model output data. The same line can be chosen for all the other process times. An example of a steady state analysis graph is shown in Figure 6.7.

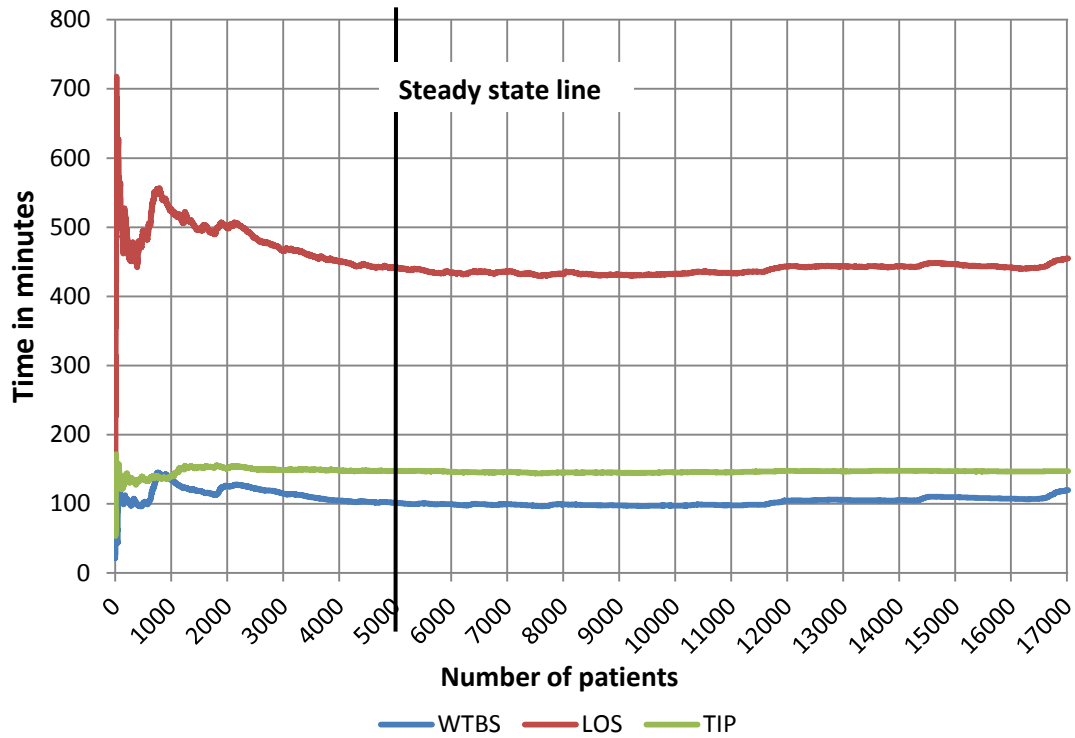


Figure 6-7 Steady state analysis for a typical VGH-EDsim model run

As in most of the iterations (out of 10), after around 5000 patients the slope of the graph stabilizes to approach zero, it is roughly chosen as a steady state line. To be on a safer side, 2701 patient entries starting at patient number 5000 can be picked for the model output data as shown in Figure 6-7.

In all stages of modeling where objective validation is made, the above mentioned procedure has been followed to collect model output data.

6.3. Stages of building VGH-EDsim model

In this section, the actual stages of building of the VGH-EDsim model are discussed. The simulation model has 3 main resources; beds, nurses and doctors. As mentioned before, a

divide and conquer approach was followed to build the simulation model. The model was built in 3 stages and starting with the bed resource, one resource was added in each stage. In each stage two separate identical models were developed, called as *VGH-ED data model* (or the data model) and *VGH-ED distribution model* (or the distribution model). In Chapter 5, it was mentioned how data collected from the EDIS was first converted into absolute arrival times and process times for individual patients. While this data were converted into distributions to build the final model, it was also used to build the data model. The data model was built using absolute arrival times, exact process times, and treatment locations, which helped in validating the intermediate stages where no real world data are available to validate the model. Its use is discussed while talking about the various stages of model building in the following sub-sections. Average of WTBS values generated from data and distribution model is used as a validation parameter. The average WTBS of patients in the real VGH-ED is about 134 minutes.

6.3.1. Stage 1: Building model with bed resource only

In stage 1, both of the data and distribution models are built with beds only and neither nurses nor doctors are modeled. It can be said that the model in this stage has an unconstrained number of nurses and doctors.

The VGH-ED data model uses input data from 7883 patients with absolute arrival time, process times and treatment location tied to the patient number. Since the model has unconstrained number of resources no wait-times are generated and the model output for each patient matches model input. This is the validation criteria for the VGH-ED data model.

Similarly the VGH-ED distribution model is built without nurses and doctors. Instead of absolute values for arrival time, process times and treatment location, distributions and probability functions are used to generate these values. The model is run to generate and discharge all 7883 patients (~6400 arrivals for walk-ins and ~1500 arrivals for ambulance patients), which takes about 134000 minutes (~3 months) in the real ED.

The process time distributions are added one by one so as to validate the performance of each of them. Arrival distributions are validated by running the model for 134000 minutes and checking for the number of arrivals from each source to be nearly equal to real data. This type of validation is also known as *event validity* where the number of occurrences of a particular event is compared [13]. Average of values generated from process time distributions is compared against data average. Overall to validate the first distribution model, a qualitative validation approach is followed.

When all the distributions are included in the model, the average WTBS for 10 runs for each of the data and distribution models is compared. This average is about 20 mins for both models, which is understandable as the model has only one constrained resource.

6.3.2. Stage 2: Building model with bed and nurse resource

In this stage the nurse resource was added to each of the data and distribution models developed in stage 1 respectively. Every process as per simulation model logic that required a nurse resource is modeled accordingly. The behavior of task-executers can be particularly hard to model and this stage needed a lot of verification. Since all the distributions had been verified there was no need for their validation in this stage and similar to stage 1, average value of WTBS was calculated for both models and was found

to be near 54 minutes in both of them. This slight increase in average WTBS is also as expected, as the nurse resource is in abundance with 1 nurse for 4 patients in comparison to 2 doctors for 26 beds. Moreover since the behavior of both distribution and data model is similar it could be assumed that the model is moving towards the right direction.

6.3.3. Stage 3: Building the model with all three resources.

In the third and final stage, doctors are included in distribution models. The reason is that this is the final step of model building. The model is run 3 times of the original length (400000 minutes) so that the steady state of the model can be collected and the model output data may be collected from a pool of stable WTBS values. This stability comes when the model has warmed up and is now behaving like a real ED.

The average values of WTBS, LOS, TIP and Output phase processes (TBADM, ERH, PD combined) collected from the steady state of the model are shown in Table 6.1.

Table 6-1 Comparison of average wait-times and length of stay (time in minutes)

	WTBS	LOS	TIP	Output status
Model output data	116.77	408.95	161.77	126.71
Model validation data/Real data	129.06	395.85	146.90	119.88
% difference	9.53	-3.31	-10.12	-5.70

From Table 6.1 it can be said that the model is reasonably close to real ED, i.e. the model is qualitatively validated. This however is not a sure enough way to say that the model is validated. To ensure that the model is validated, a robust quantitative analysis is required.

To determine the statistical test to be used for validation, the data sets need to be analyzed for normality as there are different tests for analyzing normal and non-normal data. For this, the SPSS software from IBM was used to analyze data and conduct normality tests [55]. SPSS can conduct two kinds of normality tests: Kolmogorov-Smirnov and Shapiro-Wilk. The Shapiro-Wilk test is considered to be better for a sample size of around 2000, moreover research recommends against using Kolmogorov-Smirnov test [56].

The significance value of the Shapiro-Wilk test tells us about the nature of the data. If it is less than .05 the data are considered as not-normal [57]. The results of the Shapiro-Wilk test are shown in Table 6.2.

Table 6-2 Normality test results for all data samples

	Tests of Normality		
		Shapiro-Wilk	
		Sample size	Significance
Model validation data	WTBS	2701	.000
	TIP	2701	.000
	Output status	2701	.000
	LOS	2701	.000
Model output data	WTBS	2701	.000
	TIP	2701	.000
	Output status	2701	.000
	LOS	2701	.000

Since the significance value is 0 for all data sets it can be easily said that none of the data sets are normal. As the data are not normal, the data sets can be compared using a non-parametric test and the Mann-Whitney U test is one such test. To conduct the test in a simple worksheet like Microsoft Excel, the model output data and model validation data

are listed in column 1. In front of each of the value in column1, in column 2 the group name is written. The user can then use the sort command in Excel, to organize the data and the corresponding group number in an increasing/decreasing order. The user can then look at the mean ranks and sum of ranks of the two groups and these values can be used in a hypothesis test. A significance value (Z-value/critical value) can also be calculated as a function of means of both data sets and variance. The Mann-Whitney U test was conducted in SPSS and results are given in Table 6.3.

Table 6-3 Mann-Whitney U test results for VGH-EDsim model built using DES only

	Group	Sample size	Mean Rank	$\frac{\text{Mean rank model}}{\text{Mean rank data}} * 100\%$	Z values
WTBS	Data	2701	3078.44	75.51%	-17.76
	Model	2701	2324.56		
TIP	Data	2701	2795.01	93.31%	-4.42
	Model	2701	2607.99		
OUTPUT	Data	2701	2774.00	94.77%	-4.07
	Model	2701	2629.00		
LOS	Data	2701	2721.30	98.54%	-0.93
	Model	2701	2681.70		

Although only one test of validation has been conducted, the hypothesis test has been broken into two parts depending upon the measure chosen. In the first part of hypothesis part, the mean rank is used as a measure to compare model output and model validation data sets. The Z value is chosen as a measure of validation in the second part of the hypothesis test. In the event of successful validation the model in the second hypothesis, it is assumed that the model is at least mediator in nature if nor predictive. The reason for more weightage being given to the second hypothesis is because the Z value is a more

objective measure. The value of Z needs to be in an allowable range of -1.96 to 1.96 unlike mean rank, its range can be set by the user. The tests conducted are as follows:

Part 1: Hypothesis test using mean rank as measure

Null hypothesis (H_0): The mean of the model validation data is equal to the mean of the model output data; i.e., the model is valid.

Alternate hypothesis (H_a): The mean of the model validation data is not equal to the mean of the model output data; i.e., the model is not valid.

Part 2: Hypothesis test using significance value (Z) as measure

Null hypothesis (H_0): The Z value falls within -1.96 to 1.96.

Alternate hypothesis (H_a): The Z value does not fall within -1.96 to 1.96.

6.3.4. Analysis of results

The results in **Error! Reference source not found.** show that the mean rank for LOS data sets is very close, however it is not so for WTBS. The first hypothesis test is subjective in nature due to the fact that the modeller can define the allowable range of mean rank.

Even so the model output of WTBS being only 75% of the validation data shows that the null hypothesis in part 1 cannot be accepted convincingly. The second hypothesis however clarifies the picture completely as none of the Z values (except for LOS) in Table 6.3 are even near the permissible values (-1.96 to + 1.96). Therefore the model developed at this stage failed the quantitative validation.

Since the model is validated qualitatively (see Table 6.1) and the first hypothesis is partially correct, it can be said that a reasonably good model has been built, however

predictions based on this model may not be accurate. To be able to make accurate predictions, the model needs to be statistically validated for which the modeling strategy needs to be revisited.

The reason for the behavior of model output WTBS data set can be understood using the concept of *outliers*. This can be understood from Figure 6.8.

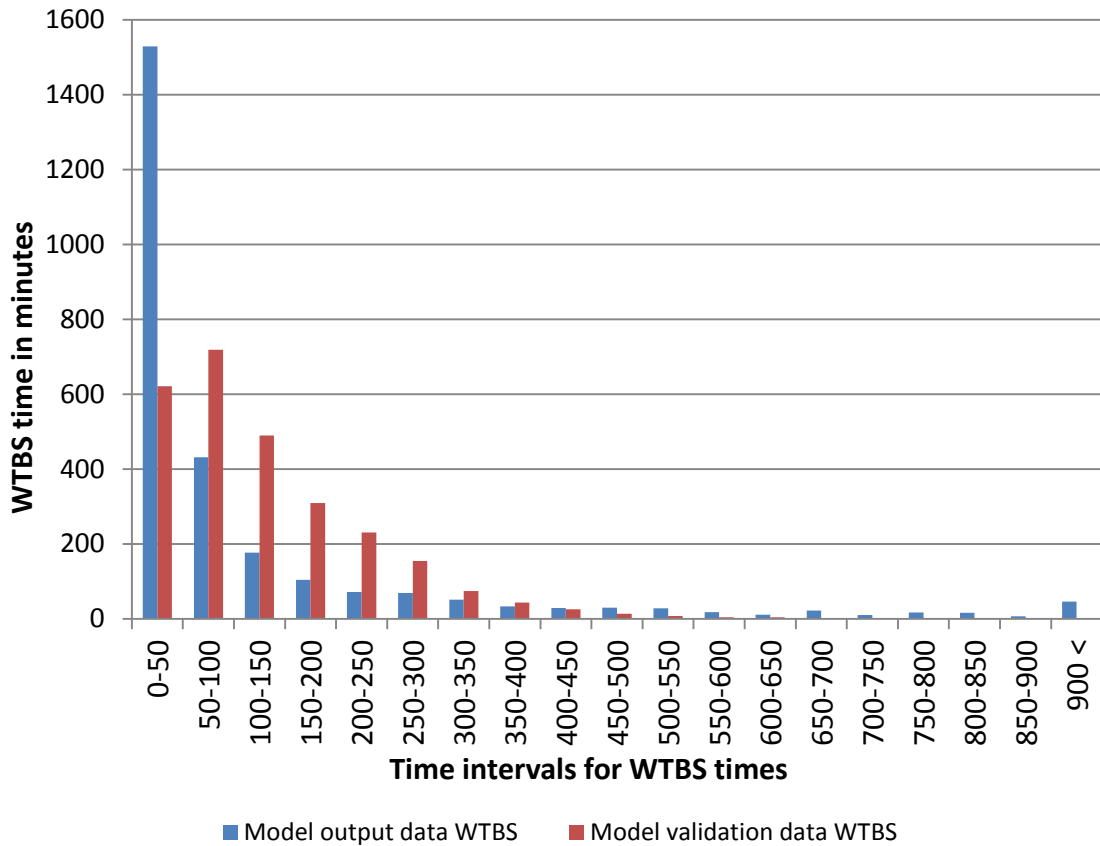


Figure 6-8 Frequency distribution histogram to compare model output data with model validation data (DES model)

It is clear from Figure 6.8 that most of the values in model output of WTBS data set are either too small or too big in contrast with model validation WTBS data set, in which values are distributed more evenly. The extremely small and large values can be called as *outliers*. In statistics outliers are observations that lie outside the normal pattern of

observations. The number of outliers is much more in the model output of WTBS data set compared to the real WTBS data set.

