MBSE DRIVEN SIMULATION OF A MID-SIZE EMERGENCY DEPARTMENT OPERATION

A Thesis

Submitted to the Faculty

of

Purdue University

by

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In Partial Fulfillment of the

Requirements for the Degree

of

Masters of Science in Mechanical Engineering

December 2017

Purdue University

Indianapolis, Indiana

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ACKNOWLEDGMENTS

I would like to express my deepest gratitude to my advisor and my graduate committee chair, Dr. Hazim El-Mounayri for his guidance and support through the entire project. The success of this phase of the project wouldn't be possible without the support he provided over the years. I would like also to thank Dr. Zina Bin Miled and Dr. Tamer Wasfy for serving on my committee.

I would like to thank Dr. Alice Mitchell, who provided me with a considerable amount of clinical knowledge.

I would like to acknowledge the support of Cientive Group Inc., represented by Dr. Ajay Thukral who provided me with support in systems engineering, simulation and modeling; and Dr. Vijay Thukral who helped in the development of the models and provided feedback throughout the entire project.

I would like to thank Dr. Rapeepan Promyoo who helped me develop, verify and validate the simulation platform. I would also like to thank two students, Kalpak Kalvit and Hosein Khazaei for providing support in MBSE and data analysis.

Special thanks to Dr, Omar El-Mounayri for managing the project at an early stage and developing a project charter document.

This work was funded by IPLI SCI and Indiana University Collaborative Research Grant (IUCRG).

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ABBREVIATIONS

AD Test	Anderson-Darling Test
BDD	Block Definition Diagram
CAD	Computer Aided Design
CDU	Critical Decision Unit
COPD	Chronic Obstructive Pulmonary Disease
CT	Care Technician
DES	Discrete-Event Simulation
ED	Emergency Department
EMR	Electronic Medical Record
HA	High Acuity
HIPAA	Health Insurance Portability and Accountability Act
IBD	Internal Block Diagram
INCOSE	International Council on Systems Engineering
IPO	Input-Process-Output
LA	Low Acuity
LOS	Length of Stay
MBSE	Model-Based Systems Engineering
MOEs	Measures of Effectiveness
MRI	Magnetic Resonance Imaging
NEDOCS	National Emergency Department Overcrowding Score
OMG	Object Management Group
OOSEM	Object-Oriented Systems Engineering Methodology
Patients LWBS	Patients Left Without Being Seen
PCAST	The Presidents Council of Advisors on Science and Technology

P-Value	Probability Value
RN	Registered Nurse
SE	Systems Engineering
SOI	System of Interest
SoS	System of Systems
STM	State Machine
SysML	Systems Modeling Language
T-Test	Student's T-test
UML	Unified Modeling Language

ABSTRACT

Elshal, Mohamed M.S.M.E, Purdue University, December 2017. MBSE Driven Simulation of a Mid-Size Emergency Department Operation. Major Professor: Hazim El-Mounayri.

Healthcare system in the United States faces multiple issues including quality, rising cost and outcome of the healthcare care delivery process. Systems engineering methodologies and tools have been proposed to address the complexity of healthcare delivery processes as well as the challenges facing the industry, including emergency departments. However, very few initiatives have considered such promising methodology to address the current limitations and improve the quality of care.

The objective of this work is to develop and validate an innovative framework based on model-based systems engineering (MBSE) and discrete-event simulation (DES) to accurately model patient flow and predict resource utilization at a mid-size emergency department. MBSE framework is developed using OMG systems modeling language (SysML); which provides a better understanding of the system, supports multiple system views, and enhances the verification and validation process. Data protocols are implemented to define data inputs and requirements. Time studies are conducted inside the ED to collect patient and human resource processing time data to run the simulation. Two discrete-event simulation models were implemented to evaluate the key performance measures of the ED system. Results are validated by comparing the output behavior of the model to the output behavior of the ED system using different data sources. The resulting simulation platform is able to predict human resources utilization, patient throughput and length of stay (LOS); in order to support clinical decision making (e.g. resource allocation) and improve the outcome of the emergency care delivery process.

The systems engineering approach provided a better understanding of the problem, data needs and requirements, the function, the structure and the behavior of the ED system. Simulation results show an observed crowding situation at the ED, where room utilization rates range between 75% to 100%, and patients wait inside the ED rooms more than 55% of the time. Results also show large utilization rates and workload for ED physicians. Sensitivity analysis was conducted on ED resources to optimize the average length of stay and the current resource allocation. Simulation results show that re-allocation of existing ED resources will result in 15% reduction in the average LOS, and allocation of more staff to the ED will result in more than 25% reduction in the average LOS.

1. INTRODUCTION

This chapter gives an introduction of the research project, which aims at applying systems engineering approach to a mid-size emergency department operation. First, problems in healthcare delivery are described. Second, the motivation behind applying the systems approach is given. Finally, the thesis specific aims and contributions are stated.

1.1 Emergency Care Delivery Problem Statement

The healthcare system in the United States has multiple issues regarding rising cost, increasing patients' volume and outcome of patient flow process. There are multiple reasons for these problems including data challenges, overloading, medical errors, variability of demand, government laws and regulations, data storage issues, clinicians' fatigue and others [1]. Emergency Department (ED) is a service within a hospital that operates 24/7, and is responsible for minimizing early complications. EDs in the United States of America provide 24/7 access to all people visiting with different medical conditions [2]. EDs cover more than 141.4 million people a year, and most of the visits occur after typical business hours. EDs have several growing challenges due to the increasing patients' volume, where it is reported that the number of ED visits have increased by 19% over the past decade. Those challenges result in an increased length of stay (LOS) for ED patients, where it is reported that more than 67% of patients wait more than 15 minutes in order to get assigned to a healthcare provider. This impacts resource utilization rates inside the ED and increases the workload among the medical staff. Moreover, 50% of the EDs reported that they operate at or above their capacity, which also impacts the LOS and resource utilization rates [3] [4].

1.2 Systems Engineering as a Methodology For Improving The Healthcare Delivery Process

The research project is motivated by PCAST report, which came out in 2014 to address healthcare delivery challenges for patients and healthcare organizations [5]. This report came to recommend applying systems engineering methods and tools to improve the healthcare delivery process in the United States. The author spoke about the importance of systems engineering by describing multiple success stories of other organizations who implemented systems engineering either in healthcare delivery or other industries, which made systems engineering methodologies and tools carry a huge promise for improving the healthcare delivery process including emergency departments. The report suggests using multiple systems engineering tools such as: MBSE, computer simulations, operations management, lean techniques, human factors engineering, predictive analytics, big data and other tools. The author spoke about the value of implementing those tools on multiple healthcare stakeholders such as: patients, clinicians, small clinics, large healthcare organizations and the overall community. In this thesis, we used different SE tools and methods such as MBSE, discrete-event simulation and process modeling to analyze resource availability at the ED.

Systems Engineering (SE) provides methods for modeling systems that have multiple interacting entities such as the ED. SE has the full set of tools that can analyze, design and manage a system from stakeholder needs to solution [1]. There are several well-known system life-cycle process models in systems engineering that define systems development process such as the "vee model" which has been developed by Forsberg at al. (2005), the Spiral Model and the Waterfall model [6]. The most widely used one is the vee model, which has been widely used in multiple industries. It defines a series of steps from concept development to system disposal that can be used to reflect a generic systems engineering approach for designing, developing and testing a system. As shown in Figure 1.1, the left side of the Vee diagram demonstrates the definition and decomposition sequence of the system all the way from concept development to system design. The right side of the Vee model demonstrates the system's integration, verification and validation sequence.

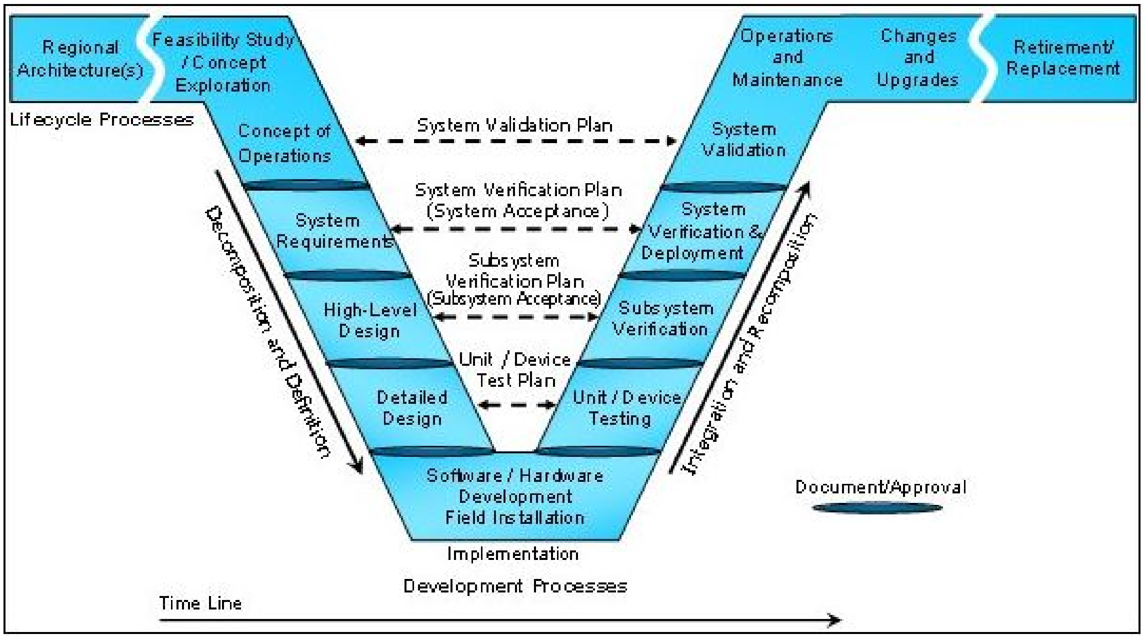


Fig. 1.1.: Systems Engineering vee-cycle: methodology for life-cycle process modeling & development [7].

This diagram is widely applied by companies and industries that use systems engineering as a methodology for designing and building their systems such as aerospace, defense, information technology and medical devices industry. Moreover, the vee diagram represents a generic system life-cycle methodology that can be applied to other industries including healthcare. In our research application, we used the left side of the vee diagram to define and decompose the ED system using multiple layers of abstraction [6].

We considered the ED as a complex system that has multiple interacting entities such as patients, physicians, support units such as labs and care units, medical devices, instruments, pharmacy, health information system and compliance requirements. Figure 1.2 shows the organization structure of healthcare providers including the ED [1] [8].

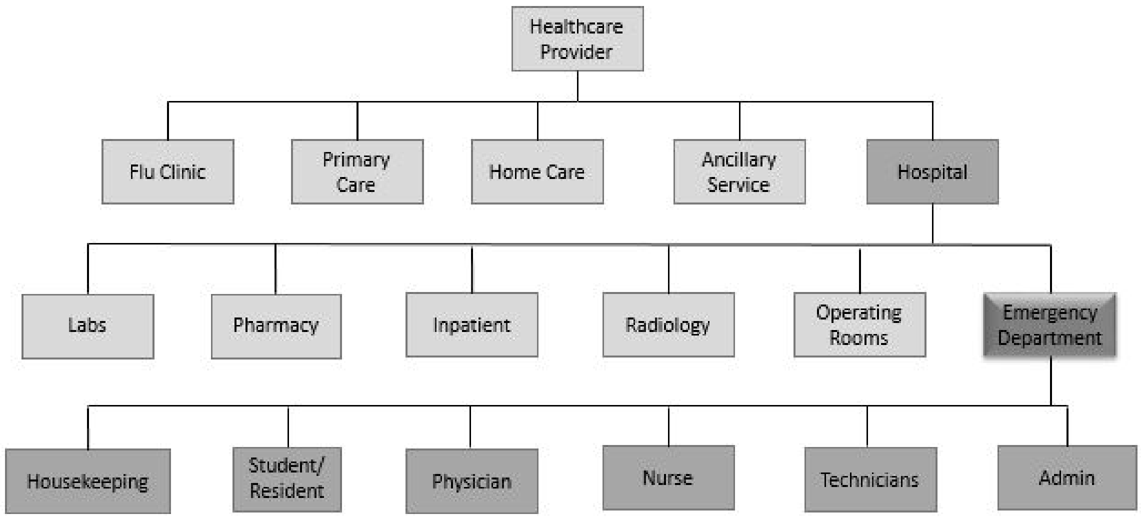


Fig. 1.2.: Healthcare system stakeholder decomposition [8].

1.3 Eskenazi ED Overview

The case of Eskenazi Health ED is used as an example application in our research project. Eskenazi treats around 100,000 patients annually, and approximately 80% of the hospital admissions occur through the ED. Eskenazi provides care to a population with one of the highest indigent care rates (more than 60%) in the nation. Median boarding time for admitted patients is seven hours and LOS exceeds six hours for more than 25% of admitted patients [1]. Eskenazi Health ED has capacity of 90-beds, and more than 60 Registered Nurses and 30 Physicians. Figure 1.3 demonstrates the ED physical layout model, showing the main treatment areas at the ED: Registration Desk, Front Assessment unit, Intake unit, Low Acuity unit (LA), High Acuity unit (HA), Shock rooms, CDU, Holding Area, Ambulance, Lab, X-ray and others [1].