The reason behind the presence of outliers will be discussed in Chapter 7 which introduces the concept of agent- based simulation. The model up to this point is named as VGH-EDsim-DES model.

7. Agent-based simulation

The concept of agent-based modeling was introduced briefly in Chapter 2. This chapter focusses on the concept of ABS and the use of ABS to validate the VGH-EDsim model. The first half of this chapter discusses the literature related to use of ABS modeling technique in the ED. In the second half its use in validating the VGH-EDsim model is discussed.

7.1. Need for Agent-based simulation

7.1.1. Shortcomings of DES

Before investigating the causes of failure of validation, specifically for the VGH-EDsim model, it is important to revisit the basic concepts used to build the simulation model. According to Escudero and Pidd in predicting performance of manufacturing systems, errors usually happen because of inadequate representation of human behavior [12]. In case of ED the results of these errors become even more profound since human-decision making is a big factor in a service-based system like ED. On the contrary, in the VGH-EDsim-DES model, human decision-making factor has not been considered.

ED is a very dynamic environment and is full of human interactions. The outcome of these interactions is based on human behavior. The entities of a real ED, such as patients, nurses, doctors etc., are humans with thinking and reasoning abilities. On the other hand entities in a DES model are simple, reactive and limited in decision making capabilities [11]. As a result DES dehumanizes the entities of the ED [58]. Moreover human capabilities such as multi-tasking need to be captured to build a more validated simulation model as argued by Gunal and Pidd [59]. Dubeil and Tsimhoni stated that to build models which involve a lot of human movement, DES is an insufficient tool since in a DES model the possible path of the entity has to be pre-determined [60]. In order to model the human discretion factor in a simulation model, agent-based simulation is the most suitable methodology [11,12,58,60].

7.1.2. Agent and agent-based simulation

According to Chan et al., an ABS model is essentially for a DES model, but with entities that are pro-active, autonomous and intelligent [11]. These entities are known as *agents* in an ABS model. In general terms, an agent is the decision-making component of a system [11, 12]. The agent can make decisions based on a set of rules. Escudero and Pidd define master rules and maker rules [12]. The master rules represent agent's own behavior, whereas maker rules modify the master rules based on agent's interactions with other agents of the system. In an ABS model, the model behavior is produced by the outcome of these interactions [12, 24]. In contrast, in a DES model, the model behavior is controlled by some kind of central mechanism [11]. In simple words, in DES the focus is to directly replicate system behavior and the entities simply react as per the logic written

by the modeller, whereas in ABS, the modeller captures the behavior of all decision-making components (agents) of the system and expects them to interact and replicate system behavior. For example in the VGH-EDsim DES model, patient attributes are generated based on the arrival mode and treatment location, time is generated based on patient attributes. ED conditions or behaviors of different entities have no bearing on these decisions. In a purely ABS model for VGH-ED, these decisions would be generated by the behavior of agent-based entities.

ABS has been used previously to model the ED. Wang developed an ABM model to understand the ED performance under 2 different settings [61]. The model was coded in way that it was equipped to handle certain situations automatically. In the first setting called *Triage adjustment*, an extra triage nurse was called if the number of patients in the waiting room exceeded 10 patients and is sent back once the number of patients in the queue has been reduced to less than 2. In the second setting the lab-testing times were reduced by about 10-15%. The study concluded that throughput could be reduced by about 26% under the triage adjustment and reduction in 10% lab-testing-times improved ED efficiency.

Cabrera et al used different optimization techniques along with agent-based simulation for an optimal ED staff configuration [24]. To optimize the number for each of the ED staff such as nurses, doctors, health-care aids etc., a multi-objective problem was formulated. An ABS model was used to represent the ED and optimization techniques to find the optimal number of each of the resources.

Rahmat et al presented a very good example of ABS used to model scenarios which involve considerable human decision-making [62]. The authors tested a strategy called

re-triage, in which patients waited for a considerable amount of time in the waiting room are re-triaged, if their condition has deteriorated significantly, the triage score is upgraded and these patients are put in priority sequence. This research uses ABS to model patients with dynamic attributes (such as rate of deteriorating clinical condition) and to model the behavior of triage nurses, who determine whether at any given time the condition of the patient is sufficient for an up-gradation in triage score. Results show that the re-triage strategy can improve average waiting-time of the ED.

7.1.3. Modeling of an Agent

Most agent-based modeling literature advocates using a Moore machine to represent an agent [24, 63]. A Moore machine is state machine, which means that it can exist in many states and each state is defined by a set of state variables. The change in these variables (and therefore the state) is invoked by an input. The output depends on both original state variables and input. The output state is a function of the input and the original state. This transition from input to output can also be probabilistic; the combination of a particular input and state can lead to many possible outcomes based on random probabilities. The concept is illustrated in Figure 7.1. States such as S , S_1 , S_2 and S_3 are defined by state variables.

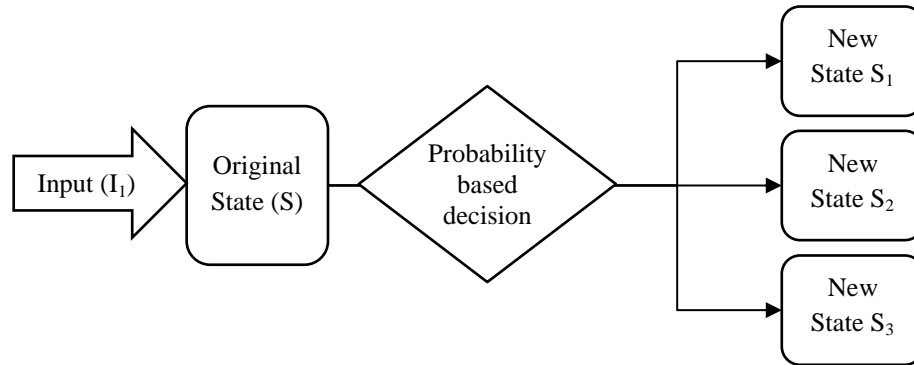


Figure 7-1 Example of a Moore machine [63]

7.1.4. Need for integration of DES and ABS

There are some major hurdles in applying a purely agent-based approach to model the ED. One of them is that human behavior is hard to capture and requires considerable shadowing of the ED staff. Such data collection can be a tough and time-consuming process. Other hurdles, such as lack of a common methodology used to implement ABS and lack of a common pictorial representation, are also mentioned in literature [12].

Dubeil and Tsimhoni argued that DES and ABS can be integrated to achieve benefits of both worlds [60]. According to their argument, an ABS model has 3 components: agents, environment, and rules. DES can provide a good environment or a framework for agents and rules to work. Especially in absence of detailed data about human factors, parts of the model can be built with DES and parts where human decision-making is the most crucial ABS can be used to enhance the model.

Therefore in this research, an attempt has been made to integrate DES and ABS. The next section will discuss reasons for failure of validation followed by using ABS to validate the model.

7.2. Model validation using Agent-based modeling

7.2.1. Understanding the cause of outliers

Resuming the discussion of outliers in the VGH-EDsim DES model from Chapter 6, it is found that the waiting times generated by the model are either too small or too big (Figure 6.8).

Referring back to Section 6.2.2.1, the bed allotment step is based solely on the CTAS score of the patient. In the VGH-EDsim DES model, the patient is sent to the respective *waiting for bed area* queues irrespective of the fact whether beds are available in that bed area. Patients thus are pushed to these queues and if no beds are available in the respective queues, the patients stay there until a bed becomes available. At no point can the patient be treated in a bed area other than the one decided based on CTAS score. However in the real ED, the bed allotment step is not entirely dependent upon patient's CTAS and the availability of beds also plays a major role. According to a managerial estimate (Table 7.1), not all patients who end up being treated on monitor beds actually need that bed. It can be said that for such patients their *actual treatment location* is different than their *desired treatment location*.

Table 7-1 Actual and desired treatment location percentages

	Monitor	Resus	Treatment	MTA
Actual treatment location in VGH-ED	45.64%	1.99%	27.12%	25.24%
Desired treatment location estimated by ED managers	26.26%	2.14%	39.43%	32.18%

It is clear from Table 7.1 that while 39% patients desire a treatment bed, only 27% of them end up getting one. Similarly while only 26% patients desire a monitor bed, 45% patients end up being treated on monitor beds.

ED managers reveal that triage and charge nurses often decide to move lower acuity patients to higher acuity beds, if the lower acuity bed area is full and sufficient beds are available in the higher acuity area. This explains the fact that a lot of patients desiring treatment beds end up being seen in monitor beds.

However this decision is discretionary based on the judgment of the charge and triage nurses. Some health care personal argue that moving a low acuity patient to a higher acuity bed, treating him/her quickly and thus having less patients in the waiting room, is ideal for the patient flow. But others argue that this is detrimental to patient safety.

Especially in cases where monitor beds are occupied by low-acuity patients, new emergencies have to wait longer. Thus it can be said that nurses are always in a dilemma of whether to move lower acuity patients to higher acuity beds.

It is apparent that bed allotment decision is largely based on human factors and thus need to be accounted for, for the model to work. Thus a part of the VGH-EDsim-DES model is modified and coded using an ABS strategy. The bed-allotment strategy discussed in section 6.2.2.1 is now replaced by a new strategy called *Dynamic bed-allotment strategy*.

7.2.2. Dynamic bed-allotment strategy

The dynamic bed-allotment strategy (DBA strategy) aims to replicate the complex bed-allotment decision-making process of the ED. It is an enhancement to the existing bed allotment strategy and is based on ABS modeling approach. This strategy has 3 main

parts; the agents, the communication model /simulation logic of these agents, and the validation of the model with this strategy. The following sections are dedicated to each of these parts.

7.2.2.1. Agents

As discussed in Section 7.2.1, in the real ED the outcome of the bed allotment decision is dependent upon the patient's medical condition, bed availability and discretion of the charge nurse. To include these factors in the VGH-EDsim model, the entities involved in the bed allotment decision are modeled as agents based on the concept of Moore-state machine discussed in section 7.1.3. These agents are patient agent, bed agent and charge nurse agent. To keep the track of all available beds a database agent is also created. This agent has been created for modeling purposes only and does not have a physical representation.

The agents can be classified as cognitive and in-cognitive agents. For example patient agent and the bed agent are considered as in-cognitive agents as they do not take decisions themselves but influence the decision of charge nurse agent which is the cognitive agent. The in-cognitive agents influence the behaviour of the cognitive agent by the virtue of their state which is defined by state variables. Following is the description of these agents:

1. Patient Agent

State Variables: The patient agent represents a patient as a state machine with two state variables. First variable is called *desired port* and it stores the value of the desired treatment location. Second is called and *actual port* which stores the value of the actual

treatment location. Both these variables can take 4 integral values each representing one bed area, i.e. resus (1), monitor (2), treatment (3) and MTA(4) beds.

Possible states: There are two possible states of this agent, $P_{original}$ and P_{new} . When both the state variables are equal i.e. the actual treatment location equals the desired treatment location, the patient agent is in state $P_{original}$. If the value of Actual_port is different from Desired_Port, the patient agent is state P_{new} .

2. Bed Agent

State Variables and possible States: The bed agent represents the different beds with only one state variable called *availability*, which takes binary values 0 and 1 where 0 means unavailable and 1 means available. Thus it can have two possible states.

3. Database Agent

State Variables: The database agent represents the information on the basis of which the nurses in real life decide the treatment locations. It has 4 state variables representing the four bed areas. The purpose of database agent is to collect and store information regarding bed availability in different bed areas of the ED. The Table 7.2 below shows each of the 4 variables and there possible values.

Table 7-2 Possible values of all state variables for database agent

Bed area	Range of possible values (where n = number of beds available in a given bed area)
Resus Area	$0 \leq n_r \leq 2$
Monitor Area	$0 \leq n_m \leq 15$
Treatment Area	$0 \leq n_t \leq 4$
MTA area	$0 \leq n_{mta} \leq 5$

Possible States: This agent can have many possible states and each state determines the available number of beds in each of the bed area.

4. Charge Nurse/decision Agent

The Charge nurse agent (or simply the decision agent) represents the charge nurse behavior and is the only cognitive agent. The decision agent can send the patient agent to a location other than its *desired treatment location*, if it is unavailable.

The decision agent decides the value of the *actual port* variable based on the following rules.

- 1.) Rule 1: If the desired treatment location is available then the patient is always released to that location.
- 2.) Rule 2: A lower acuity patient can be seen in a higher acuity bed but reverse is not true.
- 3.) Rule 3: If the treatment location is unavailable, the decision agent checks the availability of a higher acuity bed. Some minimum number of available beds is required in the higher acuity area if a lower acuity patient is to be treated in that area. Even if the minimum number of beds is available, the decision agent can decide not to alter the treatment location of the patient. This is a random probability decision and represents *nurse's dilemma*. For example if nurse's dilemma is set to 20% then that is the chance of patient moving to an alternate and better location. The minimum number of beds required to move a lower acuity patient in monitor area is set to 2 and for treatment area it is set to 1 based on managerial estimates.

- 4.) Rule 4: A low acuity patient is moved to a higher acuity bed only if there is no other higher acuity patient in the waiting room.
- 5.) Rule 5: If there is more than one patient requiring a particular bed, preference is given to patient with lowest CTAS. If the CTAS is also same then patients are seen on first-come-first-serve basis.

7.2.2.2. Communication model/Simulation model logic for DBA strategy

To build the DBA strategy in the simulation model, two queues are inserted between Triage and the respective bed area queues. These are called *Guide patients queue (GPQ)* and *Hold patients queue (HPQ)*. The logic written on the triggers of these queues represents the *decision agent* and this is where it interacts with the patient agents. The decision agent requires bed availability information in order to alter the state of the patient agents. This information is stored in the *database agent*. Every time the state of the *bed agent* changes, it sends a message to the *database agent* which then decodes this message and keeps a tally of available beds in the ED. The communication logic is shown in Figure 7.2. In this diagram the solid lines indicate the possible routes for patient flow while dotted lines indicate communication between agents.

The role of the GPQ is to distribute patients appropriately, if beds in the ED are available.

The GPQ either releases the patient to the *desired treatment location* or decides to move the patients to a higher acuity location if the desired location is unavailable. If the decision agent decides not to move the patients, the patients are moved to HPQ.

The patients held in HPQ are released whenever a bed becomes available. The HPQ receives messages from all the bed agents at every time their state changes to 'available'.

On receiving this message, the decision agent checks all the patients in the HPQ and releases the patient whose desired treatment location matches with the location of the bed from where the message was received. If there is no patient in the HPQ waiting for this particular bed, the next best patient is chosen. The decision agent can again decide to release or not to release the next best patient based on the probability.

In any case these queues release patients only when the beds are available. Thus the flow generated using DBA strategy is *pull patient flow*. The pull patient flow along with the DBA strategy ensures that treatment and MTA patients don't keep waiting for appropriate beds even when many monitor beds are empty. Thus it removes unexpectedly high waiting time values from the model output WTBS data set. The highest value seen in the three months ED data is only 900 minutes. Therefore in the model the highest wait-time should be around this value, which can be achieved with DBA strategy put in place.

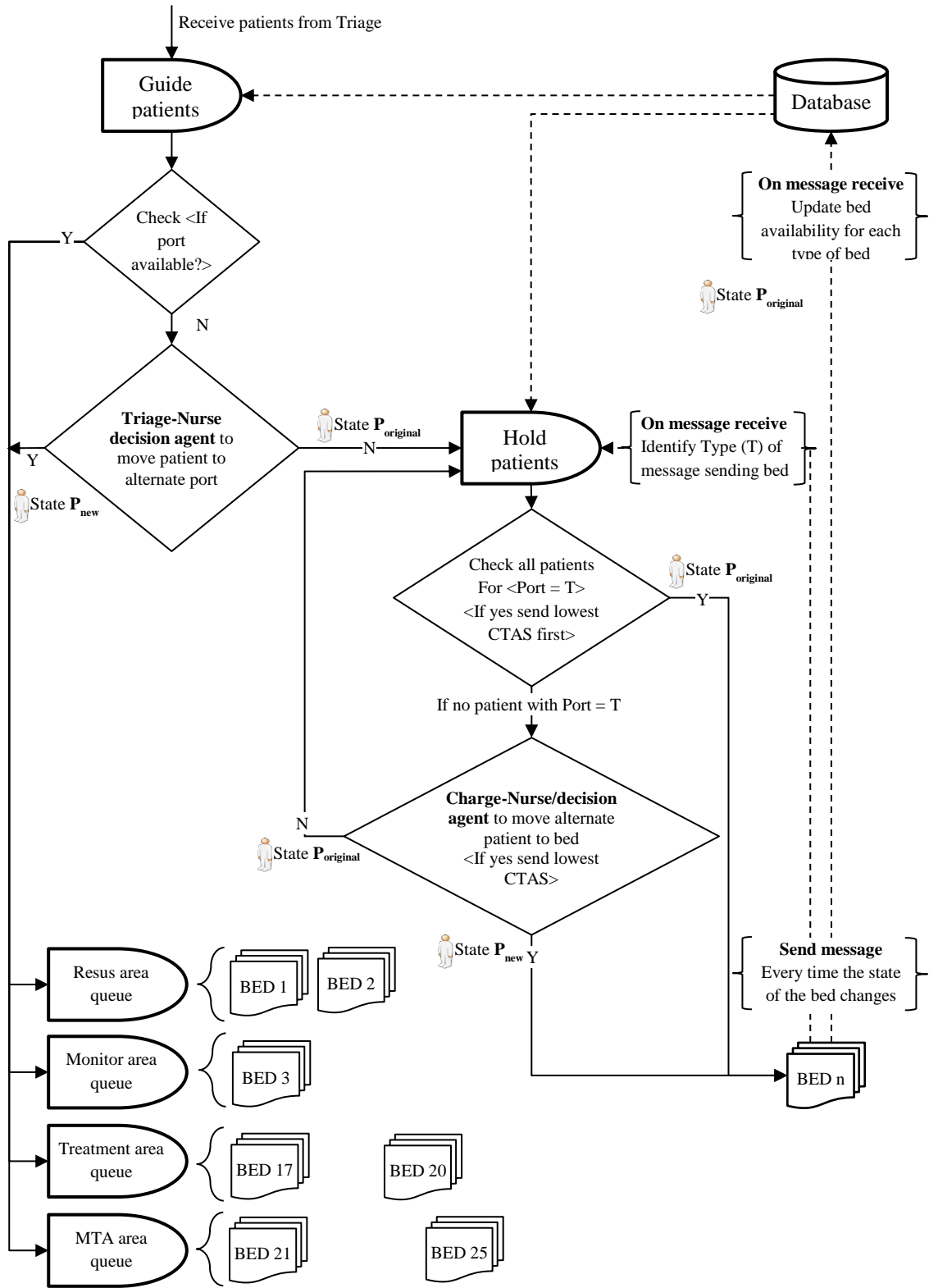


Figure 7-2 Simulation model logic for Dynamic bed-allotment strategy

7.2.2.3. Coding of charge nurse/decision agent

As mentioned earlier the code for the decision agent is written on the triggers of *guide-queue* and *hold-queue*. The algorithms for the codes written on these queues are shown in Algorithms 7.1 and 7.2. The code written in italics represents a decision agent.

Algorithm 7-1 Charge nurse/decision agent working on the entry trigger of guide-queue

On-Entry Trigger of Guide-queue

```
contact DATABASE;
get number of beds available in each bed area;
get patient's desired treatment location;
if (number of available beds in desired location > 0)
{
    release patient to desired location;
}
else (check if number of beds in higher acuity bed area > minimum number of beds required for moving a
lower acuity patient)
{
    change treatment location?
    {
        bernoulli (nurse dilemma%, 1, 0); //represents toss of a coin, where
        } //probability of getting 1 = nurse dilemma%
        if yes (or 1)
        {
            actual treatment location = higher acuity bed area; //actual treatment location ≠ desired
            release patient as per actual treatment location; //treatment location, patient agent's
        }
        state
        } changed
        else if no (or 0) release patient to hold-queue
    }
}
```

Algorithm 7-2 Decision agent working on the message trigger of Hold-queue

On-Message trigger of Hold-queue

```
decode message
{
    get bed number of the bed that sent the message;
    get bed area type of the bed that sent the message;
}
for (all patients present in the hold-queue)
{
    match bed type with desired treatment location of all patients;
    if (number of patients with treatment location matching bed area type > 0)
    {
        choose patient with longest wait-time and lowest CTAS;
        release best patient to message sending bed;
    }
    else if (bed area of message sending bed = Monitor bed area)
    {
        for (all patients with desired treatment location = treatment area)
        {
            if (number of patients with desired treatment location equal to treatment area > 0)
            {
                choose patient with longest wait-time and lowest CTAS;
                change treatment location?
                {
                    bernoulli (nurse dilemma%, 1, 0);           //represents toss of a coin, where
                }                                           probability of getting 1 = nurse dilemma%
                if yes (or 1)
                {
                    actual treatment location for best patient = monitor area; // patient agent's
                    release patient to message sending bed;                 state changed
                }
                else if no (or 0) hold patient
            }
            else for (all patients with desired treatment location = minor treatment area)
            {
                repeat same code for MTA patients as for treatment patients
            }
        }
    }
    else if (bed area of message sending bed = treatment area)
    {
        for (all patients with desired treatment location = minor treatment area)
        {
            repeat decision agent code
        }
    }
}
}
```

7.2.2.4. Verification and Validation of the VGH-EDsim model using DBA strategy

Verification of the DBA strategy is done in the same way as the rest of the VGH-EDsim model. The validation is done both qualitatively and quantitatively. As mentioned earlier the decision agent changes the desired treatment location decision based on a probability called *nurse's dilemma* and number of beds available in the proposed bed area. While the threshold values are estimated by the ED staff, nurse's dilemma value is moved on an arbitrary range. The value at which the final treatment location percentages of the model match that of ED data is chosen as the value of nurse's dilemma. The value of nurse dilemma is found to be 25% for moving treatment patients to a monitor area and 40% for moving patients from MTA to treatment area or monitor area. The treatment location percentages are found to be near equal as those in Table 7.3. Moreover the average WTBS and LOS values generated are near equal to model validation data. The data are shown in Table 7.4. (To re-run this experiment refer to user manual section

A.2.1 Experiment 1: Change parameters of DBA strategy)

Table 7-3 Treatment location percentages (Nurse Dilemma = 30%-40%)

	Monitor	Resus	Treatment	MTA
Model output data	47.92%	1.00%	23.88%	27.20%
Model validation data	45.64%	1.99%	27.12%	25.24%

Table 7-4 Comparison of average wait-times, processing times and length of stay (Nurse dilemma = 30%-40%)

	WTBS	TIP	OUTPUT STATUS	LOS
Model output data	139.14	153.09	137.83	439.22
Model validation data	129.07	146.90	119.88	395.85
% difference	-7.81	-4.22	-14.97	-10.96

The model with DBA strategy is also validated quantitatively. The results from the Mann-Whitney U test are shown in Table 7.5.

Table 7-5 Mann Whitney u test results for VGH-EDsim model built using DBA strategy

	GROUP	Sample size	Mean Rank	$\frac{\text{Mean rank model}}{\text{Mean rank data}} * 100$	Z values
WTBS	Data	2701	2715.00	99.01 %	-0.64
	Model	2701	2688.00		
TIP	Data	2701	2729.27	97.97 %	-1.31
	Model	2701	2673.73		
OUTPUT	Data	2701	2714.79	99.02 %	-0.71
	Model	2701	2688.21		
LOS	Data	2701	2731.35	97.81 %	-1.41
	Model	2701	2671.65		

If the same hypothesis tests are conducted as those conducted for the VGH-EDsim DES model, it can be easily said that the model is now statistically validated since the mean ranks are close to each other and all Z values are with-in the allowable range of ± 1.96 . The WTBS times generated by the model using DBA strategy are compared with model validation data in a frequency distribution graph in Figure 7.3. It is clear that if compared to Figure 6.8 which is a similar plot for the VGH-EDsim DES model, the model output values are distributed much more evenly.

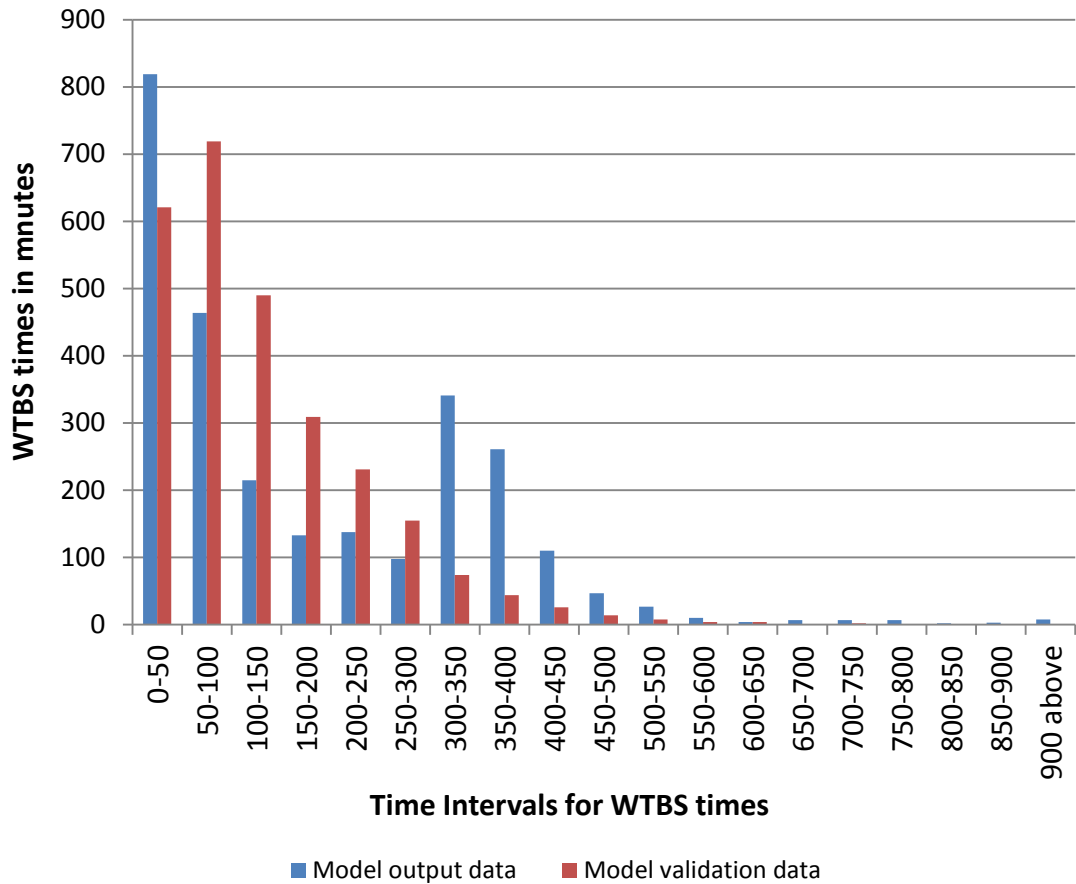


Figure 7-3 Frequency distribution histogram to compare model output data with model validation data (Model with DBA strategy)

It can be said that the model built using the DBA strategy is validated. This also demonstrates how integrating ABS with DES can help building a model that is closer to reality. The next chapter discusses how this model can be used to design solutions to improve the ED.