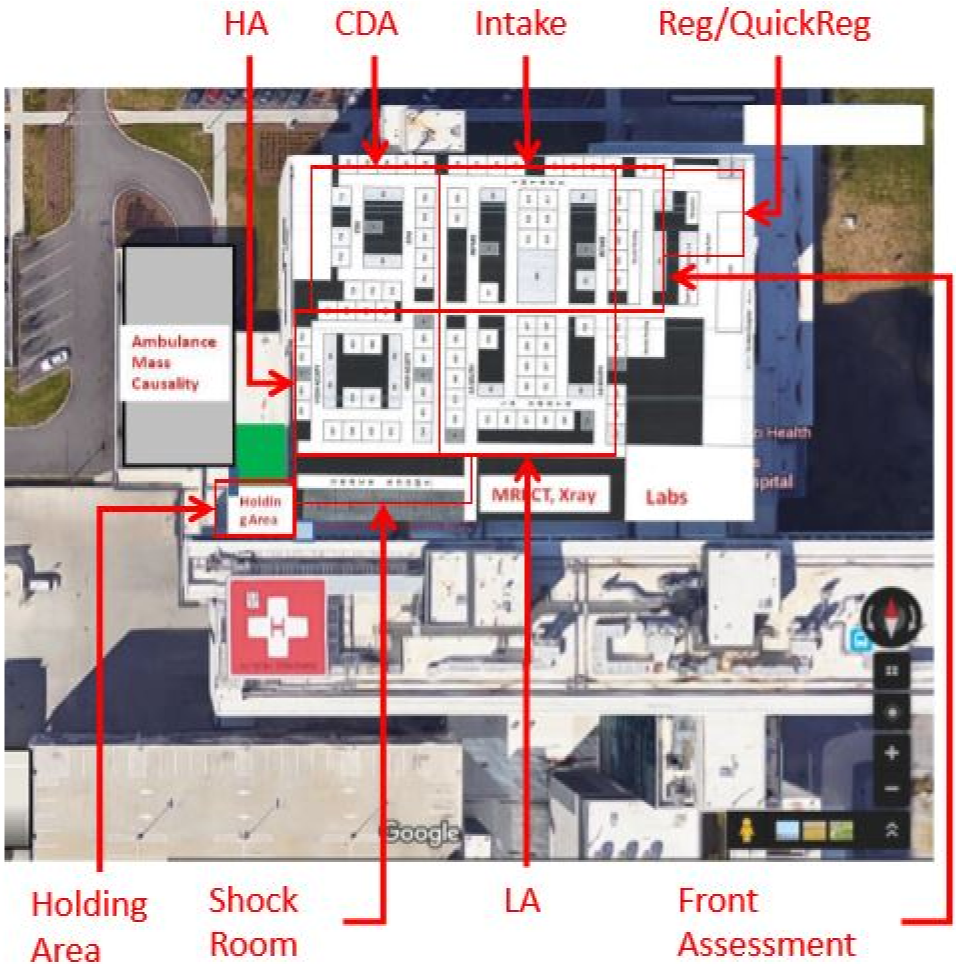


Fig. 1.3.: Eskenazi ED layout model, showing a plan view of the ED.

1.4 Thesis Objective and Outline

The thesis objective can be stated as using SE driven modeling and simulation approach for accurate representation of the patient flow process at Eskenazi ED. The patient flow process at the ED can be described as the pathway of the emergency care process from the time patients walk into the ED to the time they discharge. The discrete-event simulation model is used to estimate the key performance outcomes such as: LOS, patient throughput and resource utilization. We can summarize the thesis specific aims as follows:

The first aim is to use systems engineering methods and tools to create a verified and validated simulation model to simulate the current operation at the ED.

The second aim is to gather the required data and accurately analyze model inputs.

The third aim is to run a group of testing cases to verify and validate the model, and examine the change in the output in response to different conditions.

The forth aim is to validate the model with ED output data, a simulation expert and an ED clinician.

The fifth aim is to run a group of "what-if" scenarios for ED process improvement and resource allocation optimization.

In chapter 2, a literature overview is given on similar work. The overview shows similar case studies for using systems engineering, DES, MBSE and SysML in healthcare delivery applications; specifically the ED. The chapter also discusses some of the limitations.

Chapter 3 describes the SE approach and the implementation of the MBSE model using Cameo, and the implementation of the simulation model using Tecnomatix Plant Simulation 13.0 from Siemens. Two different simulation models were implemented: 1. Model A: is a generic "black-box" model, developed to predict high-level patient and room utilization data, and 2. Model B: is a more detailed model, which has been developed to predict human resource utilization rates for three different types of ED clinicians by applying the queuing theory. Model B is a more detailed model, which has been implemented over a longer period of time to capture the interactions between patients and human resources; therefore, we used this model for analyzing resource availability.

Chapter 4 demonstrates the verification and validation methods applied on the models, including running multiple testing cases and the results from each case.

Chapter 5 demonstrates the results and discussion, including the discussion of the resulting SysML diagrams from Cameo; and the discussion of the simulation results. Chapter five also demonstrates the results from the different "what-if" scenarios.

Chapters 6 summarizes the conclusion and future work.

1.5 Thesis Contribution

The contributions of this thesis can be summarized as follows:

1. The thesis describes a methodology for improving the healthcare delivery process at Eskenazi ED by applying a systems approach, which provided a better understanding and specification of the ED system and its requirements.

2. MBSE framework was developed to drive process simulation and inform resource allocation optimization. The MBSE framework models the four pillars of SE: requirements, structure, behavior and parametric under three layers of system's abstraction: concept, problem and solution.

3. A number of systems engineering tools were used and demonstrated in this thesis such as time studies, process modeling, systems modeling, discrete-event simulation, statistical analysis, use-case analysis, computer programming and design of experiments.

4. Two discrete-event simulation models were implemented to model the patient flow process. The simulation models provide a tool for understanding the ED behavior in the form of animation of the patient flow, and provide a decision making tool that can be used by ED stakeholders in allocating their human and treatment rooms.

5. The thesis demonstrates a better approach for verifying and validating the DES models using multiple methods and case studies.

2. LITERATURE OVERVIEW

This chapter gives an overview of similar SE and DES applications. The chapter discusses the on-going efforts on using DES in modeling the ED operation. In addition, the chapter gives an overview of systems engineering including systems engineering standard process models and modeling languages such as UML and SysML. MBSE is introduced as a novel methodology for modeling complex systems. The limitations in similar work are discussed in this chapter as well.

2.1 Modeling and Simulation of The ED Process

Modeling and simulation of the patient flow process has been an on-going and a well-studied topic over the past 40 years. Discrete-event simulation (DES) models have been used by various organizations, since the 1960s as an industrial engineering tool that helps in improving business processes. DES models helped hospitals and healthcare organization in process design, resource allocation, cost optimization, clinical assessment and scheduling (e.g. hospital) [9] [10].

DES is commonly used to represent a complex system that involve production or a service. DES is a method that uses mathematical and logical models to portray a change in the state of the system at a specific time. Simulation outputs can be interpreted by decision makers to make conclusions and recommendations. Common applications for DES are managing clients in a service center, Military system simulations and Inventory management [10]. According to (Anu Maria, 2007), there are eleven steps involved in designing any DES experiment. Those steps are flexible and may include multiple iterations and sub-stages. Those steps are: 1. Identify the problem. 2. Formulate the problem. 3. Collect real system data. 4. Formulate and develop a model. 5. Validate the model. 6. Document the model for future use. 7.

Select appropriate experiment design. 8. Establish experimental conditions for run. 9. Perform simulation runs. 10. Interpret and present results. 11. Recommend a future course for action [9].

DES applications for modeling the patient flow are characterized by having constraint resource models. These models are used for measuring the utilization of human and physical resources such as clinicians, beds and treatment rooms. DES has been used for resource management applications either to optimize the current resource allocation, or for hiring new staff. Decision makers are using DES to study the impact of the current staffing allocation on various performance metrics such as: length of stay, resource utilization, workload, waiting times and idle times. The problem of ED crowding is widely addressed in similar applications; since it is a common problem that affects the quality of emergency care and patients' satisfaction. This problem happens at most of the EDs due to: increasing patients' demand, increasing number of patients who board to the hospital (long boarding time), resource management problems (scheduling and optimization), delay in test results, under-staffing and other problems that impact the efficiency of the process [11] [12].

Multiple research surveys have come out to cover a number of clinical models for similar ED applications. Muhammet Gul, and Ali Fuat Guneri (2015) provided a comprehensive review study that covered a number of ED simulation and modeling applications, used for either assessing day-to-day ED conditions, or for modeling the readiness of ED resources and clinicians at disaster times [13]. This review paper provides a comparison of 58 different ED simulation models from different countries, which have a wide range of objectives such as: staffing analysis, resource allocation, crowding assessment, examining ED readiness at extreme conditions, and prediction of patients' demand patterns. Moreover, multiple tools have been used and implemented in those models including systems modeling, process modeling, operations research, lean, value-stream mapping, agile and others [13] [14].

DES has also proven to be a powerful decision-making tool in modeling extreme emergency care conditions. Lisa Patvivatsiri (2006) implemented a discrete-event simulation model to evaluate the readiness of the ED in the case of a bio-terrorism attack scenario, which is expected to result in a higher demand of patients visiting the ED in study. Erik W. Kolb et al. (2008) studied the problem of ED overcrowding and measured the impact of adding buffering areas by testing five different buffering concepts to reduce patients' waiting times and enhance their treatment experience. Camila Espinoza et al (2013) implemented a real-time simulation model of a public Chilean ED to predict the patient throughput for three different demand scenarios [15] [16] [12].

DES has been commonly used by engineers and hospitals' managers to optimize the allocation of ED resources: nurses, physicians, technicians, beds, equipment, rooms and other ED resources. Michael Thorwarth and Amr Arisha (2011) applied a modeling mechanism that can be used for designing an automated ED resource allocation model [17]. D.M Koster (2013) measured the effect of integrating the ED and the GP post, primarily on patients by verifying the general applicability of an existing discrete-event simulation model. Shao-Jen Weng et al (2011) used the NEDOCS (National Emergency Department Overcrowding) score as a performance metric for predicting the optimal resource allocation inside the ED. Stuart Brenner et al (2010) implemented a DES model to evaluate the optimum resource configuration, based on analyzing the amount of resources (e.g. Nurses, Technicians, Beds, etc.) over various performance measures [18] [19] [20] [21] [22].

There are other different case studies which used DES in modeling the patient flow process. Paola Facchin et al. (2010) implemented a generalized flexible ED model that can be applied to different Emergency departments regarding their size and operation. Yong-Hong Kuo et al. (2015) embraced big data methods to improve and automate the data collection process for enhancing the accuracy of the DES models. Eddy de Haas et al. (2010) implemented a comprehensive simulation model to investigate multiple modification scenarios for ED process improvement. Aaron E. Bair et al. (2009) measured the impact of inpatient boarding on the NEDOCS crowding score [23] [24] [25] [26].

2.1.1 Limitations and Gaps in ED Simulation Studies

DES has proven to be a significant system analysis tool that provides multiple solutions to hospitals and healthcare organizations; however, many limitations have been observed in similar work. Those limitations can be summarized as follows:

1. Re-usable modeling methodologies or a frameworks were not applied in similar work; although, many have created conceptual models for their studies and some used process modeling tools to conceptualize the process.

2. Difficulty of customization and generalization of these models.

3. Complexity of the healthcare delivery processes were not fully addressed.

4. Limited accuracy and scope of some of these models.

5. Limited use of verification and validation techniques.

8. Some of these models have limited prediction capabilities and limited data value [27].

2.2 Applying Systems Engineering Principles in Healthcare Delivery

Complexity and high cost of care brought the need of understanding the healthcare system as a whole, as well as understanding the function and the behavior of the modeled system. According to William B. Rouse (2000), there are still barriers to achieving success in implementing the systems approach in healthcare delivery [28]. These barriers are due to: 1. Extensive data requirements. 2. Laws and regulations that govern healthcare organizations and stakeholders. 3. The ability of all providers in the healthcare domain to think analytically in a systems thinking way. 4. Lack of documentation.

The author suggested in his article to consider the healthcare system in the United States as a "complex adaptive system", not a system that follows a hierarchical decomposition; therefore, we need to consider that the dynamic properties of the system change over time [28].

Sloan Elliot (2008) summarized a group of systems engineering efforts that adopt both quantitative and qualitative methods; in order to support the systems of systems (SoS) practice, showing two different exploratory cases in UK and USA that are used to assess quality of healthcare delivery [8].

Levis (1993) defined an analytical process for carrying out the discrete-event simulation of the systems' functions by mapping its functional architecture with its physical one. The process starts from the operational concept of the system, which considered a representation of what the system is, including its requirements and interfaces; then decomposing the system into functional and physical architectures that describe the functions the system shall perform and the physical resources available to perform those functions. Both functional and physical architectures are mapped to carry-out discrete-event simulation of the system functions. Figure 2.1 shows the architecture breakdown according to Levis (1993) [29].