8. Model analysis and solution design for ED improvement

8.1. Model analysis

The prima facie solution discussed in Chapter 4 (4.3.1) mentions that the aim of the research is to identify solutions to improve the ED, preferably without adding more resources to the ED. This calls for identifying bottlenecks in the existing system and designing process change solutions to alleviate them.

It was also mentioned during problem formulation (Section 4.3), that the clinical component of care cannot be altered, therefore no reduction can be done in the TIP times. To achieve reduction in the WTBS times, focus should be given to the input and output phases of the patient's journey in the ED.

8.1.1. Analysis of Output phase of ED

The Output phase of the patient journey in the ED represents the time the patient spends waiting for the final destination, be it waiting for admission (TBADM), waiting for discharge (PD) or waiting for a decision (ERH). All of these wait-times add little more to

the patient in terms of treatment. Instead patients hold on to doctor and nurse resources for monitoring, which is not the top priority of the VGH-ED. Moreover these resources are required to see patients who are still waiting to be seen by a doctor (WTBS) or in their treatment phase (TIP). Therefore it is desirable that the output phase of the patient journey be as small as possible. However the causes of these wait-times lie beyond the scope of the ED that has been considered in this research. As a result, in the VGH-EDsim model, these wait-times have been modeled as black box processes, which means, that only their effect on the ED is modeled. Therefore the simulation model, in its current form, can only be used to study the effects of reduction of output wait-times on WTBS and LOS.

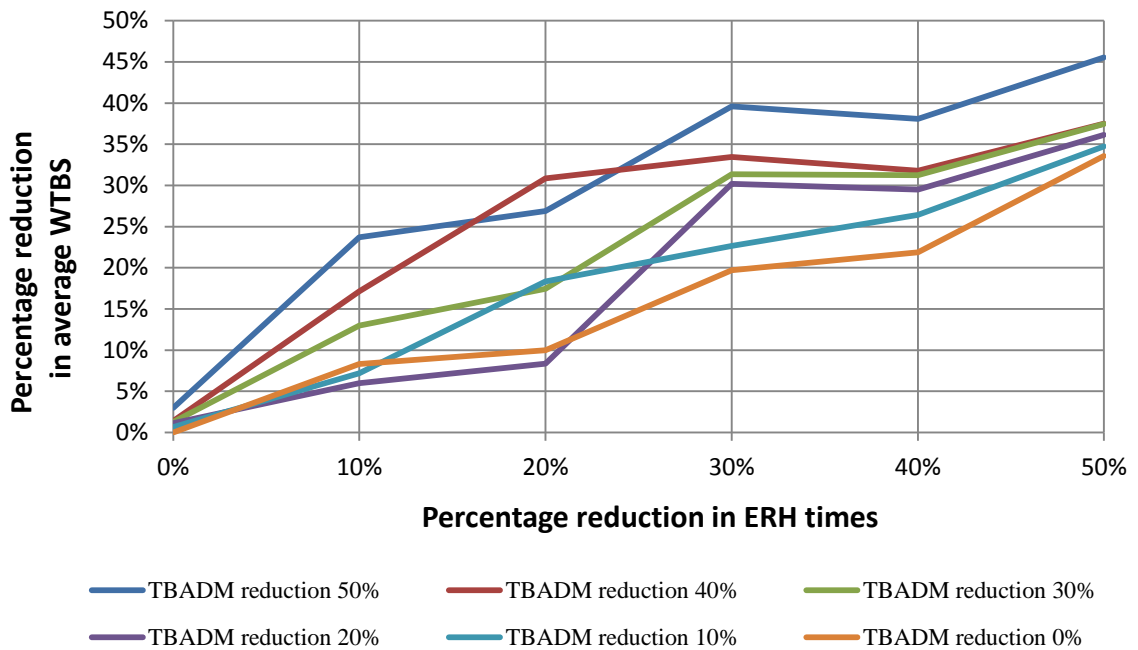


Figure 8-1 Percentage reduction in WTBS at different levels of reduction in ERH and TBADM times

Since PD status-time of a patient is generally small and the patients do not utilize nurse and doctor resources, only TBADM times and ERH times are looked as parameters that can be reduced to have a significant impact on WTBS and correspondingly the LOS. Five levels of reduction are chosen for each parameter. Keeping reduction level constant for TBADM, ERH is reduced by a factor of 10-50%. This is repeated for all 5 levels of TBADM reduction as shown in Figure 8.1. (To re-run this experiment refer to user manual section A.2.2)

There are 3 main inferences that can be drawn from Figure 8.1. These are:

- 1.) When ERH reduction is 0%, any amount of TBADM reduction fails to achieve major reduction in WTBS. This shows ERH wait-time has a more dominating effect on WTBS compared to TBADM wait-time.
- 2.) At any given level of TBADM reduction, increase in ERH reduction percentage directly improves WTBS reduction.
- 3.) At any given level of TBADM reduction, ERH reduction of 30% causes a major reduction in WTBS. The next big jump happens when ERH is reduced by 50%. Thus it can be said that with a 30% reduction in ERH, WTBS can be reduced significantly.

To achieve a 30% reduction in ERH, there needs to be a separate study in which the ERH phase of the patient's journey is built in greater detail in a simulation model. Such a model could be used to identify the bottlenecks within the ERH process and alternate process flow can be designed according to those bottlenecks. For now it can be predicted that a 20-40% improvement in WTBS times can be achieved (based on TBADM reduction), if ERH can be reduced by 30%.

8.1.2. Analysis of Input phase of ED

The wait-time in the input phase is caused directly by the ED performance. Since VGH-EDsim model has built the input phase in detail, it is easier to design an alternate process to improve wait-times.

If the average WTBS data from the VGH-EDsim model are broken down into W_{BED} , W_{NURSE} and W_{DOCTOR} , the biggest component of WTBS is W_{BED} as seen in Figure 8.2.

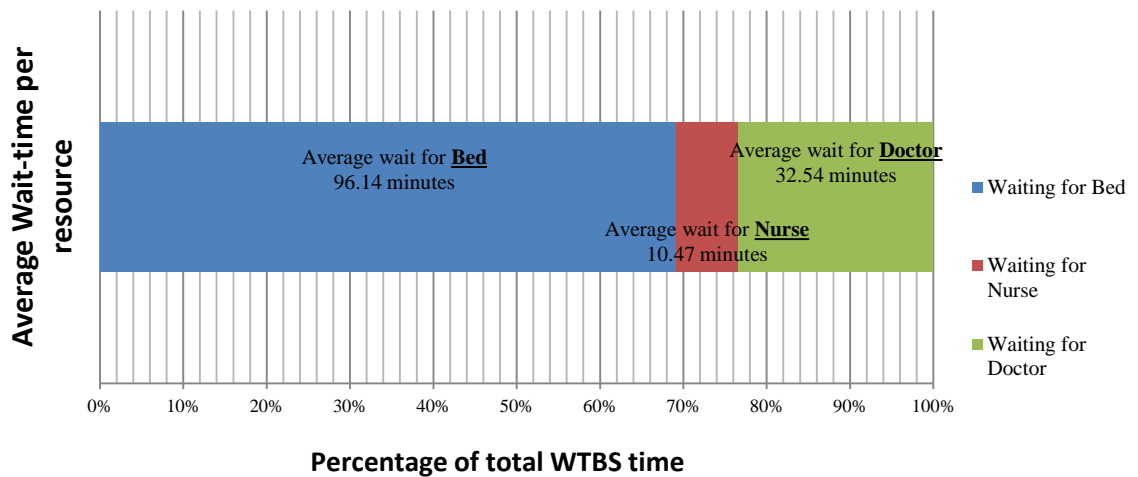


Figure 8-2 Breaking down WTBS into its components

The W_{BED} is higher among patients with CTAS 4 and 5. If W_{BED} values collected from the model are broken down into time-intervals, a lot more CTAS 4 and 5 patients experience W_{BED} higher than 250 minutes as shown in Figure 8.3.

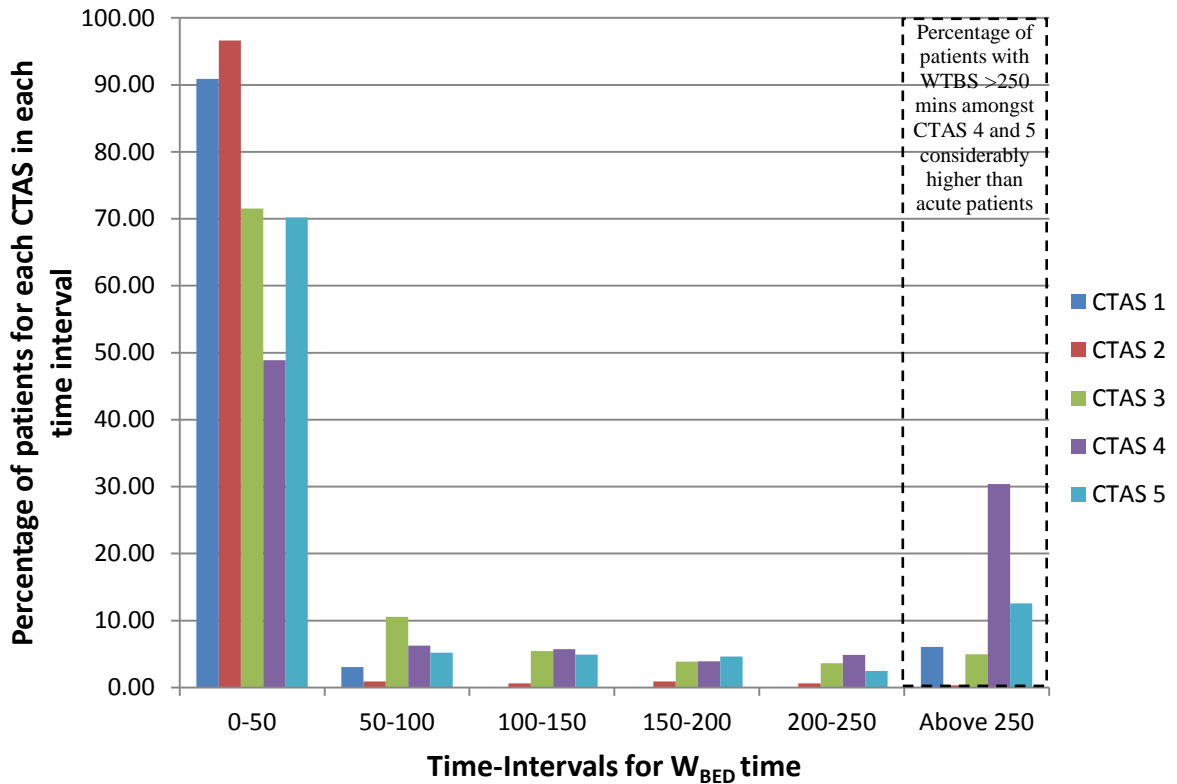


Figure 8-3 Model output: W_{BED} time broken into time intervals for all CTAS types. It can be seen from Figure 8.3 that more than 30% CTAS 4s and about 12% CTAS 5s experience more than 250 minutes of wait-time. The average waiting time amongst this group is actually about 569 minutes. These high wait-time values lead to higher average wait-times in the ED. One of the reasons could be that the VGH-ED has a policy of seeing the sickest patients first. In fact a lot of ED staff had predicted that average wait-times are higher simply because they do not focus too much on the least sick patients. However a majority of these patients require very less treatment time and could be quickly seen and discharged. Amongst CTAS 4 and 5, more than 35% patients need less than 50 minutes of treatment time as shown in Figure 8.4.

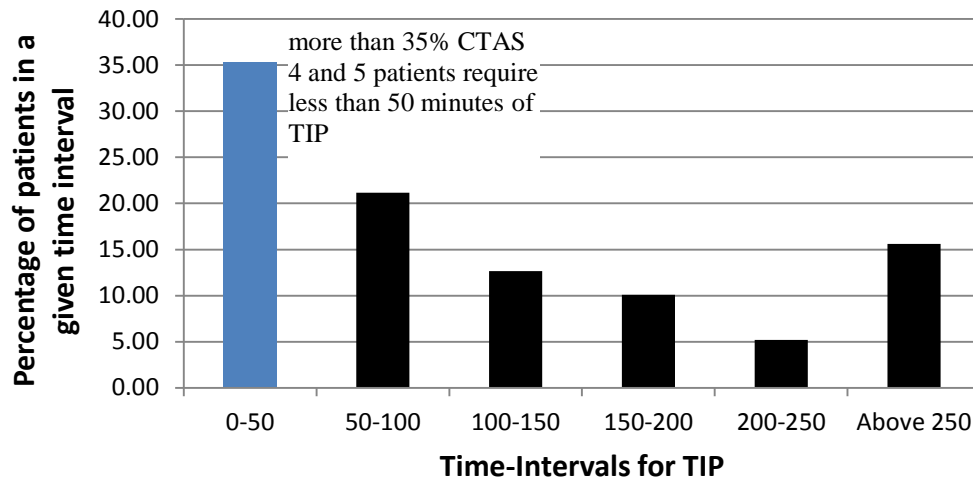


Figure 8-4 TIP times for CTAS 4 and 5 broken into time intervals

The result of the input phase analysis proves that if a solution is designed for reducing W_{BED} for CTAS 4 and 5 patients without increasing the wait-times for acute patients and without increasing TIP or LOS, significant improvement in ED performance can be achieved. The solution designed to achieve this reduction is discussed in the following section.

8.2. Fast track treatment (FTT) strategy

To help alleviate the waiting times for lower acuity patients without affecting the waiting-time for higher acuity patients a special solution is designed. This solution is named as the *fast-track treatment strategy* or the *FTT strategy*.