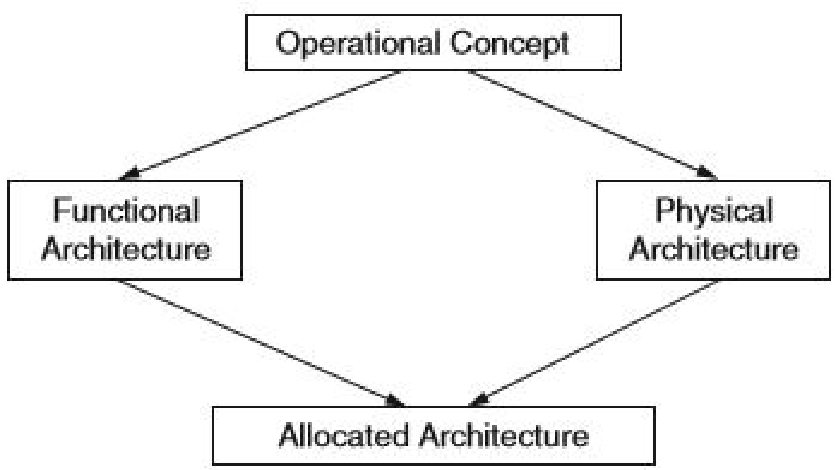


Fig. 2.1.: Development of three system architectures from the operational concept of the system according to Levis (1993) [29].

2.3 MBSE As a Novel Approach

Model-based systems engineering (MBSE) is defined by INCOSE as "systems engineering using models". According to Holt and Perry (2008), MBSE is "an approach to releasing successful systems that is driven by a model that comprises a coherent and consistent set of representations that reflect multiple viewpoints of the system [1]."

MBSE can also be described as the use of models to implement the systems engineering approach. MBSE has evolved as a novel methodology to reduce the application of traditional text-based systems engineering, which makes it easier to access the information. It also aids in performing traceability and perform change management [30] [31]. MBSE uses a single point of reference to which design criteria can be met. This results in an abstraction of systems of interested (SOI), which results in multiple benefits to all stakeholders. Those benefits are:

1. Reduced Risks: Modeling results in an early and on-going validation process through simulation, modeling and analysis.

2. Improved Communication: Modeling enhances communication among all systems stakeholders and among engineering teams, where communication happens through the models.

3. Improved Quality: Modeling enables the early identification of requirements' issues before moving to testing and integration.

4. Increased Productivity: Reuse of existing models improve the impact of analyzing requirements and evaluating changes in design.

MBSE methodologies and tools have been used to support the discipline of systems engineering by many organizations [32]. Some examples of standard MBSE methodologies are:

1. Object-Oriented Systems Engineering Methodology (OOSEM). OOSEM has been evolved in the mid 1990's by the systems and software consortium and Lockheed Martin Corporation. The methodology utilizes a top-down modeling approach that

uses SysML language to support multiple system activities [33]. Figure 2.2 shows both unique and common methods and tools applied using the OOSEM approach [32].

2. IBM: Telelogic Harmony Systems Engineering.
3. Vitech: Model-Based Systems Engineering Methodology.

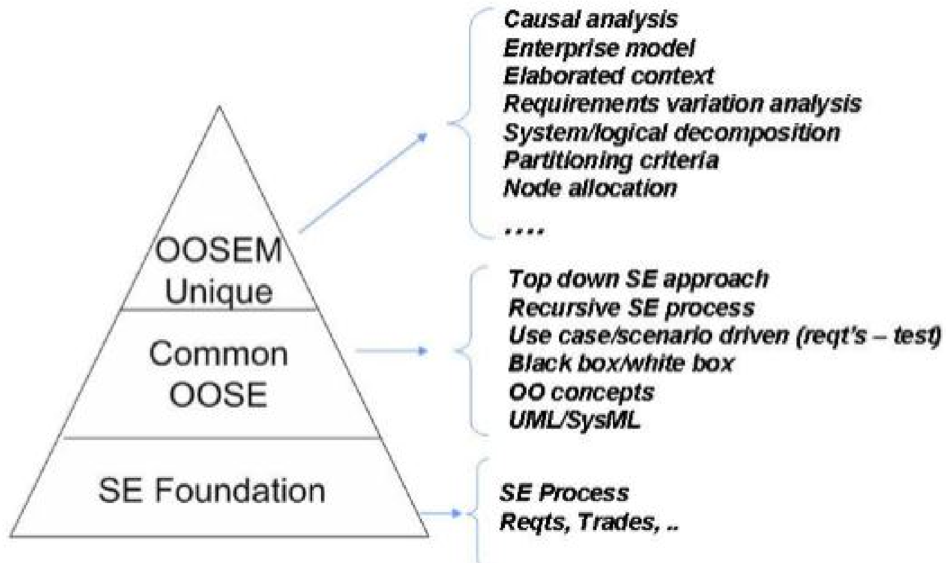


Fig. 2.2.: Demonstrates OOSEM foundation, common and unique techniques [32].

The Unified Modeling Language (UML) is one of the common techniques applied by OOSEM, and maintained by the Object Management Group (OMG). OMG has created the System Modeling Language, namely SysML; in order to support modeling of complex systems that involve multiple abstraction layers and interacting entities [33].

MBSE provides systems engineers with a framework to integrate multiple tools, track changes in the design, and provide re-usability of data and information through the life-cycle process. According to OOSEM, a modeling framework is defined as "conventions, principles and practices for the description of systems established within a specific domain of application and/or community of stakeholders". INCOSE UK provided a modeling representation of MBSE concepts using SysML block definition diagram (BDD) as shown in Figure 2.3. The figure is implemented to specify MBSE concepts, which are: 1. Model, which is a representation of the system, 2. System of Interest, covers a problem or the overall project, 3. Representation, which is a system's description that reflects a particular viewpoint, 4. Viewpoint, represents the purpose of the system's representation, 5. Quality Criterion, which is a quality measure of the model., 6. Concern, represents a stakeholders' concern addressed by a viewpoint, and 7. Stakeholders, represent the group of people concerned about the system of interest [34].

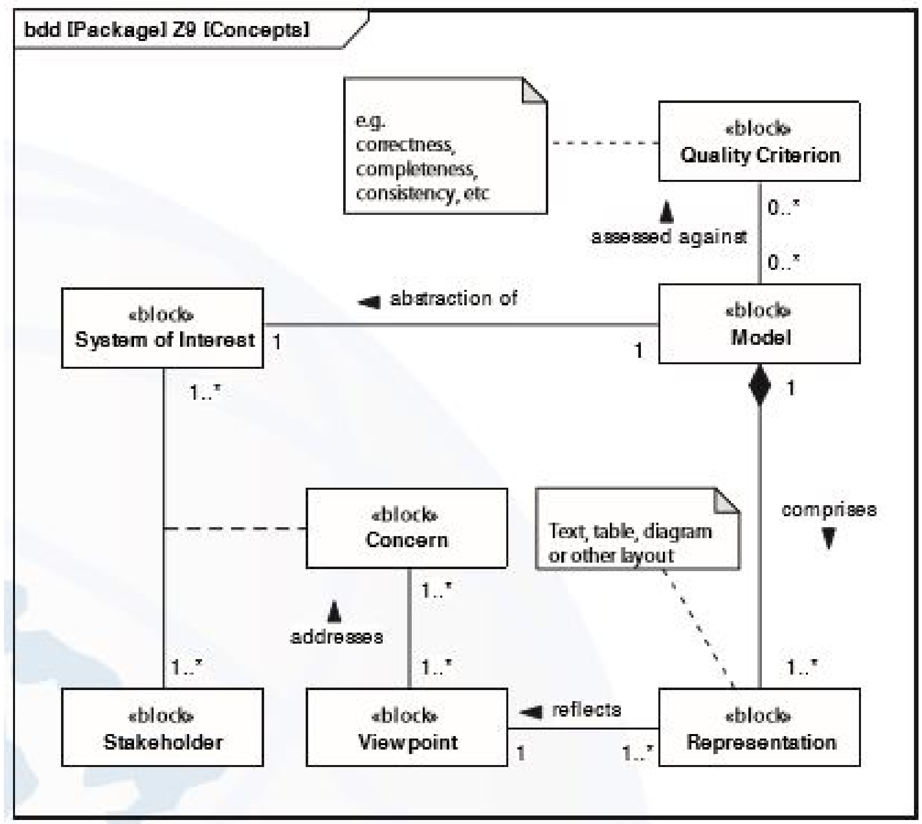


Fig. 2.3.: MBSE concepts as defined by INCOSE UK [34].

SysML offers multiple diagrams to model the views of the system and perform traceability. These diagrams are all connected to represent system's layers of abstraction. SysML is also used in clarifying system's inputs, outputs, constraints, assumptions and simplifications; all which are essential for a successful simulation study.

SysML is commonly applied in industries such as aerospace, defense and information technology; however, very few researchers have considered applying SysML to model the ED process. Ola G. Batarseh et al (2013) proposed SysML as a replacement for traditional process documentation; in order to facilitate communication, verification and validation between all stakeholders involved in the modeling process. The author reported that such approach helped in getting the clinicians involved in the modeling process by transferring a considerable amount of information using a number of SysML activity diagrams. The author reported that such modeling activity improved the decision making process with minimum risks and less modeling errors [35].

3. METHODOLOGY

This chapter demonstrates the detailed implementation methodology of Eskenazi ED systems model using MBSE and DES. First, the chapter describes the underlying theory behind each. Second, the chapter describes the approach and tools used for modeling the ED work-flow using systems modeling and DES methods. Finally, it describes the implementation process of the SysML model using Cameo and the DES model using Tecnomatix.

3.1 Theory

A model is considered as an abstraction of the system, since it first starts as a simple representation, and then it develops to define the whole system including its mathematical and physical details. Each modeling technique is considered as a language that answers a group of questions about the system. SysML is applied to support modeling the behavior of the system, including modeling activity and state machine diagrams to model a given process. SysML also supports parametric and structural modeling using SysML block definition diagrams and internal block diagrams, where both are used to model the system's components. Modeling system requirements is also supported by SysML, including modeling stakeholder needs and use-cases, and mapping those into technical and logical requirements [36].

Simulation is considered as an important tool for modeling the performance of any given system. Since world war II, computer simulations have been applied to estimate the performance metrics of a system and conduct sensitivity analysis. Simulation model building is not considered an easy task, since it requires the application of both critical thinking and engineering concepts. Discrete-event simulation models a discrete system, which has its state changes with time at discrete-points. A state is a collection of attributes, which represent the entities of the system. Events, attributes, entities and activities are all considered the components of DES [36].

DES is a dynamic stochastic simulation, where time is considered as a significant variable. Monte Carlo simulation is another common type of stochastic simulation, which uses sampling of random variables between zero and one. Figure 3.2 shows the taxonomy of different types of system models including DES and Monte Carlo simulation [36].

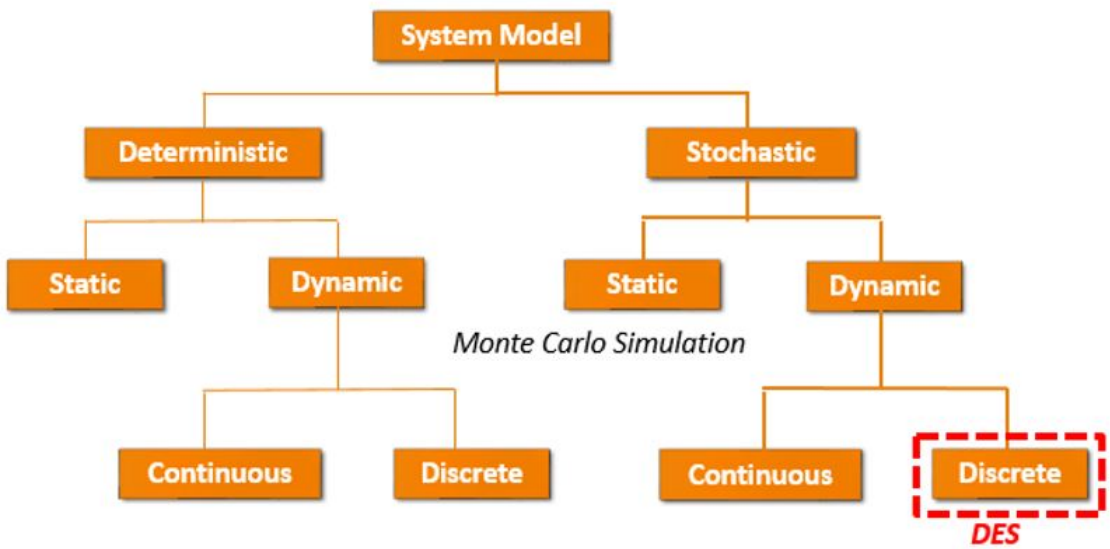


Fig. 3.1.: Models taxonomy showing DES as a stochastic and dynamic type of simulation [36].

DES uses probability theory including conditional probability theory to determine the likelihood of an event (X) in occurrence of another event (Y). The conditional probability theory is defined by:

$$Pr\{X \mid Y\} = \frac{Pr\{X \cap Y\}}{Pr\{Y\}} \tag{3.1}$$

DES uses continuous distribution functions, which generate a number of random variables. Four different distribution functions were used in our application: Uniform, Gamma, Triangular and Lognorm.