In this strategy the ED resources are re-allocated under certain circumstances to treat minor patients in a dedicated bed area called *Fast-track treatment area*. Two beds from the MTA area are reserved to be used as fast-track beds. If certain conditions are met, this

strategy allocates a doctor resource and nurse resource (from triage) to form a *meet and greet* team to the fast-track treatment area where they see minor treatment patients. When the strategy is implemented, the usual ED protocol is by-passed and the doctor assesses the patient before nurse assessment. In this way, the time taken to see the doctor for the first time is reduced considerably. If the doctor assesses that the patient requires a quick procedure, the patient is treated on the fast track beds, else they are sent back to the waiting room where they wait for a bed in the major ED. The fast-track treatment strategy is based on similar strategies such as “physician triage” [38] and “triage team method” [39] which also involved doctors coming to the waiting room to quickly see and discharge patients.

However the downside of most traditional strategies which involve bringing doctor to the patients in the waiting-room is that an expensive doctor resource is allocated to minor patients only, whereas it might be needed in the main ED for major patients. The problem worsens if there are not enough minor patients and the doctor, being bound by protocol, is sitting idle while major patients suffer. However FTT strategy is different from the traditional strategies found in literature as it is dynamic, i.e. it is implemented only when certain conditions are met and its implementation is not bound by a fixed time frame. FTT is more like the “triage adjustment” strategy discussed in the literature [61].

The implementation of FTT is based on need and feasibility. The FTT is only applied when the average waiting time increases beyond a certain limit, which means when a considerable demand for bed and doctor resource is present. This limit is called *threshold of demand* to represent the need for FTT. The feasibility of FTT is dependent upon how badly the doctor resource is needed in the major ED. The doctor resource can be allotted

to FTT only if the number of patients in their treatment phase (or throughput phase of their journey) is less than a certain ceiling limit. This limit is called the *ceiling of supply* and determines the feasibility of FTT.

Thus current average wait-times and number of patients can be looked as state variables whose values define the state of the ED. The FTT is implemented only when the values of these state variables fall in a given range. The dynamic implementation of the FTT strategy ensures that the resources are not wasted.

8.2.1. Simulation model logic for FTT strategy

This sub-section is focused on simulation model logic for the FTT strategy. The simulation logic for FTT strategy can be broken down into two parts. The first part is shown in Figure 8.5 for details how the model triggers FTT, based on ED conditions. The second part is shown in Figure 8.6 which shows what happens when the FTT is triggered and how it is turned off when the waiting room is relieved sufficiently.

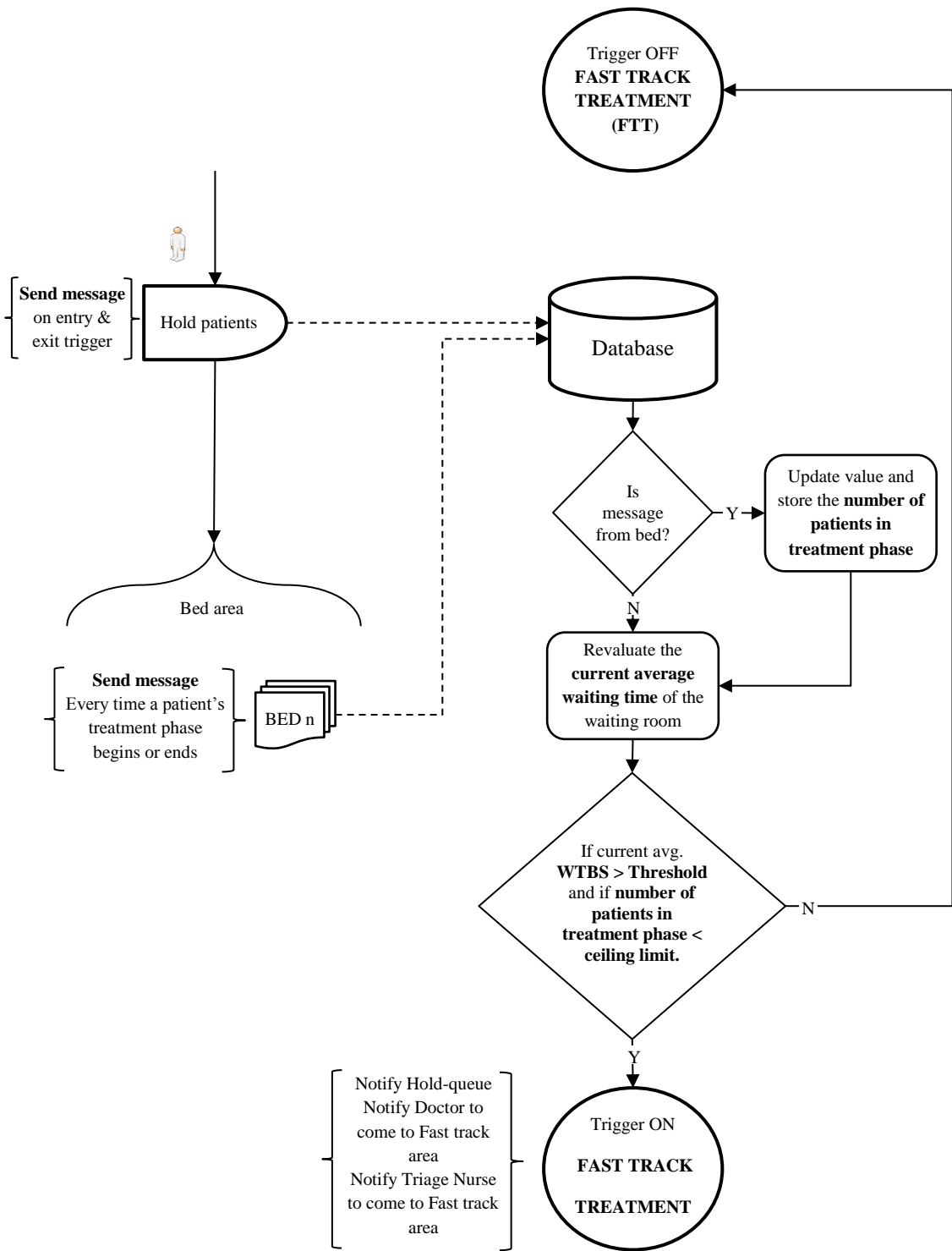


Figure 8-5 Simulation logic for Fast track treatment strategy part 1

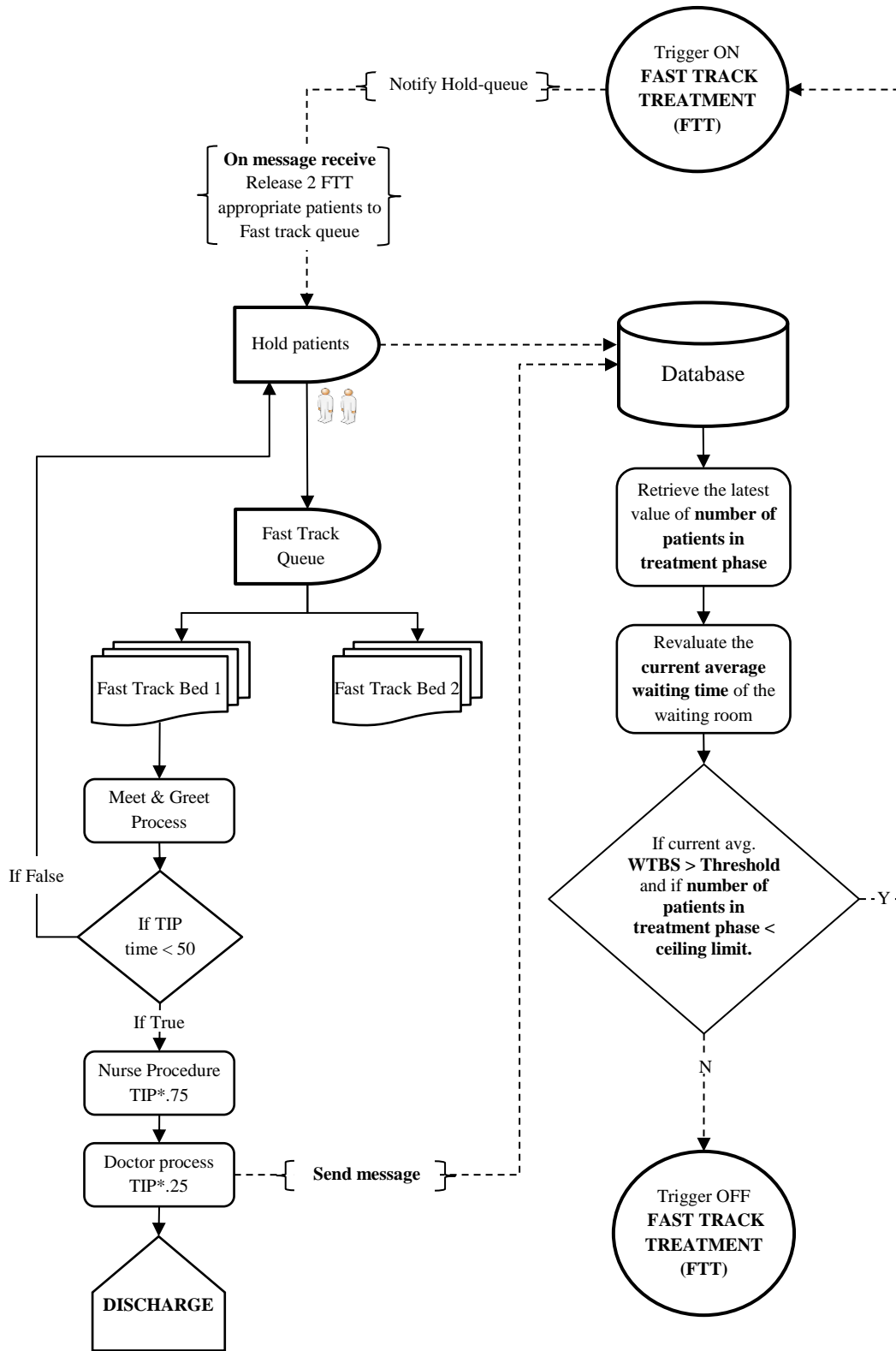


Figure 8-6 Simulation logic for Fast track treatment strategy part 2

The database agent and the charge nurse agent described in chapter 7 are assigned additional qualities and capabilities so that they can implement the FTT strategy automatically whenever the ED conditions are favorable.

As shown in Figure 8.5, every time when the state of the *hold-queue changes*, it sends a message to the *database agent*. Similarly the bed agent also sends a message to the *database agent* every time when a patient enters or leaves treatment phase. The code written on the 'on message' trigger of the *database agent* acts as the *decision agent* and processes the signals sent by hold-queue and bed agents. Every time a message is sent to the *database agent*, *decision agent* checks if the conditions are favorable for implementing FTT. In other words every time when the state of the ED changes, the *decision agent* checks whether the ED conditions are favorable for FTT or not.

Figure 8.6 shows what happens after the FTT is triggered in the ED. The *database agent* notifies the doctor resource and the triage nurse resource so that they come towards the fast track area. The hold-queue is also notified and the *decision agent* picks a maximum of 2 FTT appropriate patients. Since the aim is to quickly see and discharge the minor treatment patients, the patient with the highest CTAS and highest waiting time is given priority. The patients are seen on fast track beds, where the first process is the *meet and greet* process which is a 3-5 minutes process. At the end of this process, the doctor quickly analyzes if the patient can be treated in less than 50 minutes. If so the doctor writes orders for the nurse and the nurse process happens followed by a final quick doctor assessment. If the doctor analyzes that the patient cannot be treated within 50 minutes, the patient is sent back to the hold-queue.

8.2.2. Coding for FTT strategy

Each bed agent sends a message to the database when a patient is released. On every such message the database agent runs the algorithm 8.1. If the FTT trigger is turned on the hold queue releases patients as per algorithm 8.2.

Algorithm 8-1 Database agent evaluating to turn the FTT trigger ON/OFF

On-Message Trigger of Database

```
Update the number of available beds in each bed area;
get the value of 'threshold of demand' and 'ceiling of supply';
get number of patients in treatment phase;
for (all patients present in waiting room)
{
    calculate average WTBS;
}
if (average WTBS > Threshold && number of patients in treatment phase < ceiling)
{
    turn on the FTT trigger;
    Send message to waiting room; // refer to algorithm 8.2
}
else
{
    if FTT trigger was ON turn it OFF;
}
}
```

Algorithm 8-2 Hold queue evaluating which patients to release to the fast track area

On-Message Trigger of Hold Queue

```
If FTT trigger is turned ON
{
    check number of beds in the FTT area;
    if bed is available
    {
        For(all walk-in patients present in the waiting room with CTAS 3 or higher)
        {
            Choose patient with longest WTBS;
        }
        Release patient;
    }
}
}
```

8.2.3. Results from Fast track treatment strategy

The aim of the FTT strategy is to relocate resources in the ED in such a way that WTBS for minor injury patients is reduced without any significant impact on the WTBS and treatment times of lower CTAS patients. In this section an analysis is done how FTT can improve wait-times and how its performance is affected by varying the values of the ED state variables.

The state variable called *threshold of demand* (T value) can have any possible positive value theoretically, but the ceiling limit value (C) has a theoretical upper bound of 22 that is the total number of beds (excluding the fast-track treatment beds). It is impossible to find the optimum values of these variables through an exhaustive search; therefore some other search strategy is required to determine the optimal values. However even without finding the optimum values, some general trends can be identified. Two experiments are conducted in order to identify these trends. (To re-run these experiments refer to user manual section A.2.3)

8.2.3.1. Experiment 1: Change C Value keeping T constant

In the first experiment, the value of T is held constant and value of C is varied. For example, Figure 8.7 shows the effect of varying ceiling limit on WTBS and LOS when threshold is held constant at 50 minutes. Another statistic measured is the percentage of time FTT trigger that was turned on in the model for each value of C (at T = 50) as shown in Figure 8.8. This statistic is called as *FTT trigger time percentage* and indicates the duration when the crucial *doctor resource* is relocated to the FTT area.