3.2 MBSE Approach

The proposed MBSE framework is used to model the ED work-flow and capture multiple system views all the way from stakeholder needs to solution under three layers of abstraction: concept, problem and solution; and by modeling the four pillars of systems engineering: structure, behavior, parametric and requirements. The general methodology is driven from the "Magic Grid" developed by NoMagic Inc., which is a generic grid developed by the software company to model complex systems with multiple layers of abstraction using SysML language. In this section, the MBSE modeling framework for the ED is generally described. The MBSE framework was implemented using Cameo Systems Modeler and other modeling tools such as microsoft visio and power point [37].

3.2.1 MBSE Framework

As mentioned earlier, MBSE framework is developed to allow a comprehensive representation of Eskenazi Emergency department operation all the way from requirements to simulation of the ED process. Information and data from these models feed into the simulation software. A specific pathway has been defined in the modeling framework through the MBSE diagrams. Resulting MBSE views are used to derive process simulation and inform resource allocation optimization [38] [35].

A group of SysML diagrams are developed within the modeling framework and described in terms of: structure, parametric, requirements, and behavior. SysML has nine different types of standard diagrams as shown in the Figure 3.3. Eight diagrams out of the nine were used in our application. SysML sequence diagram was not used. SysML Package diagram was constructed to describe the model organization in a group of packages, and is not included in the framework. Figure 3.3 shows the modeling framework, which starts from the identification of stakeholder needs and requirements, followed by use-case analysis. Selected use-cases provided a high-level functional analysis of the ED work-flow and allowed us to develop a group of functional activity diagrams to analyze the process. System's measures of effectiveness were identified and logical requirements were put together to define the ED requirements including patient, staffing, process and others requirements. An architecture block digram was developed for the ED and system's structure was put together to decompose the ED system into different components. Tecnomatix model was built to estimate the key performance measures of the system and optimize resource allocation [39] [38] [40].

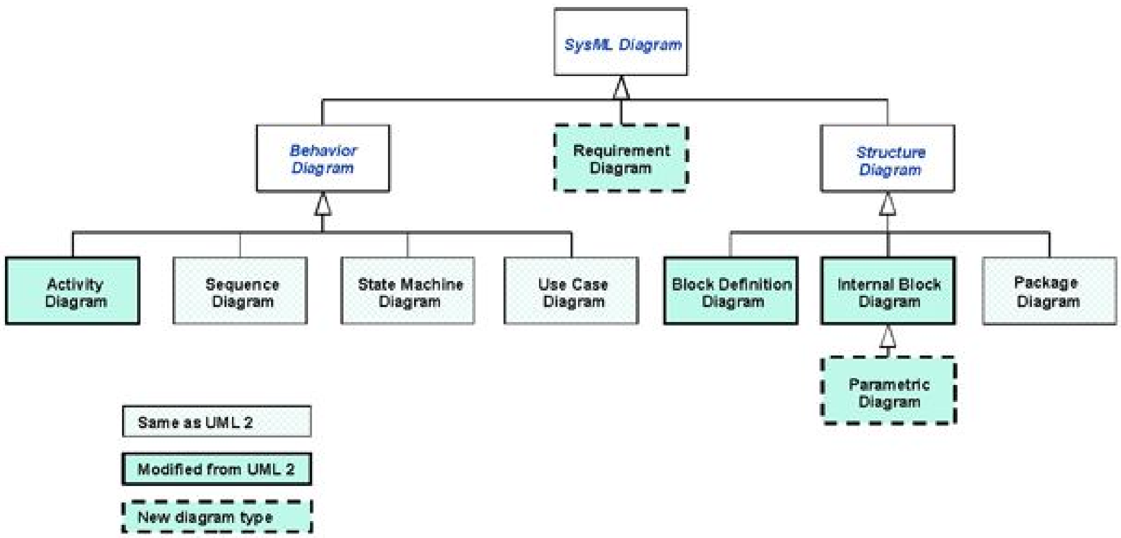


Fig. 3.2.: Classification of SysML diagrams [40].

3.3 Implementation

This section describes the implementation process of the SysML model using Cameo, and the simulation model using Tecnomatix.

3.3.1 MBSE Model Using Cameo

Eight different types of SysML diagrams were implemented using Cameo. Those diagrams are:

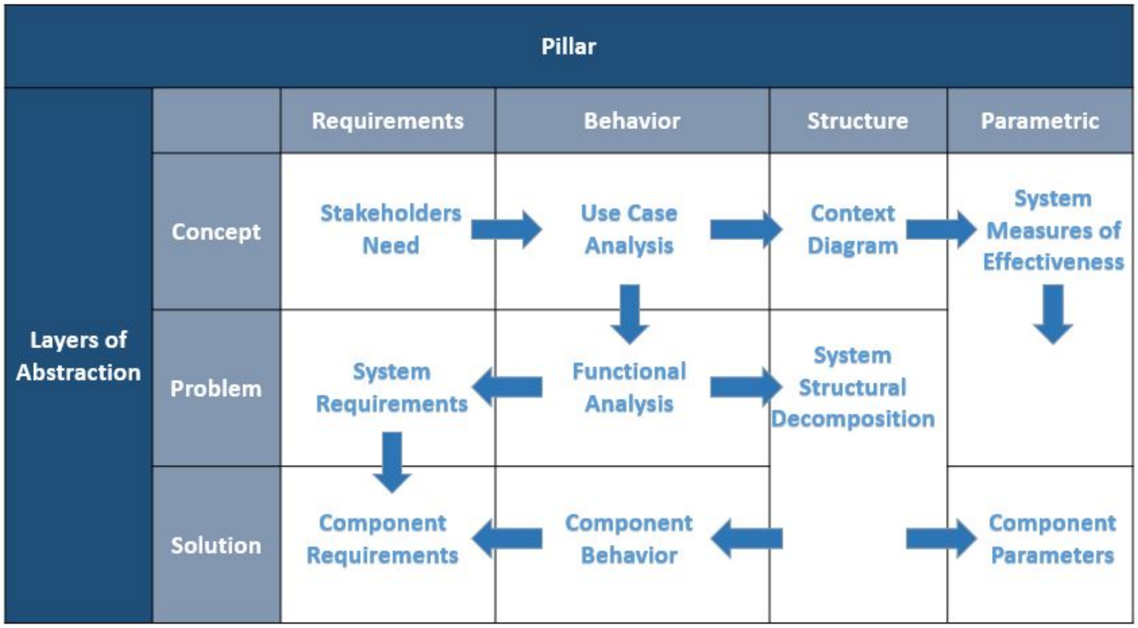


Fig. 3.3.: ED modeling framework pathway from user needs to solution.

1. Requirement Diagram: Requirement diagram is used to specify conditions and functions that shall be satisfied. The first requirement diagram was implemented in the form of IPO (Input Process-Output) diagram, which was developed by INCOSE for the design definition process in general. The other requirement diagram was developed using Cameo; where basic staffing, process and input requirements are derived. Both diagrams are shown in the framework in Figure 3.4 as (i) and (v).

2. Use-case Diagram: Developed to define the high-level system function and use-cases. It is shown in Figure 3.4 as (II).

3. Internal Block Diagram (IBD): Developed in the form of a context diagram for the ED, which shows a high level Black Box understanding of the modeled system of interest. It is shown in Figure 3.4 as (III).

4. Parametric Diagram: Developed to define the measures of effectiveness (MOEs) of the ED system. It is shown in Figure 3.4 as (IV) and (IX).

5. Activity Diagram: Activity diagrams were developed to model the work-flow of patients, including treatment unit sub-flow. It is shown in Figure 3.4 as (VI).

6. Block Definition Diagram (BDD): The BDD diagram is developed to describe how the system of interest (ED Work-flow model) is put together. It defines each of the blocks in terms of structure and behavior features and relationships. It is shown in Figure 3.4 as (VII).

7. State Machine (STM) Diagram: STM diagram is developed to define a state dependent behavior of a block through its life cycle. The STM diagram acts as a blueprint of the simulation model that shows all factors and elements that define the patient work-flow behavior in the simulation and in the real ED system. It is shown in Figure 3.4 as (VIII) [39].

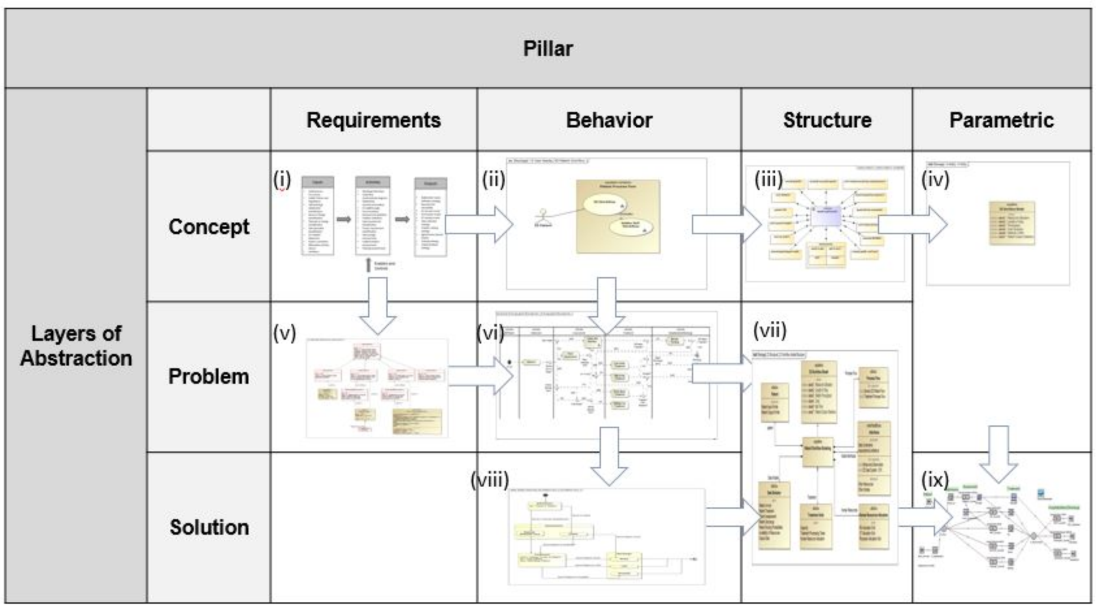


Fig. 3.4.: ED system views contained in the modeling framework.

Figure 3.5 shows the flow path between the different MBSE diagrams from stakeholder needs to the Tecnomatix model. Each of the highlighted MBSE diagrams will be discussed separately in the results section.

Cameo Systems modeler is the major software platform used in our application to design the MBSE architecture of the ED using multiple SysML views. It is considered one of the popular SysML tools in the market, widely regarded as the most standard

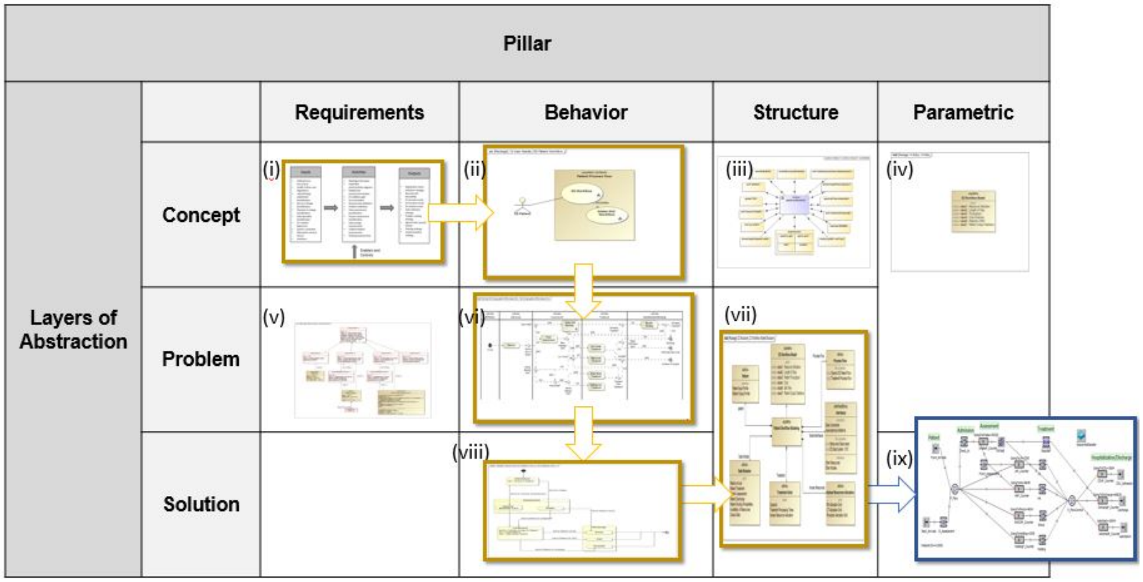


Fig. 3.5.: Pathway between MBSE views from stakeholder needs to simulation. Five different diagrams were used to derive the ED process model and inform resource allocation optimization.

tool that design for customization to satisfy customer needs. It also supports system's integration, specification, analysis, verification and validation.

Figure 3.6 shows the modeling framework interface as implemented in Cameo. SysML version used in our application is 1.4. Diagrams supported by SysML language include those similar to UML 2.0 diagrams, and others have been modified from it. In addition to the eight SysML diagrams used in our work, a content diagram is also used which can be found in the Cameo expert mode. This diagram is used to provide a window for each package to upload and contain all related diagrams and files.

SE Tools and Data

The MBSE driven approach required using different types of tools including SE tools, process modeling and computational tools. Each tool has its own usage and ED application. SE tools are used to capture stakeholder needs including data needs

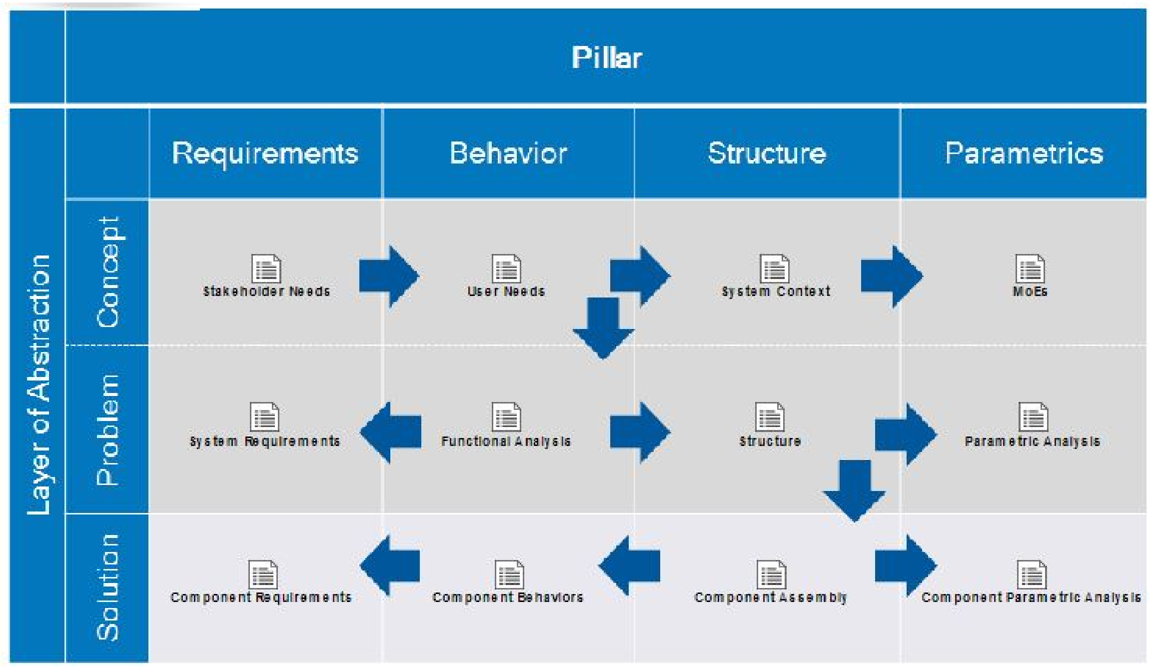


Fig. 3.6.: MBSE framework as implemented in Cameo.

and requirements. Process modeling tools are used to implement those requirements and provide a visual representation of the ED process. Computational tools provide a platform to analyze the behavioral models and perform various predictions. Data is a key element to our simulation study, and is obtained from multiple sources: 1. ED data systems (Picasso and Epic), 2. Interviews with key ED stakeholders, 3. process documents, and 4. direct observation of patient flow. Data collection tools are used such as time studies and data templates. Time studies were conducted inside ED using physical observation method. Interns and students used a data protocol and a formal data collection table to collect human resource time-spans and patients' processing times. Table 3.1 shows Data categories and sources.

3.3.2 DES Model Using Tecnomatix

DES approach is applied to develop a simulation model for the ED process to estimate the performance measures of the ED such as LOS, patient throughput and

Table 3.1: Summary of data used for developing the models

Category	**Source**	**Description**
Operational Data	ED Databases	Work-flow Data
Patient Data	ED Databases	Arrivals' Timestamps
Staffing Logs	Process documents and Interviews	Staffing Schedules
Direct Observation	Manual Data Recording	Processing Time Data

human resources utilization. Two simulation models were developed as mentioned earlier: 1. Model A: is a time-in-motion black-box model developed to evaluate and predict the high-level room data, and 2. Model B: is a model developed to predict human resource utilization inside the main treatment units for three different types of ED clinicians by applying a queuing approach.

This section describes the development of the DES model in detail using the following approach: 1. ED process review, 2. data collection, 3. input data analysis, 4. computerized model development, 5. model verification, 6. model validation, and 7. output analysis and interpretation. Steps from 1 to 4 are demonstrated in this chapter. Steps 5 and 6 are demonstrated in chapter 4 and step 7 is demonstrated in chapter 5.

Tecnomatix Plant Simulation 13.0 is the main software tool used to implement the ED simulation model. It supports a wide range of functionalities for modeling healthcare facilities and operations. Tecnomatix has been used in multiple healthcare applications and digital hospital planning case-studies. In our models, most Plant Simulation features are used to design a successful ED process simulation application including: models, sub-models, user interfaces, information flow objects, entities, resources, methods, material flow objects and animation of the process. Moreover, a group of powerful data and statistical analysis tools are used such as: Experiment Manager, Genetic algorithm and Sequential Sampler. These tools are used to help in performing data fitting, sensitivity analysis, and resources scheduling. In addition, charts and graphics are used in our application to provide better output reporting and better visibility while the simulation is running.

The key DES concepts represented by Tecnomatix are entities, attributes, variables, resources and queues. Entities are the dynamic objects flowing through the simulation model from source to drain and their state might change at any time during the simulation. In our case, entities represent patients visiting the ED. Model attributes are the characteristics of the model that define model objects in the form of patients attributes such as arrival times and patients processing times, and resource attributes such as staffing schedules and the amount of resources. Model variables represent the characteristics of the system. Tecnomatix model is adjusted to track some variables such as queuing time, length of stay, resource utilization and others. Tecnomatix enables users to create and track his own variables according to their need. Model resources represent both physical and human resources. In our application, resources are used to define rooms, pods, physicians, nurses, and care technicians. Resources utilization and availability is considered as an important variable in the model, which can define the overall performance of the system and impacts other variables such as LOS and waiting times.

A queue represents a place where patients wait until a resource becomes available to serve them. The constructed DES model for the ED is considered as a queuing model, where resource utilization and capacity highly impact the time patients wait inside the queue; and thereby, impact the overall process efficiency. A patient waiting in a queue is modeled in two ways using Tecnomatix. The patient stays inside the queue either in the form of waiting inside a buffering (waiting) area or waiting inside his treatment room. ED buffering areas and patients' rooms have an assigned capacity [41].

ED Process Review

The ED in study is a mid-size ED, with six-trauma levels. Unlike other EDs, the ED operates based on a queuing system, where patients are assigned to the first available room in case the room is equipped with what they need for treatment. Figure 3.7 shows the generic patient work-flow model implemented using Microsoft Visio. This model is considered as a conceptual model for the patient flow process, which is validated by an ED physician. The model represents the pathway of the ED patient from arrival to discharge by capturing the main decision points and activities. As shown in Figure 3.7, there are two arrival modes: Front and Back registration. The front registration represents patients who are arriving by bus, walking, or with a personal car. The workflow initiated at the front registration is defined as the "Front Registration". The Front registration desk does a rapid sort of the incoming patients and sends them to appropriate acuity level within the ED. The Back registration represents patients arriving via ambulance or police car. The workflow initiated at the back registration is defined as the "Back Registration". Most of these patients are considered as "High Acuity" patients. We can summarize the ED patient generic workflow process in the following five stages using the flow model shown in Figure 3.7: 1. Arrival, 2. Admission, 3. Assessment, 4. Treatment, and 5. Discharge. There are five main treatment units inside the ED, demonstrated by the different levels of acuity. The ED patient shall be admitted to at least one of them during their visit. Those units are:

1. Intake Area: Intake serves patients with minor injuries who come to the ED and leave immediately after their treatment. Approximately 70% of patients who visit Intake leave without being sent to any other unit; however, a small percentage go to Low Acuity area if more treatment is needed. Intake has seven pods including a fast-track one. Each pod has three rooms and one nurse assigned. Each pod can accommodate a maximum of three patients.

2. Low Acuity Area (LA): LA serves patients with low acuity illness who are required to stay inside the ED for a long time until their condition becomes stable. Those patients usually occupy the room on an average of 4-5 hours and sometimes for more than one day. Most of LA patients discharge the ED directly; however, some are transfered to either Shock room or HA unit. LA has four pods, and each pod has six rooms and one nurse assigned.

3. High Acuity Area (HA): HA serves patients with high acuity illness who need to stay inside the ED for a long period of time on an average of six hours. More than 50 percent of HA patients are admitted to the hospital after receiving treatment. HA has a total of four pods and 16 rooms.

4. Shock Room: Patients who need immediate rescue are treated inside the Shock room. After being stabilized, Shock patients might get admitted to either LA, HA or Holding unit, in order to complete their treatment. The majority Shock patients are admitted to the hospital after leaving the ED.

5. Holding Unit: where incarcerated patients are treated and held until they leave the ED or go to the Shock room to complete their treatment. Holding patients account for 3% of the overall ED patients.

Data Collection

Data is collected from five different sources: 1. Interviews with ED stakeholders, 2. Observation of emergency patients, staff and process, 3. Staffing schedule data sheets, and 4. Datasets of patient arrivals from the EMR system (Picasso and STAR). Interviews were conducted with two physicians, ED nurse-in-charge, registered nurses, one technician, one environmental services, three radiologists, and one with Director of laboratory services at the ED. The type of data and information collected pertains to requirements, ED processes, resources, duties, tasks, constraints and challenges at ED. Interviews served to instruct the SysML based model. The data is also used for

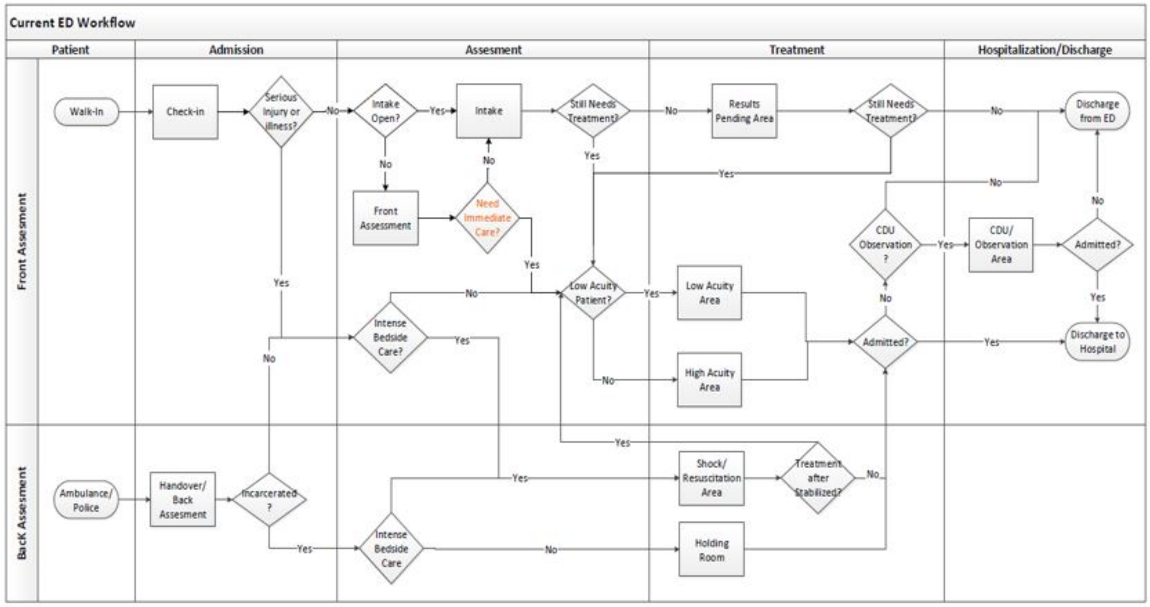


Fig. 3.7.: Generic patient work-flow model in Microsoft Visio.

ongoing work to create more detailed models and analysis. In addition to process information, ED stakeholders helped in validation of the data.