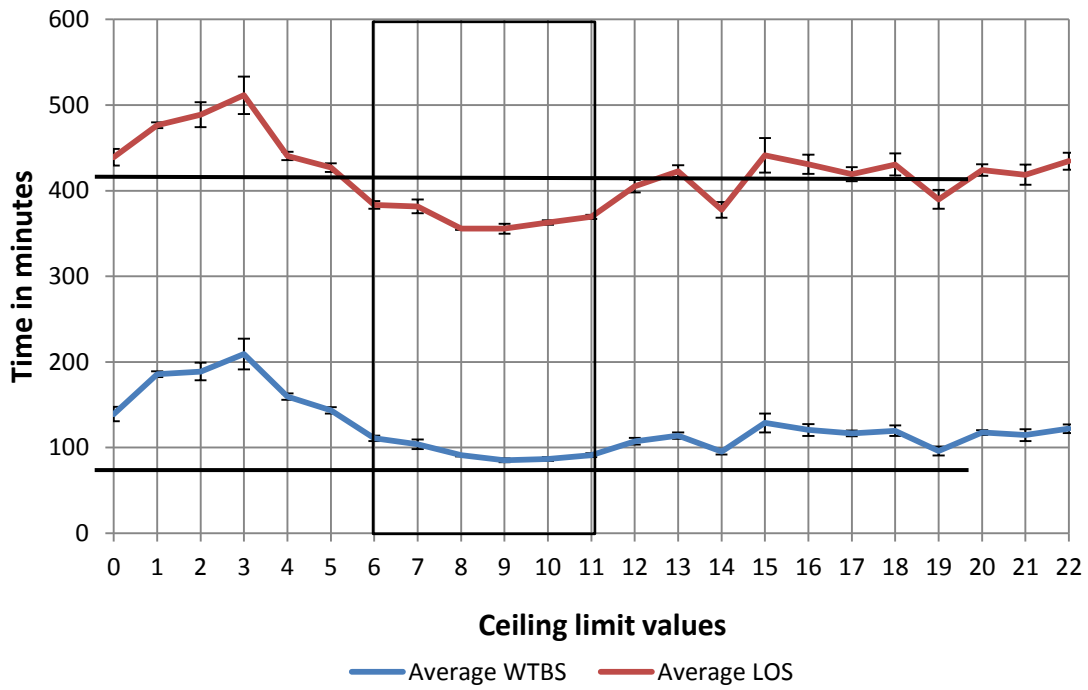


Figure 8-7 Average WTBS time and LOS time plot versus ceiling value (at threshold=50)

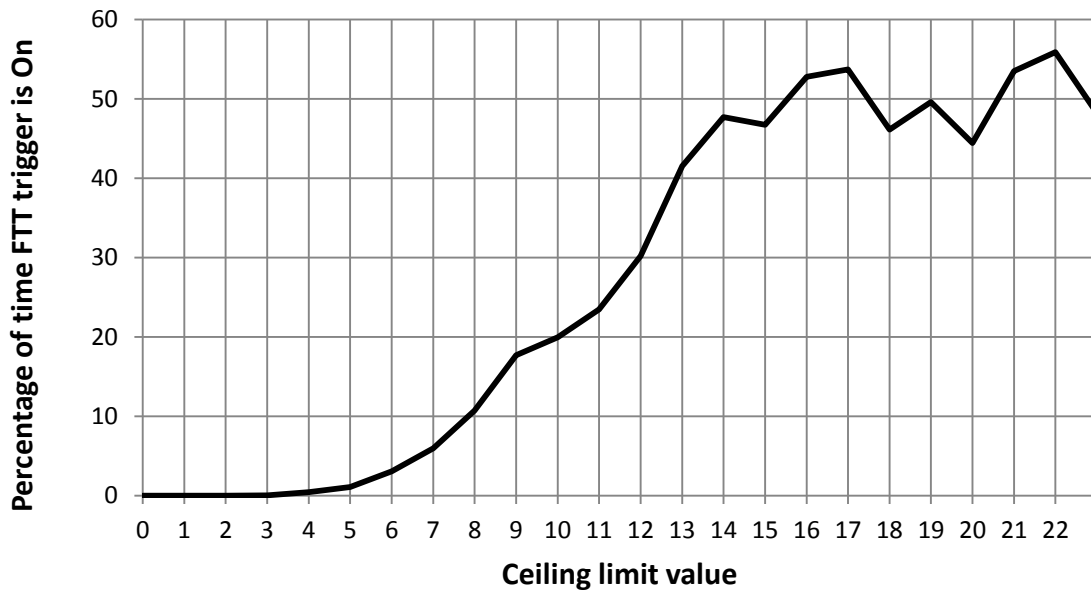


Figure 8-8 Percentage of time fast track treatment strategy is implemented versus ceiling limit value (at threshold = 50)

In both Figures, the point where C is zero is the base case, i.e. model run where FTT is always turned off. The right extreme, where C equals 22, is the upper bound of the ceiling limit value.

Analysis

- 1.) As evident from Figure 8.7, the WTBS actually worsens for C 1 to C 4. This is easy to explain since when FTT is implemented, two beds are dedicated to the fast-track area. However since the ceiling limit is very low, the FTT trigger is hardly ever turned on. This is evident from Figure 8.8 where percentage of time trigger was turned on for C 1-4 is almost 0. Therefore as a net result, the advantages of FTT are not realized and instead WTBS worsens because of loss of two beds.
- 2.) From C = 6 to 11, the average WTBS value goes below base case and correspondingly the LOS value also goes down. The average WTBS value is found to be the lowest when C equals 9. After this value, there is no further reduction in WTBS; however WTBS value remains near constant irrespective of increase in ceiling limit. As the ceiling limit moves towards the upper bound the FTT trigger becomes less and less dependent on the ceiling limit and finally becomes completely independent on it at C = 22. With increase in C value, the *FTT trigger time percentage* increases drastically (see Figure 8.8). It can be inferred that increasing the C value beyond a certain limit leads to no further improvement in WTBS and instead leads to the wastage of the doctor resource.
- 3.) Another inference from Figures 8.7 and 8.8 is that at no value of C, FTT reduces WTBS and increases LOS simultaneously. Thus it is safe to assume that the reduction

in average wait-times caused by implementation of FTT strategy does not come at the cost of increase in LOS.

8.2.3.2. Experiment 2: Repeat experiment 1 at different values of T

The second experiment is to investigate how the *threshold value* impacts the performance of the FTT strategy. Graphs similar to Figure 8.7 are plotted for 3 more threshold values; 100 minutes, 150 minutes and 200 minutes. The graphs are shown in Figures 8.9 and 8.10.

Analysis

Interesting results can be seen from Figures 8.9 and 8.10. The average WTBS values do not vary much with varying T value at lower and higher C values. The threshold only seems to have an impact when C lies between 6 and 11. The C values from 9 to 12 seem to give the best results at every value of T.

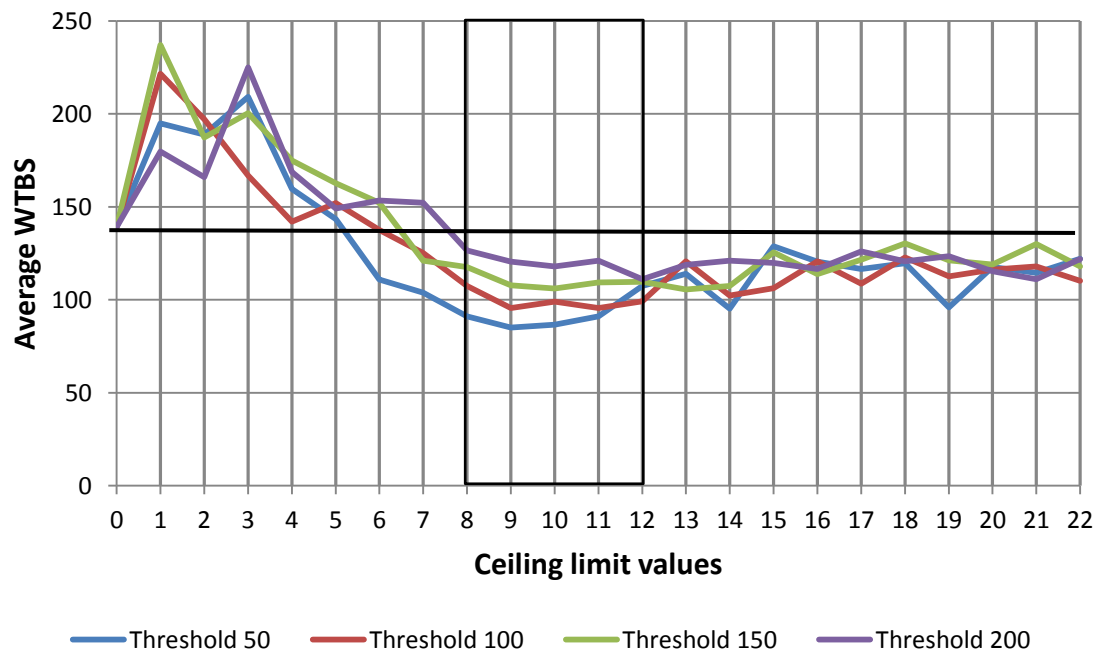


Figure 8-9 Average WTBS time versus ceiling value (at threshold = 50,100,150,200)

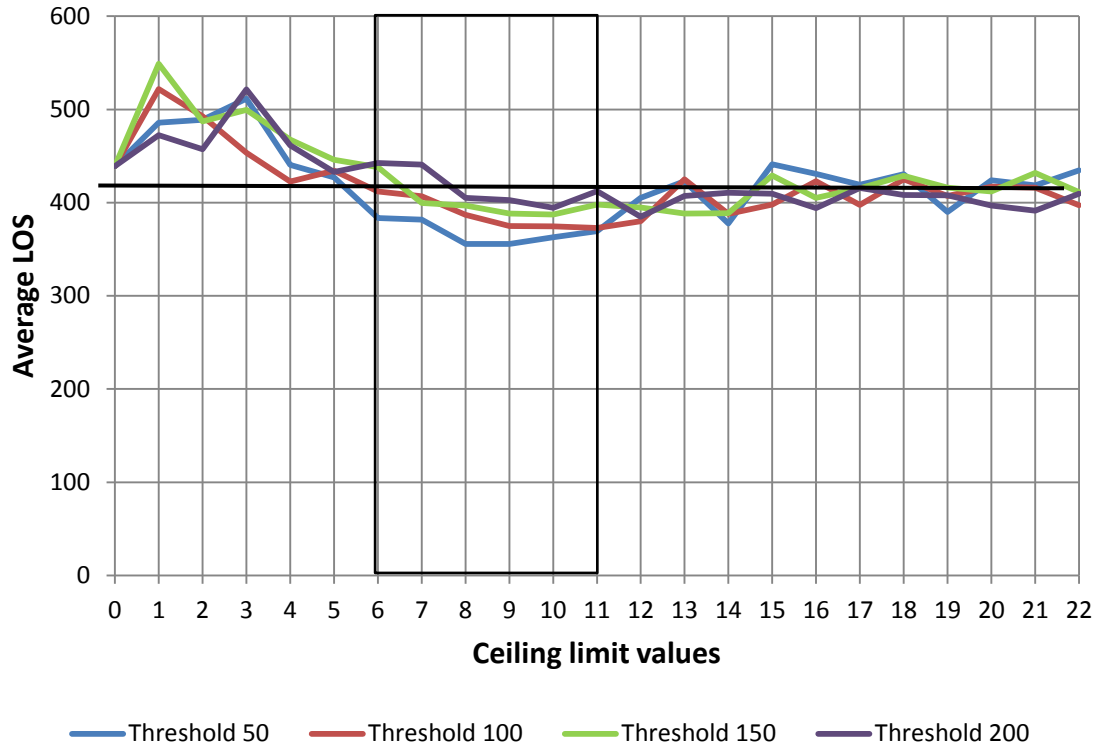


Figure 8-10 Average LOS time versus ceiling value (at threshold = 50,100,150,200)

8.2.4. Conclusion of FTT strategy

The first conclusion (from Figures 8.7 and 8.9) is that beyond $C = 6$, the performance of the ED either improves or remains same under the FTT strategy. Thus it can be said that generally FTT is a good strategy and will, at-least, not worsen the performance of the ED as long as C is greater than 6.

The second conclusion is that the maximum reduction in WTBS happens within a certain range of C values ($C = 9-12$) at any particular T value as shown in Figure 8.9. The T values only have an impact on average WTBS within this range and WTBS reduces with threshold. The maximum reduction in WTBS is experienced when $C = 9$ and $T = 50$ (Table 8.1 and Figure 8.11).

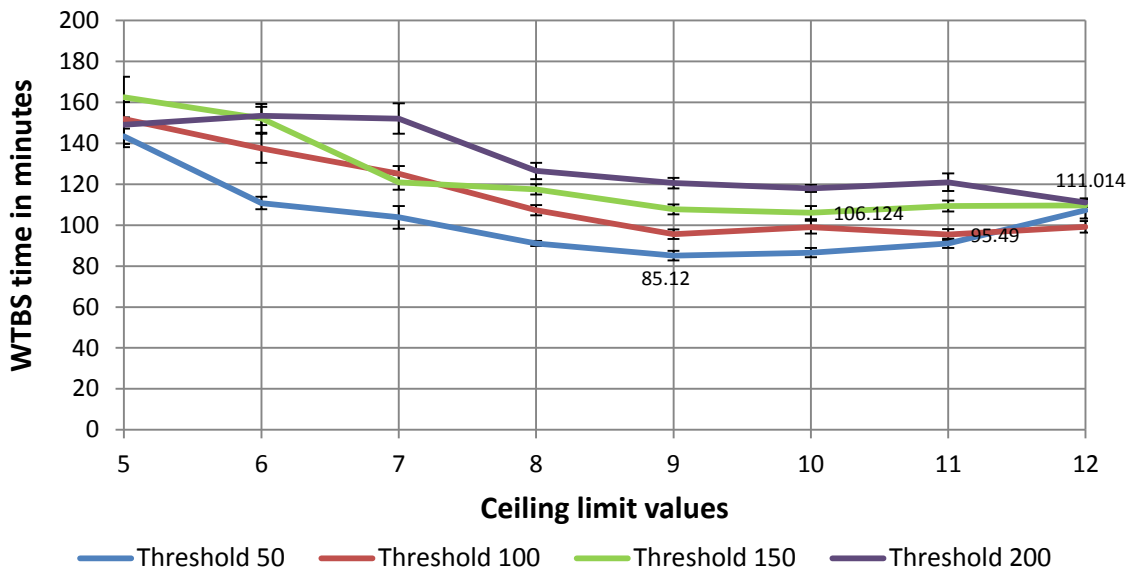


Figure 8-11 Range of ceiling limit values in which threshold has maximum impact on WTBS

Table 8-1 Percentage reduction in WTBS (local best at each T)

T values	Best C value for a given T value	Average WTBS	Percentage reduction
Base case	Base case	139.14	0.00
<u>50</u>	<u>9</u>	<u>85.12</u>	<u>38.82 %</u>
100	11	95.61	31.29 %
150	10	106.12	23.73 %
200	12	111.01	20.21 %

The third conclusion that can be drawn on the basis of Figure 8.12, is that FTT when implemented at optimum values of threshold and ceiling (T = 50, C = 9), is able to achieve the reduction of wait-times (W_{BED} time) for lower acuity patients without affecting wait-times for higher acuity patients.