A time study of resource utilization in providing patient care is conducted. Observations were carried out over a 1.5-month period inside the different ED units namely, registration desk, front assessment area, Intake, Low Acuity, High Acuity, and Shock room. Timestamps were recorded for care technicians (CT), registered nurses (RN) and attending physicians when they were directly involved in providing care to a patient in a room under observation. Observations were performed as per the observation protocol. The data was captured in observation data grid (shown in the appendices). The grid specifically records the timestamps of patients assigned to specific ED unit rooms, resources entering and leaving the patient room and discharge time. Observation captured resource utilization time, and is not concerned with the actual care details provided by the resource. The data grid also captures room occupied, assigned RN patient time, assigned physician patient time, assigned CT patient time, discharge location and discharge time, and patient transfers from one treatment unit to a different treatment unit. Patient routing data was collected with the help of ED nurses. Resource rate utilization was estimated by total resource time for providing care to the patient divided by total patient time in room. Collected data were analyzed for data fitting and distribution. Data was used to configure the simulation parameters such as routing probabilities and overall patient stay times. 16 ED observations were conducted inside the four treatment units (Intake, LA, HA and Shock) room by one medical intern and two engineering students. Two observation sessions were conducted at the patient registration desk. The first one was on Tuesday at the morning shift and the second was on Saturday at the afternoon shift, where a total of 23 patients were followed. In most cases, the observation period of eight hours enabled the tracking of the patient flow from registration to discharge. There were 13.59 percent of patients who were not completely followed because they were discharged beyond the observation time period. Situations were observations lasted more than 8 hours were for patients transferred to LA or HA units. A total of 103 patient observations were conducted of which 78 patients were seen in Intake, 11 patients for LA, eight patients for HA, and six patients for shock room. All observations were made as per the HIPAA compliance guidelines [42]. Majority of the observations were carried out by medical students, which allowed them to observe and record resource utilization from within the patient room. Inputs defined in the grid are:

1. Time Patient occupies Intake Room: Time patient starts occupying his treatment room (Physically).

2. Time CT enters patient room: Time CT starts treating the patient inside his room.

3. Time CT exits patient room: Time CT exits patient room. The CT might enter and exit a patient's room one or two times per visit.

4. Time Nurse enters patient room: Time registered nurse starts serving a patient in his room.

5. Time Nurse exits patient room: Time registered nurse exits a patient's room. The Nurse might enter and exit a patient's room multiple times, up to 6 times for each patient (maximum recorded).

4. Time Physician enters a patient room: Time attending Physician starts treating a patient in his room.

5. Time Physician exits a patient room: Time attending Physician exits a patient room. Physicians might enter and exit a patient's room up to five times.

6. Time Patient discharges the room: Time stamp patients leaves his treatment room (physically) either to get discharged or transfered to another unit.

7. Room Occupied: Room Number occupied by patient.

8. Assigned RN: Name of assigned RN.

9. Assigned Physician: Name of assigned physician.

10. Assigned CT: Name of assigned CT.

11. Discharge Location: Patient Discharging location after treatment.

Staffing grid charts were obtained, which provided seven days staffing details for nurses, technicians and attending physicians for ED units. The charts were used to configure the resource availability and room availability schedules. On day-to-day basis, there are resource availability changes due to ED priorities, presence of student nurses and physicians and absence of some staff members. However, for our simulation model purpose, such changes are not taken into account. Each unit is broken down into pods. Each pod has two or more rooms. Nurses are assigned to pods or a fixed number of patients. Physicians have shifts assignments that are managed independent of the nursing grid. Physician grid has changes that are more frequent and is managed actively. For the current work, a specific physician grid was considered representative of physician staffing. Physicians might be assigned to more than one treatment unit at a time. Manipulating the grid data provides one way to verify the model, such that treatment units in the model are divided into pods and patient rooms, where clinicians serve patients according to their grid assignments and shift times. To conduct what-if analysis, simulations were carried to observe changes in response to modification of the resource grid.

Table 3.2 shows the CTs grid. It shows the number of CTs assigned to each unit over six different shifts defined by the ED. The number could be zero, one or two CTs at each shift. Sample from the nursing and physicians' grids are shown in the appendix section. Nurses and CTs have the same exact shift durations, while physicians have different shifts durations and assignments. Physicians might be assigned to more than one treatment unit at a time. Nurses are assigned to pods, which represents a specific number of rooms or patients at each unit. Exact nurse to patient ratios will be demonstrated in the next section.

Table 3.2: ED Care Technicians' Grid

Treatment Unit	**7a 11a**	**11a 3p**	**3p 7p**	**7p 11p**	**11p 3a**	**3a 7a**
Intake	1	2	2	2	1	1
LA	0	1	1	1	1	0
HA	1	2	2	2	1	1
Shock	0	0	0	0	0	0

For all remaining data, we relied on data extracted from the ED system either from Picasso or Epic, especially for the operational and patient data with the help of a data specialist from the ED. Data collected from the ED system were cleaned and analyzed using multiple software tools, in order to fit our modeling need. A summary of data inputs including data analysis is demonstrated in the next section.

Model Input Data Analysis

Simulation model inputs are: 1. Arrival timestamps, 2. Processing time data, 3. Routing probabilities, 4. Room data, and 5. Staffing grids. Patient arrival dataset from 2014 to 2016 was obtained from Picasso. Arrival dataset was cleaned and analyzed using Matlab and Excel. A total of 281,562 patients visited the ED from Jan 2014 to Dec 2016. Patient arrival data was provided as number of arrivals in 10 min intervals. Figure 3.8 plots the number of patients arriving per hour over 0-24 hours. Figure 3.8 consists of multiple plots, one for each day of the week. Each data point on the plot is a mean value over one year time period with corresponding confidence interval. The arrival pattern seen in the plot is observed to be very similar to the ones found in the literature for similar applications [12]. Arrivals data was converted from the original data provided in 10-min interval to individual patient timestamps. A random generator was used to generate specific time points for each of the patients arriving at each of the 10-min intervals. Data used in the DES model were analyzed, and their distribution characteristics were defined using Tecnomatix. Distribution functions used are gamma, log-normal, triangular and constant distributions. The distribution functions and their corresponding parameters are obtained by fitting the observation datasets to various distribution functions. We used log-normal, triangular and gamma distributions for processing time data, and average distribution percentages for patient routing data. Anderson-darling (AD) test was used to assess the fitness of each distribution. AD statistic values were estimated directly using Tecnomatix. The resulting values from the AD statistical test were compared with a predefined level of significance of 2.5 percent to select the best distribution function.

ED data were collected and analyzed through many iterations by our research team. Finally, data collected manually through observation were identified to be the major source for model's processing time data. Observation allowed us to collect the exact data required by our models to follow a model-based approach. In addition, observation Sessions were conducted over 1.5 month and over 120 hours, which is similar or more than what observed the literature for similar time studies [13]. Data were recorded by the observer in the data template using a computer or an I-Pad as shown in Figure 3.9. Timestamps recorded for each type of human resource were gathered and analyzed individually into a group of probability distribution function as discussed earlier.

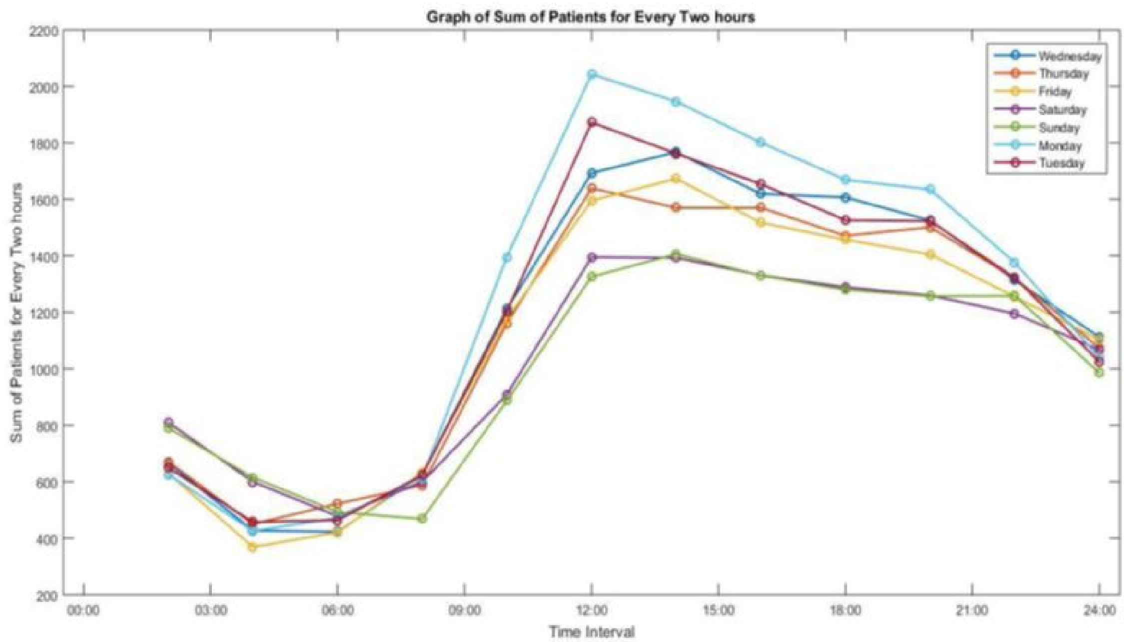
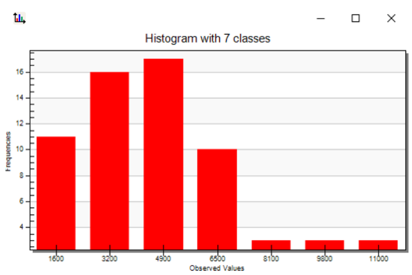


Fig. 3.8.: ED arrivals pattern over the day for all days of the week.

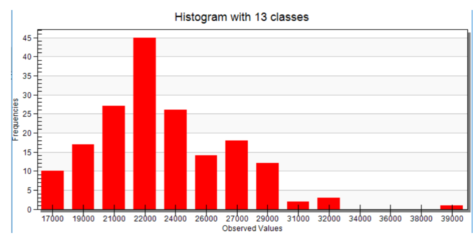
	A	B	C	D	E	F	G	H	I
1	Data Source								
2		Arrival to Room	CT Treatment				Nursing Treatment		
3	Data (Intake)	Time Patient occupies the Room	Time CT enters patient room	Time CT exits patient room	Time CT enters patient room (2)	Time CT exits the room (2)	Time Nurse enters patient room	Time Nurse exits patient room	
4	**1**	815					848	852	240
5	**2**	1005					1008	1010	120
6	**3**	1119	1129	1136			1139	1146	420
7	**4**	1149					1151	1157	360
8	**5**	1222					1237	1239	120

Fig. 3.9.: Patients' timestamps recorded in the time study template during observation.

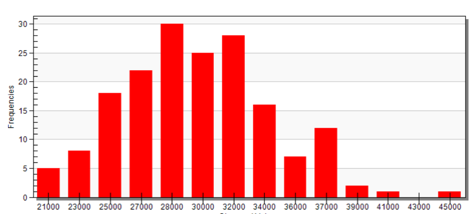
Data collected through ED observation were analyzed two times, once for the time-in-motion model (model A), and second for the resource model (model B). Figure 3.10 shows histograms of fitted data for: Intake, LA, HA and Shock room processing times for Model A. X-axis represents the frequency, and Y-axis represents the observed processing time values in seconds. Figure 3.11 shows the process sequence of data fitting using data fit tool for Intake processing time in Model A. First, processing time data are input to a table file in seconds. Then, the level of statistical significance and number of classes are identified, a histogram for the data is created and data are fitted using identified distribution functions. Reports that show all fitting results are automatically generated after that. Results of data fitting are shown in the appendices.



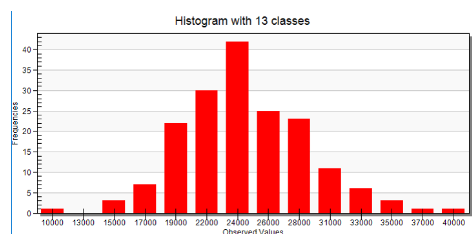
(a) Intake processing times histogram.



(b) LA processing times histogram.



(c) HA processing times histogram.

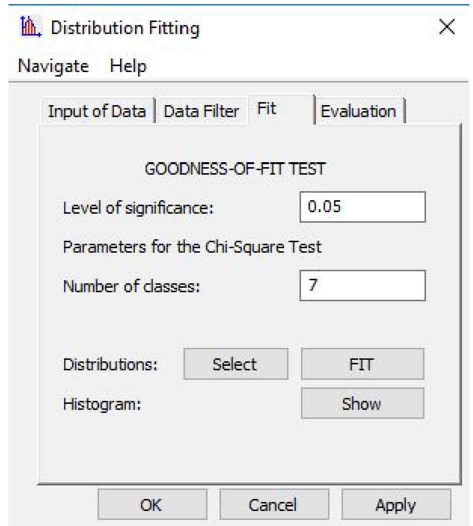


(d) Shock room processing times histogram.

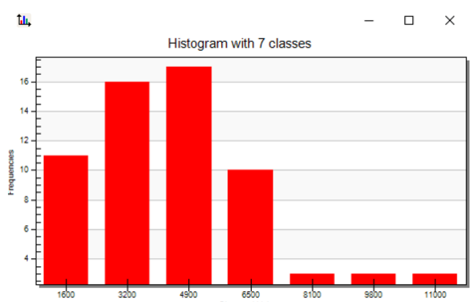
Fig. 3.10.: Histograms of fitted processing time data.

	real 1
1	8280,0000
2	3420,0000
3	5640,0000
4	6540,0000
5	7380,0000
6	5340,0000
7	8100,0000
8	10620,0000
9	8460,0000
10	7980,0000
11	9300,0000
12	10020,0000
13	12960,0000
14	7320,0000
15	3120,0000

(a) Processing times inputs in seconds.



(b) Selecting fitting parameters.



(c) Intake processing times histogram.

	string 0	real 1
string	parameter	value
1	sample size	63.00
2	min-value	1620.00
3	max-value	13020.00
4	mean	5623.83
5	mode	3420.00
6	standard deviation	2649.35
7	variance	7019033.53
8	lower quartile	3630.00
9	mid quartile (median)	5280.00
10	upper quartile	6540.00
11	skewness	0.95
12	kurtosis	0.49
13	coefficient of variation	0.47

(d) Discriptive statistics on fitted data.

Fig. 3.11.: Data fitting sequence using "DataFit" in Tecnomatix.

Nursing, CTs and physicians grids were analyzed and input manually to the model using scheduling and resourcing tools in Tecnomatix. In addition, patient room availability was defined in the model.

Table 3.3 lists the inputs namely processing times, arrivals data for admissions, routing probabilities for patients transfer, and staffing grids for the number of rooms. Table 3.4 depicts the individual processing times for clinicians. All times are in seconds except for Check-in processing times which are in minutes. Admission routing probability numbers are inserted in the following order: Intake, LA, HA, Shock room and Holding unit. Check-in processing time is assumed to be the time patient spends from admission to room, and is modeled as a single constant value for each patient type. Check-in times are inserted in the following order: Intake, LA, HA, Shock room and Holding unit.

Table 3.5 shows the statistical analysis on human resources time-spans with patients. Data were collected through observation. We can observe that the standard deviation is relatively higher for Shock room data and much lower for Intake data, which explains the variability of treatment time for Shock patients compared to Intake patients. It is also observed that patients have more face time with nurses at Shock room compared to the other units. All data in Table 3.5 are in minutes.

Computerized Model Development

ED conceptual model was captured in Tecnomatix Plant Simulation 13.0 software to carry out discrete-event simulation of the ED process. The objectives of the Tecnomatix simulation model are: 1. Replicate process and output behavior. 2. Conduct parametric analysis for measuring resource utilization. 3. Conduct trade analysis between the different modification scenarios to improve the systems performance and optimize resource allocation. The DES model has five sections as described in the process flow model: patient arrival, quick sort, assessment, treatment/re-evaluation, and discharge/hospitalization. Each section has a set of values for its given parameters that define its behavior. Figure 3.12 shows the layout of the simulation model using Tecnomatix. The base time unit for the system is seconds.

Table 3.3: Summary of the ED Time-in-Motion model input data

Input	Value	Data Source
Patient Processing Times Inside Each Unit		
Intake	Gamma (alpha = 4.86, beta = 19:17.31)	Observation
LA	Gamma (alpha = 3.47, beta = 37:37.7)	Observation
HA	Gamma (alpha = 7.17, beta = 22:35.77)	Observation
Shock	Gamma (alpha = 2.19, beta = 43:30.6)	Observation
Check-in	Constant (10:00, 5:00, 1:00, 1:00, 1:00)	Estimation
Holding	Log-norm (alpha = 22138, beta = 962)	Epic
Arrival Data		
Arrival Timestamps	For 2014, 2015 & 2016	Picasso
Key Decision Points		
First Room Routings	(71.76%, 8.86%, 10.49%, 5.72%, 3.17%)	Picasso
Intake to Discharge	(Home-71.43%, LA-28.57%)	Observation
LA to Discharge	(Home-73.68%,HA-10.53%,CDU-5.26%)	Observation
HA to Discharge	(Home-37.5%, Admitted-62.5%)	Observation
Shock to Discharge	(HA-40%, LA, Admitted, Hol-20%)	Observation
Holding to Discharge	(Admitted, Shock-50%)	Observation
Room Data		
Room Assignments	(INT-20, LA-24, HA-16, Shock-14)	ED Layout

Table 3.4: Individual processing time data for ED clinicians. Data is analyzed for the resource model

Input	**Value**	**Data Source**
	Processing Times	
Intake	CT-Log-norm (Mu = 329.79, Sigma = 254.39)	Observation
Intake	Nursing-Log-norm (Mu = 581.68, Sigma = 382.74)	Observation
Intake	Physician-Gamma (alpha = 4.14, beta = 154.65)	Observation
LA	CT-Triangle (c = 0, a = 0, b = 7:00)	Observation
LA	Nursing-Gamma (alpha = 2.84, beta = 209.4)	Observation
LA	Physician-Gamma (alpha = 1.43, beta = 527.6)	Observation
HA	CT-Gamma (alpha = 23.53, beta = 14.02)	Observation
HA	Nursing-Gamma (alpha = 6.04, beta = 229.44)	Observation
HA	Physician-Gamma (alpha = 2.67, beta = 309.09)	Observation
Shock	Nursing-Gamma (alpha = 1.83, beta = 2001.99)	Observation
Shock	Physician-Gamma (alpha = 1.06, beta = 1185.98)	Observation

Table 3.5: Statistical analysis on processing time data for Intake, LA, HA and Shock room

Variable	**Mean**	**St.Deviation**	**Variance**	**Minimum**	**Maximum**
Intake					
CT Care	1.657	2.313	5.35	0	7
Nursing Care	7.371	5.719	32.711	2	31
Physician Care	7.571	4.943	24.429	0	24
Total Time	106.17	47.16	2224.32	27	216
LA					
Nursing Care	10.14	5.64	31.81	2	19
Physician Care	15.29	12.65	159.9	2	34
Total Time	131.4	81.1	6578.6	49	289
HA					
Nursing Care	22	7.81	61	13	27
Physician Care	11.67	7.23	52.33	7	20
Total Time	182	113.5	12877	114	313
Shock					
Nursing Care	68.2	51.7	2668.7	17	129
Physician Care	45.8	47.2	2231.7	5	103
Total Time	109.6	60.4	3652.8	38	182

Patients are captured in the model as system's main entities. Three different types of clinicians are captured: CTs, registered nurses and attending physicians. Treatment rooms and beds are captured in the model; however, availability of beds is not taken into consideration. Other resources such as medical equipment are not captured in the model. Other processes such as X-ray, MRI, CT scan and lab testing are not captured as well. Process animation is captured using 2D and 3D animation for better visualization of the ED process.

Starting from patient arrival, we collected three years of patient historical data which was considered the main entity to our model. These data has been formulated, reprogrammed according to Tecnomatix formating requirements and put in a table file as shown in Figure 3.13. All patients are assumed to be of the same group regarding their illness type. For each patient, the date of the visit and its exact time are considered as the arrival time.

Patients first go to the "Check In" process, which is considered as the time patient spends between arrival and treatment including waiting at the registration desk or inside the Front Assessment area. The ED will allow all visiting patients to come inside; therefore any number of patients might go through the check In process without limitation. The "Check-in" time is defined according to patient's assignment to one of the five treatment units, and is assumed to be a constant number obtained from Epic reports.

After patient exits the "Check In" process, he goes to one of the five treatment units according to an exit strategy based on a routing probability number assigned in the "P-flow" object as shown in Figure 3.12. Once patient is assigned to one of the five treatment units, a counter records the number of patients admitted to that unit. Each one of the major four treatment units has its own sub-model. After the number is recorded, patient goes inside the sub-model for the treatment process. Figure 3.14 demonstrates a patient flowing through three stages of care: admission, assessment, and treatment. Patients are demonstrated in the small blue icon.

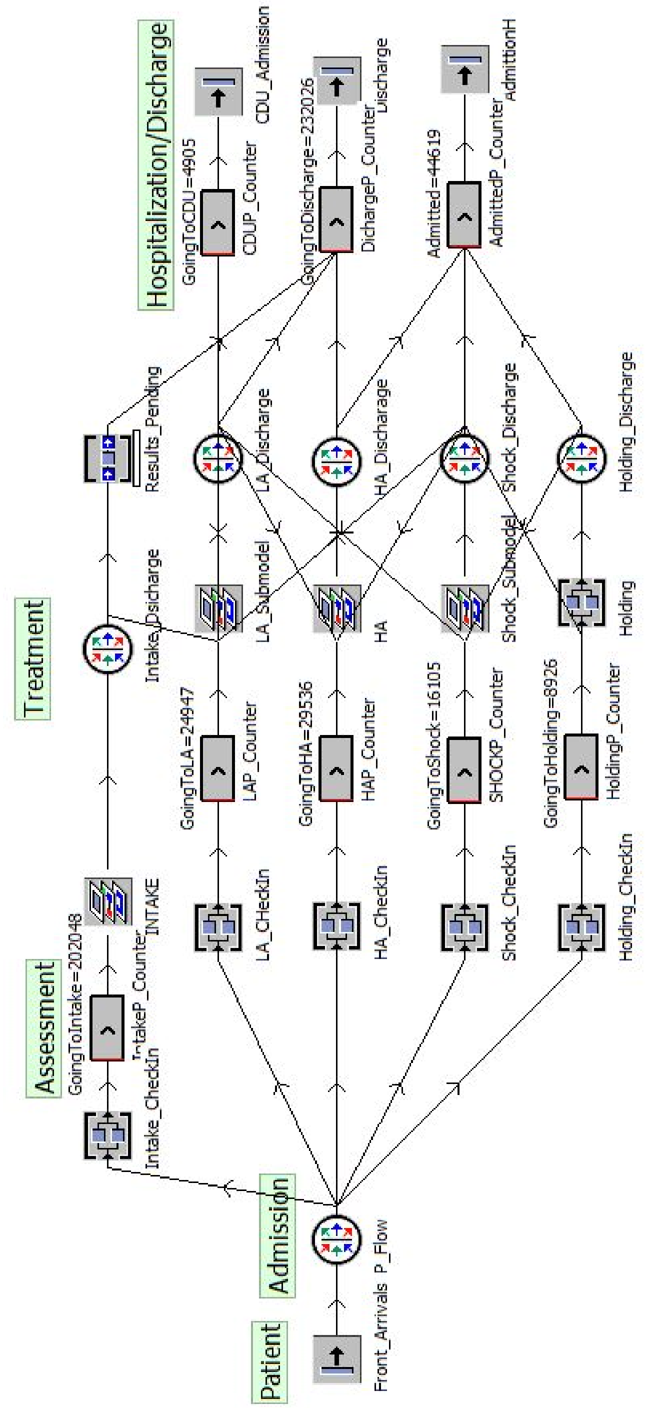


Fig. 3.12.: ED simulation model's layout, constructed using Tecnomatix.

2014/01/01 00:05:00.0000

	datetime 1	object 2	integer 3
string	Delivery Time	MU	Number
1	2014/01/01 00:...	.MUs.Pati...	1
2	2014/01/01 00:...	.MUs.Pati...	1
3	2014/01/01 00:...	.MUs.Pati...	1
4	2014/01/01 00:...	.MUs.Pati...	1
5	2014/01/01 00:...	.MUs.Pati...	1
6	2014/01/01 00:...	.MUs.Pati...	1
7	2014/01/01 01:...	.MUs.Pati...	1
8	2014/01/01 01:...	.MUs.Pati...	1
9	2014/01/01 01:...	.MUs.Pati...	1
10	2014/01/01 01:...	.MUs.Pati...	1
11	2014/01/01 01:...	.MUs.Pati...	1
12	2014/01/01 01:...	.MUs.Pati...	1
13	2014/01/01 01:...	.MUs.Pati...	1
14	2014/01/01 02:...	.MUs.Pati...	1
15	2014/01/01 02:...	.MUs.Pati...	1
16	2014/01/01 02:...	.MUs.Pati...	1
17	2014/01/01 02:...	.MUs.Pati...	1
18	2014/01/01 02:...	.MUs.Pati...	1
19	2014/01/01 02:...	.MUs.Pati...	1
20	2014/01/01 02:...	.MUs.Pati...	1
21	2014/01/01 02:...	.MUs.Pati...	1
22	2014/01/01 02:...	.MUs.Pati...	1

Fig. 3.13.: Tecnomatix table file showing the exact arrival time for patients.