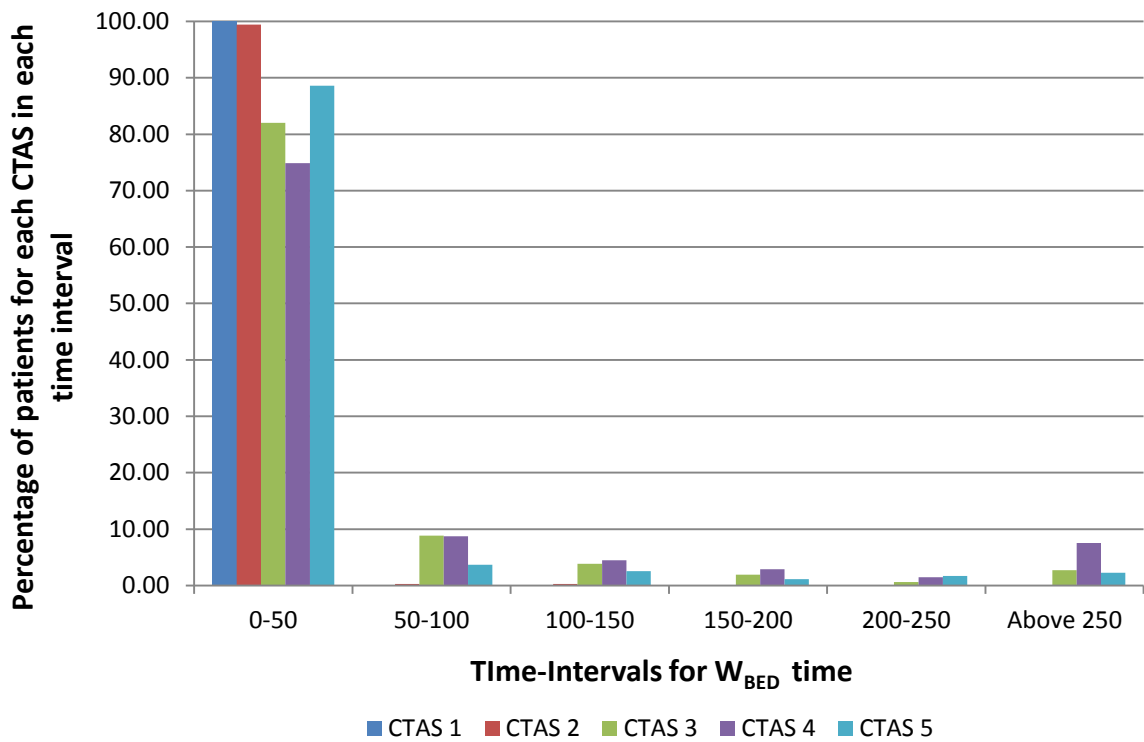


Figure 8-12 Model output using fast track treatment strategy; WTBS time broken into time intervals for all CTAS types

9. Conclusions and future work

9.1. Research Summary

In this research, an attempt to make a thoroughly verified and validated model has been made with a special focus on modeling the human decision making factors in detail. Since it is very complex to model the exact human behaviour, only certain key decisions have been replicated in the model.

The simulation model has been built in a way that the control parameters such as patient-arrival rate, number of resources can be modified and its direct effect on ED performance can be calculated. In addition to this alternate work-flows (process change scenarios) can also be tested using this model. Results indicate that certain changes in process-sequence can reduce wait-times considerably.

9.2. Research contributions

Three major contributions made in this research to the existing literature on ED improvement are discussed as follows.

9.2.1. Patient treatment captured in detail

It was mentioned in Section 2.4 that most papers in literature have treated the cyclic nature of the ED treatment as a single process. However, in reality treatment is made up of many smaller discrete processes such as various nurse and doctor assessments, specialist consults, lab tests etc. This research is able to partially capture the cyclic nature of treatment phase. The simulation model logic discussed in section 6.2.2.2 provides a realistic representation of the conceptual treatment phase described in Section 4.2.2.1. It is important to break the treatment phase into smaller process as the resource requirements for each of these processes is different. For example for lab tests or specialist consults which happen during the treatment phase, patients do not require doctor and nurse resource. Moreover nurses and doctors do not provide all the treatment to a patient in one process. Instead treatment takes place in multiple doctor/nurse visits. This also enables them to treat/monitor multiple patients at a time. Thus it can be concluded that without capturing this level of detail in treatment phase, it is not possible to model and predict the behaviour of nurse and doctor resources.

9.2.2. Integration of DES and ABS for a statistically validated model

The second contribution of this research is that two model building strategies were integrated for the VGH-EDsim model. In this research the strategy used by nurses to distribute patients amongst different types of beds was captured in detail (Section 7.2.2). Thus while DES modeling technique provides the framework for model building, ABS is utilized to model human behaviour details to build a statistically validated model. The

successful statistical validation of the VGH-EDsim model ensures that the model can be used to predict the outcome of any alternate process or variables scenario.

9.2.3. Flexible process change alternative

The third contribution of this research is the VGH-ED improvement strategy called *fast track treatment*. The dynamic and flexible nature of FTT makes it suitable for an ever-changing environment like ED. It is designed to always allocate resources in the most optimum way. Results of the FTT strategy have shown that it improves WTBS times for minor injury patients while making sure that the major patients do not suffer due to lack of resources. FTT is an innovative way to achieve considerable WTBS reduction without adding any resources to the ED.

9.3. Recommendations for the VGH-ED improvement

Based on solutions generated from this research, two recommendations can be made. First recommendation is based on the results from Section 8.1.1. A considerable wait-time reduction can be achieved if interventions are made to reduce output phase wait-times such as TBADM, and ERH. It indicates that efforts should be concentrated to reduce patient journey in the output-phase.

The second recommendation is based on results of Section 8.2.3. The results indicate that a fast track-treatment strategy can be used to achieve considerable reduction in WTBS without affecting the over-all performance of the ED. Moreover this reduction comes without having to add any additional resources. The monitors installed in the VGH-ED

display the longest wait-time and the average wait-time, while the monitors in the treatment rooms show the status of patients in each of the beds. The charge nurse in the ED can use this information to trigger the FTT strategy. The ceiling limit and threshold can be selected based on the decision of the ED staff. Any realistic value of the threshold (average WTBS of 50-150 mins) and ceiling limit (6- 11 patients receiving treatment at the same time) can provide considerable reduction in wait-times. Implementing a pragmatic strategy like FTT, will not only improve average wait-times but will also drastically improve public perception about their performance.

9.4. Future work

Based on understanding of the ED, three possible directions are suggested for the further research.

The first is to find ways to further reduce WTBS by looking for bottlenecks in the output-phase of patient journey. A detailed conceptual model will have to be made to study details inside these output wait-times. These wait-times could possibly be broken down into a sequence of smaller processes. One way to simulate the detailed output wait-times is to enhance the VGH-EDsim model so as to include all the details of the output phase. The scope of the model will have to be enlarged in order to include elements outside the ED such as admission unit. However it may be hard to validate such a complex model. To avoid building a complex model, a separate model for the output phase of the patient's journey can be built. Such a model can be called as VGH-EDsim-Discharge model. This model can be used to test ways to reduce output wait-times. The reductions achieved

from the VGH-ED-Discharge model can be fed into the VGH-EDsim model to predict the possible effect on WTBS.

One of the recommendations of this research has been the FTT strategy which gives the second research direction. It is possible that this strategy will meet road-blocks in terms of acceptability from the ED staff. Some doctors may not like this idea while others may be enthusiastic to try it. The VGH-EDsim model can be enhanced to model unique doctors, who have their preferences. Different doctor schedules could be designed so that interested doctors are scheduled when conditions for FTT are most likely to happen. This can help introducing the idea gradually to the ED-staff.

The third direction is inspired by the potential shown by ABS. Under this direction, efforts should be made towards incorporating more human-decision making elements in the VGH-EDsim model. One such example is the doctor's decision. In an ED, the treatment processes are fairly non-standardized and doctors use their expertise and experience to make these decisions. Naturally some doctors are more confident in making decisions than others. This human variability greatly affects the treatment times and the overall flow in the ED. The VGH-EDsim model has already been coded in a way that such variability and its affect can be modeled in the ED. Detailed data collection will be needed to understand the behaviour of different doctors so that it can be used to enhance the VGH-EDsim model.

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A. User Manual

This manual shall help the user of this model to re-run the same experiments as they were carried in this research. A special graphical user interface (GUI) has been made on top of the VGH-EDsim model. This GUI facilitates the user to change the variables used in the experiments and see their effect on the model output. This GUI is called the *Model control GUI* as shown in figure A-1.

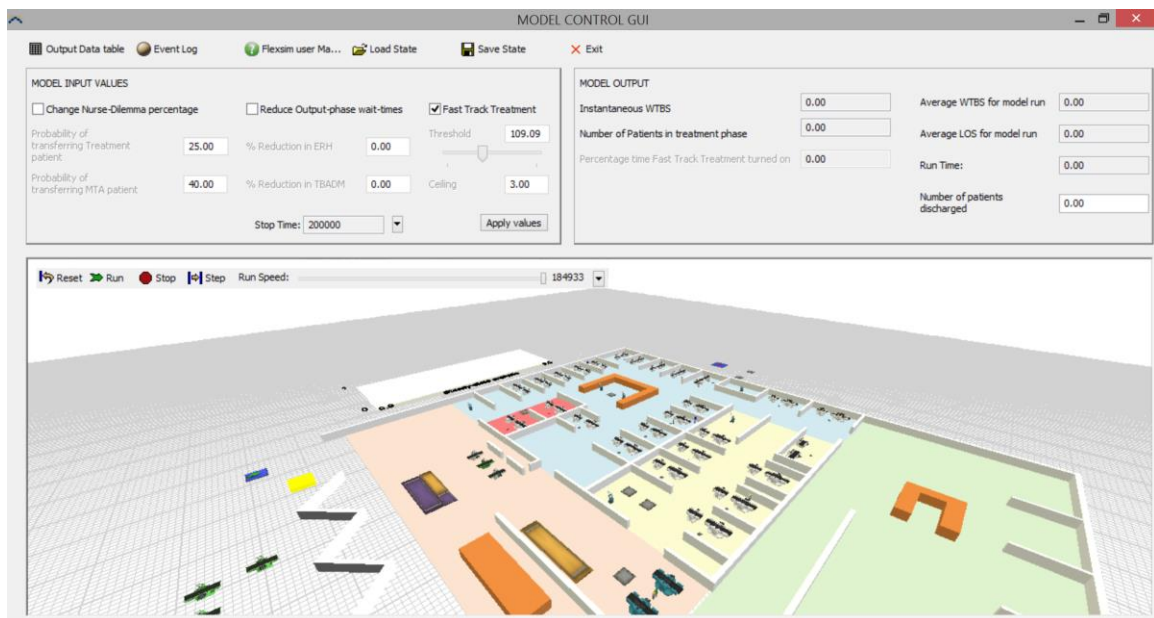


Figure A-1 Model control GUI

Notice that the GUI has three separate windows; model view window (bottom half), model input values window (upper left) and model output values window (upper right).

A.1. Model view and control buttons

The bottom half of the GUI has the 3-D view of the model as shown in figure A-2. The view also has buttons to control the model as shown in figure A-3

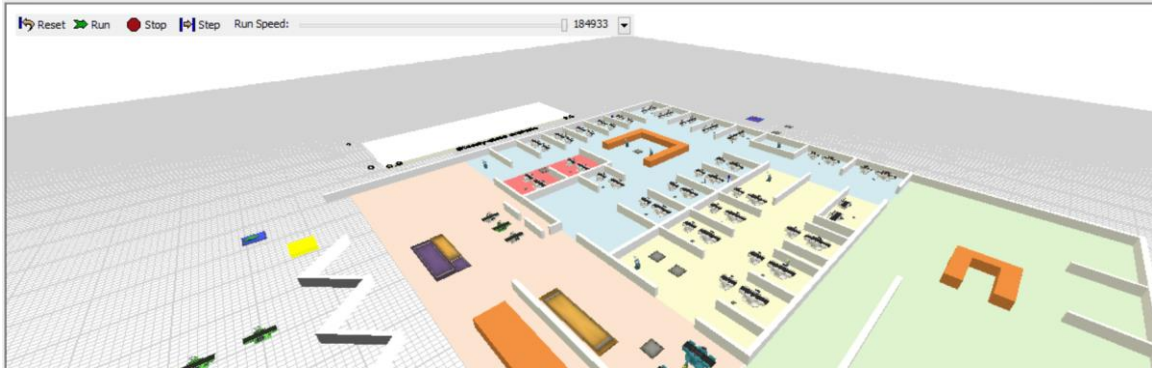


Figure A-2 Model view

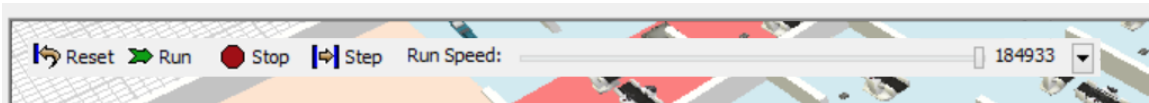


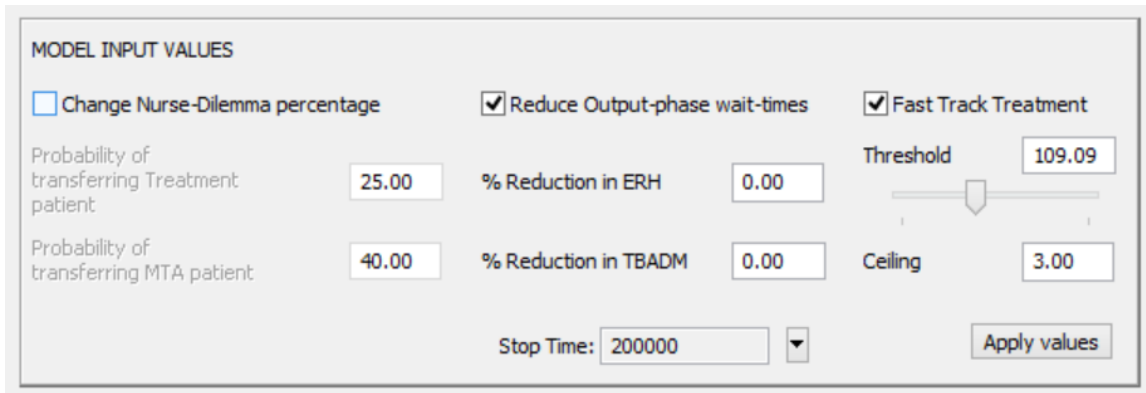
Figure A-3 Model control buttons

The reset button is to reset the model to the default state (empty model, time = 0). The model is run by the clicking the *run* button. It can be stopped at any time using the *stop* button. The step button makes the model jump to the next event in the model. It is useful if the user wants to follow the patient flow sequence at any point. The user can stop the model and then use the step button to see the model jump to the next trigger. The user can also adjust the run speed using the tracker at the top of the model view window.

A.2. Model Input window

The user can change the input variables of the model and re-run the experiments that have been conducted in this research. The model input window is shown in figure A-4.

Note: The user must hit apply values button in order to apply the changes that he/she makes to the model input variables.



The screenshot shows a window titled "MODEL INPUT VALUES" with several controls:

- Change Nurse-Dilemma percentage
- Reduce Output-phase wait-times
- Fast Track Treatment
- Probability of transferring Treatment patient: 25.00
- % Reduction in ERH: 0.00
- Threshold: 109.09 (with a slider)
- Probability of transferring MTA patient: 40.00
- % Reduction in TBADM: 0.00
- Ceiling: 3.00
- Stop Time: 200000 (with a dropdown arrow)
- Apply values button

Figure A-4 Model Input window

A.2.1. Experiment 1: Change parameters of DBA strategy

To be able to change the parameters of the DBA strategy i.e. the nurse dilemma values, the user has to check the *Change nurse dilemma percentage* button. This enables two edit boxes that were grayed out before and each edit box represents the respective nurse dilemma values as shown in figure A-5.

MODEL INPUT VALUES

Change Nurse-Dilemma percentage

Probability of transferring Treatment patient

Probability of transferring MTA patient

Figure A-5 Change nurse dilemma values to change the parameters of DBA strategy

A.2.2. Experiment 2: Study the effect of reducing TBADM and ERH times

To study the effect of reducing output-status on WTBS and LOS the user has to check the *reduce output-phase wait-times* button. The percentage value of reduction can be put in the edit boxes that follow as shown in figure A-6.

Reduce Output-phase wait-times

% Reduction in ERH

% Reduction in TBADM

Figure A-6 Enter reduction values to see their effect on WTBS and LOS

A.2.3. Experiment 3: Run model with Fast track treatment enabled

To re-run the model using the FTT strategy, the user needs to check the *fast track treatment* checkbox which will enable him/her to modify the *threshold of demand* value using either the edit box or the tracker and the *ceiling of supply* value in the edit box as

shown in figure A-7 (If the value is changed via tracker the user must click outside the window before hitting apply values button to make the changes). Note that when FTT is enabled the model output window enables a new statistic called *percentage time when FTT turned on*. This statistic tells for how long the FTT was actually enabled in the model for a given value of ceiling and threshold.

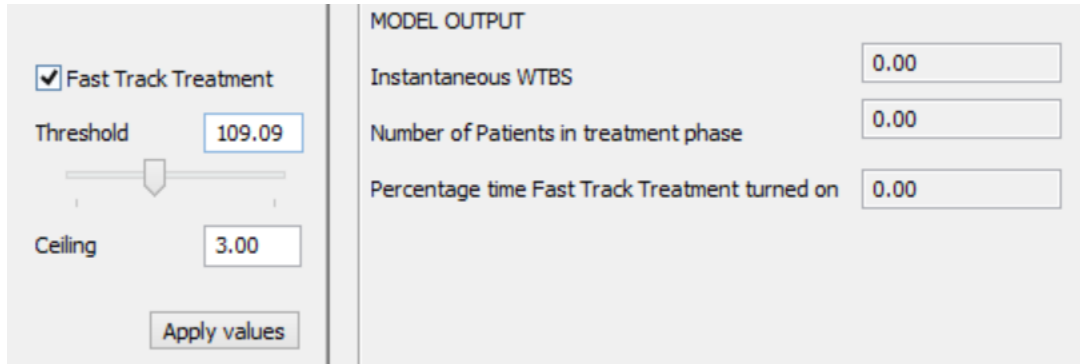


Figure A-7 Change FTT parameters

A.3. Model Output window

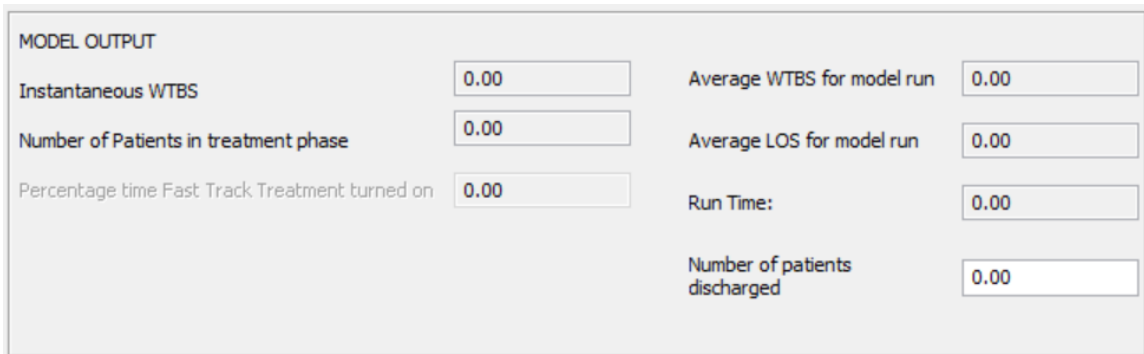


Figure A-8 Model output window

The model output window shows the basic statistics that a user would be interested in, from a particular model run as shown in figure A-8. The output window has two kinds of

statistics, static and dynamic. The two static boxes are that of *Average WTBS for model run* and *Average LOS for model run* and their values are calculated when the model run finishes.

The other boxes in this window are dynamic boxes. *Instantaneous WTBS* box displays the average WTBS of the patients present in a waiting room at any given point of time and the *Number of patients in treatment phase* displays the number of patients that are currently in treatment or TIP phase. The *run time* box tells how many minutes have elapsed since the model started to run. The *number of patients discharged* box tells the number of patients that have finished their journey in the ED.

A.4. Collecting data from the model

To collect accurate data from the model the model should be allowed to run for around 200000 minutes or around 8000 patients because only after 5000 patients that the model comes into a steady state. For a normal user the data that is generated in the model output window is sufficient for analysis. However users who want to collect detailed data will need to make some extra efforts. The model GUI also has some buttons at the very top as shown in the figure A-9.

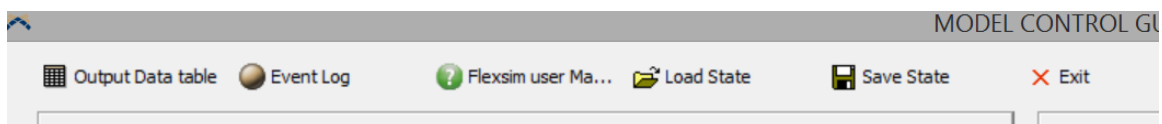


Figure A-9 Controls to record model data

The *Output data table* button towards the left takes the user to the model output data table (figure A-10). It stores all the necessary data that the model generates. It has 17 columns

and 18000 rows. Each represents data for one patient in the order of their arrival. The number of rows and columns is modifiable by changing the number in the row and column edit boxes respectively.

	WTBS	Actual TIP	Actual Output	LOS	Calculations				Average WTBS	Average TIP	Average Output	Average LOS	Desired location	Actual Location
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Figure A-10 Model Output data table

The first four columns collect WTBS, TIP, OUTPUT and LOS data respectively for each patient. Column 9 to 12 give the moving average of the above mentioned data and column 5-8 is reserved for calculating them. The table also records patient’s desired and actual treatment location along with age, arrival time and discharge time.

The *Event log button* will take the user to FlexSim’s event log where record of all the events that happen during a model run are kept. This is useful for model debugging or to study the sequence of events. (Look in FlexSim’s user manual for more details)

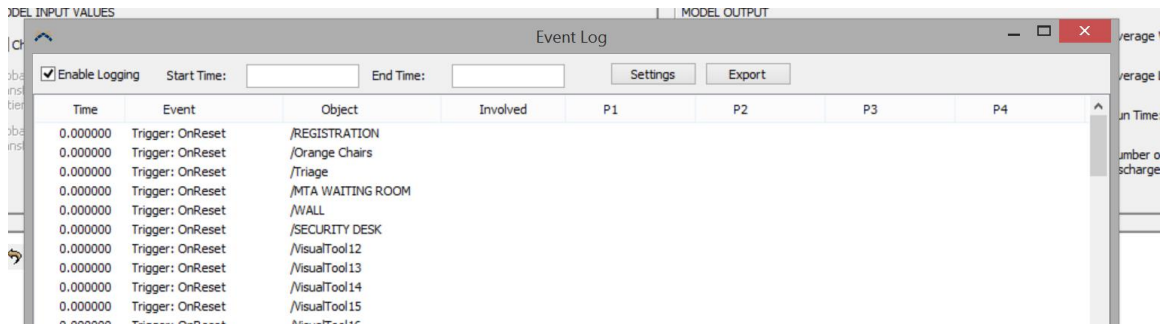


Figure A-11 FlexSim's debugging window

After running the VGH-EDsim model the user can choose to save the model in such a way that the model can be re-run from the same point where it was left. To do so, the user will need to save the state of the model using the *save state button*. Note that after saving state of the model the user should not hit save when prompted to do so while closing the FlexSim model. The user can re-load the state using the *load state* button in a fresh instance of the model. The *exit button* lets the user close the model. On exit FlexSim asks if the model needs to be saved. The user can exit saving unless some change has been made to model code.

B. Distribution Data

B.1. Arrival distributions

Appendix B-1 Arrival Distributions based on time of day

	Arrivals by Walk-ins
Busy State	pearsont5(5.188214, 180.673736, 16.026530)
Transient state	lognormal2(5.917508, 25.297048, 0.334655)
Idle State	erlang(27.858095, 12.049981, 3.000000)
Busy State	Arrivals by Ambulance
Transient state	pearsont5(0.570048, 807.816045, 9.914430)
Idle State	invertedweibull(15.091895, 115.983506, 2.337180)
	loglogistic(44.672368, 69.595665, 2.820857)

B.2. Treatment time distributions

Appendix B-2 Treatment distributions based on age and arrival mode

	Treatment times (Walk-in monitor patients)
Age-group 1	beta(0.990630, 1299.857479, 0.858461, 9.131072)
Age group 2	weibull(0.000000, 198.327122, 1.046007)
Age-group 2	pearsont6(0.000000, 1326.878515, 1.461344, 8.102238)
	Treatment times (Ambulance-Monitor patients)
Age group 1 & 2	beta(0.090057, 988.888446, 0.693112, 2.428969)
Age-group 2	pearsont6(0.000000, 1490.350586, 1.583176, 8.640500)
	Treatment times (Walk-in Resus patients)
All age groups	pearsont6(0.381489, 1174.639690, 0.924120, 9.078094)
	Treatment times (Ambulance-Resus patients)
All age groups	gamma(0.000000, 127.317587, 1.035928)
	Treatment times (Walk-in Treatment patients)
Age-group 1	randomwalk(0.000000, 0.060183, 0.019809)
Age group 2	randomwalk(0.000000, 0.057789, 0.015118)
Age-group 2	gamma(0.472112, 109.585935, 0.947939)
	Treatment times (Ambulance-treatment PATIENTS)
Age group 1 & 2	gamma(0.708169, 146.197570, 0.905142)

Age group 3	pearsont6(0.000000, 400.637689, 1.594629, 3.057326)
	Treatment times (Walk-in-MTA patients)
Age-group 1	pearsont6(0.056843, 57.191938, 1.458532, 2.395065)
Age group 2	randomwalk(0.000000, 0.064014, 0.014390)
Age-group 2	randomwalk(0.501528, 0.046141, 0.009394)
	Treatment times (Ambulance MTA patients)
All Age groups	pearsont6(1.886183, 26422.009590, 0.707575, 99.260396)

B.3. Output phase process-time distributions

Appendix B-3 Output phase process time distributions

	ERH process times
Age-group 1	beta(69.060650, 3768.695585, 0.788260, 4.788368)
Age group 2	erlang(0.034407, 398.271414, 2.000000)
Age-group 2	pearsont6(0.055658, 2535.037215, 1.877589, 5.206166)
	TBADM
Age Independent	lognormal2(0.000000, 139.778065, 1.298171)
	PD
Age Independent	pearsont6(0.617261, 66.829819, 0.728956, 2.244493)