After treatment, there is a probability that patients either transfer to another treatment unit or leave the ED directly. This probability number is assigned as an exit strategy after patients exit the sub-model. Patients coming out of Intake might visit the results pending unit to complete registration and paper work before they leave the ED. Patients discharging the ED might go to either to home, CDU or to the hospital. Each treatment unit in the model has a discharge flow object, which assigns patients to one of the discharge methods. Figure 3.15 shows a patient routed

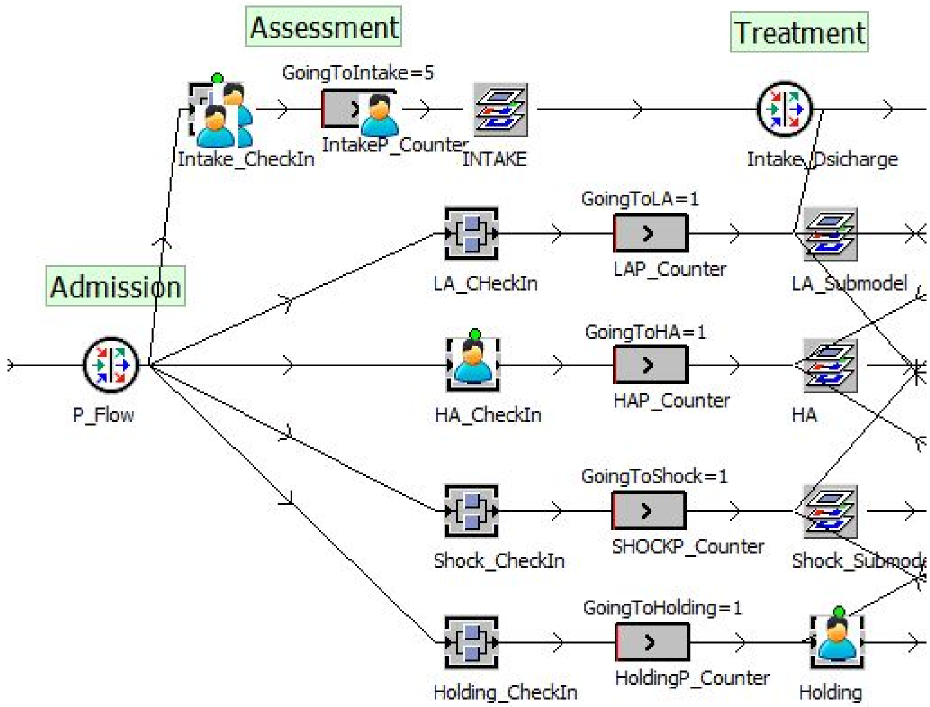


Fig. 3.14.: Demonstration of a patient going through admission, assessment and treatment.

from one of the five treatment areas to get hospitalized/discharged. The number of discharged patients is recorded using a counter as shown in Figure 3.15.

As described earlier, two different simulation models were implemented: a time-in-motion model and a resource model. Each one of the two models has the same frame but different structure for treatment sub-models. The way sub-models are structured reflects how we want to model the patient care process inside the treatment units and what performance measure we need to estimate. Figure 3.16 demonstrates Intake sub-model developed for the time-in-motion model (Model A). Similar ones are constructed for the other three treatment units.

As shown, Intake treatment is modeled as a single process only for model A. Each process is assigned to an Intake pod and each pod represents three rooms combined. We assume that Intake treatment processing time is the overall time patients spend

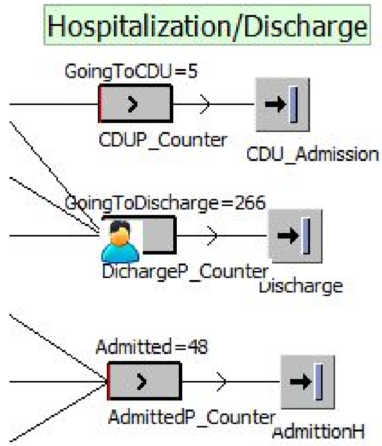


Fig. 3.15.: Demonstration of a patient going to discharge the ED using one of the three discharging methods.

inside the Intake room. For each pod, there is one nurse assigned serving three patients at the same time, except for pod 7 which has two rooms only. As mentioned earlier, nurse to patient ratios are different for each treatment unit. Once a patient is admitted to Intake, he remains in the queue "Intake Boarding" until a rooms becomes available. After that, patient goes to one of the seven pods to stay in one of its three rooms. The time of operation for each pod is defined using the "ShiftCalender" tool in Plant Simulation, where nursing grids are inserted using nursing pools shown in Figure 3.16. A method (program) is implemented using Tecnomatix to prevent sending a patient to a pod outside the time of its operation. Patients are assigned to rooms such that each nurse has an equal assignment of patients. The time of room operation as well as the treatment time can be visualized using "ResourceStatistics" chart while the simulation is running as shown in Figure 3.17. After treatment, patient exits the sub-model and move through the process. Similarly, LA, HA and shock room sub-models were constructed. We didn't implement a sub-model for the Holding unit as it represents the incarcerated patients; therefore, it was modeled as a single process where the processing time is extracted from Epic output reports.

The "LOS Counter" tool was developed and used to record the LOS for all patients going through the simulation in a table file "tab". Figure 3.18 demonstrates the LOS for discharged patients while simulation is running in the form of a plotter. Figure 3.19 shows the two tools used to input the staffing grids to the model: "shiftcalender" tool is used in defining the shift times, and "workerpool" tool is used for assigning clinicians to their pods.

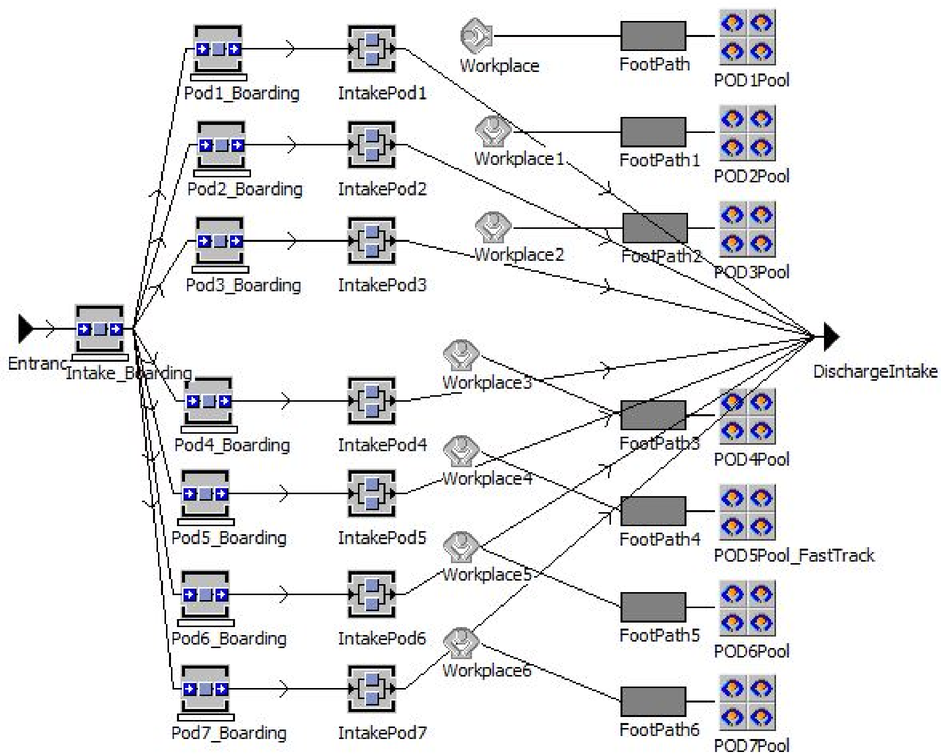


Fig. 3.16.: Intake Sub-model of the time-in-motion model.

Another detailed model was built to capture three different stages in the care process and to include both patients and clinicians flow. Sub-models for the four major treatment units were built to capture the number of rooms, CT care process, nursing care process, physicians treatment process, human resources' schedules, room and patient's status at each stage.

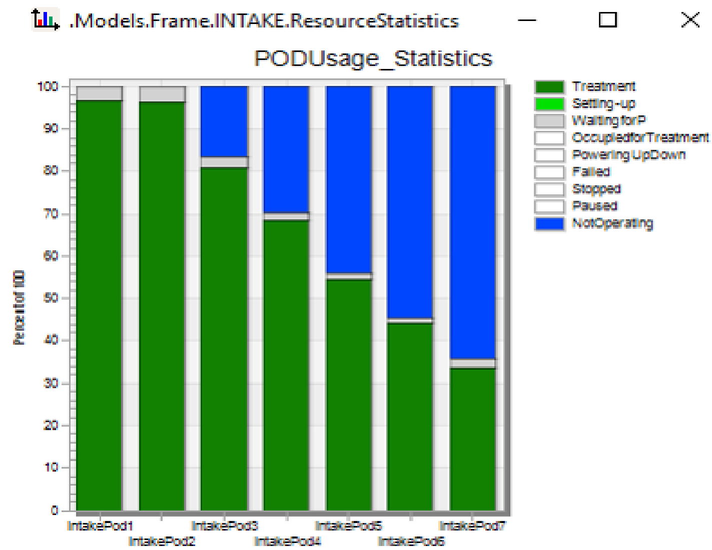


Fig. 3.17.: Intake room utilization chart, showing occupancy rate at Intake while simulation is running.

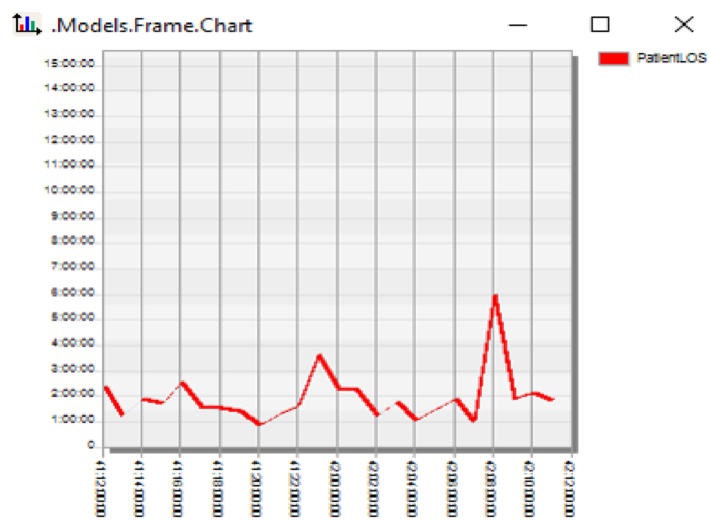
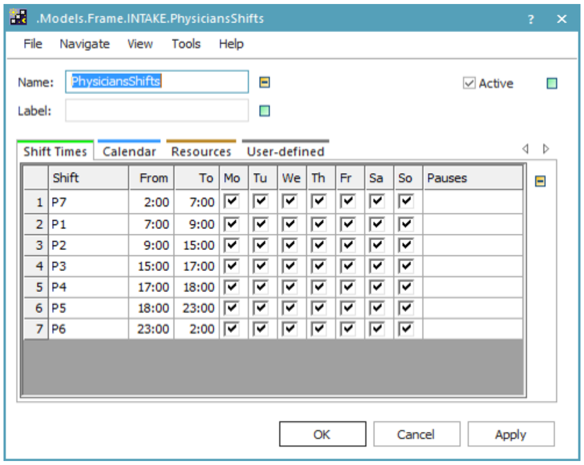
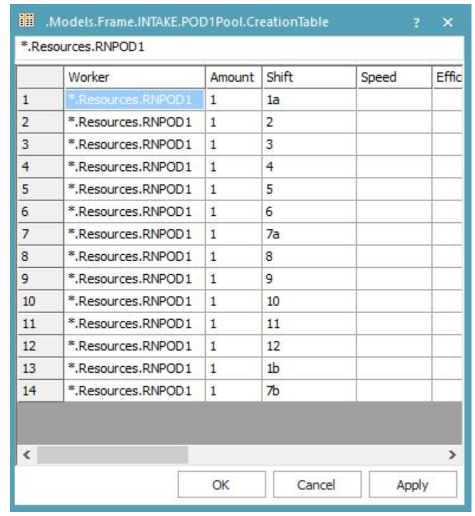


Fig. 3.18.: Real-time patients' LOS chart.

Sub-models capture all the three stages in the patient care process. In addition, another stage is added for discharging the patient. A number of methods (sub-routines) were implemented to prevent any additional patient from entering a treatment room unless the patient occupying the room has completed all the four stages of care. A



(a) definition of shift times using shift calender.



(b) Assignment of workers using workerpool tool.

Fig. 3.19.: Definition of resourcing shifts using Tecnomatix.

loop is added at each stage of the care process such that, a care provider might visit the patient inside his room more than once according to the percentage number defined in that loop. CTs, nurses and physicians shifts are uploaded into the resourcing pools using the "ShiftCalender" tool for each sub-model. The ED stops assigning new patients to certain pods 30 minutes before the nurse leaves; however, existing patients might still be served with the help of other nurses. Icons were added for each human resource type to distinguish between them and make the model easier to verify.

Similarly for the other units, physicians are assigned to HA and Shock during their shifts, while nurses are assigned according to pod distribution for each unit. CTs are assigned to all patients in a given unit except for Shock room, which doesn't have any CTs assigned. Once a patient is admitted to one of the four treatment units, he starts waiting for a room to be ready, and then he goes through the three stages of treatment sequentially. Once the patient finishes one stage of treatment, he waits inside his room until a clinician is available to serve at the next stage of care. Once he receives all the treatment needed by the three care providers, he exits the sub-model and goes through the next stage of the process which is Hospitalization/Discharge. The model is built in a way such that the main frame (process) is not affected by the sub-models.

At this stage, the model is populated with some animation such as: hospital logo, patients' icons, clinicians' icons, real-time charts and others to enhance its visualization. Some comments are added in the main frame to help the reviewer understand and verify the model. Those comments have information about data sources, the way model is built, and the model output behavior.

A method was developed to record the LOS for each patient discharging the system, while the simulation is running. This method can be easily customized such that patients' LOS can be recorded during a certain time of the day (e.g. night shift). Results of these recordings are documented in a table file each time a patient exits the system as shown in Figure 3.20. The table records patients' entrance and exit times, and LOS is considered as the difference between them. This method is important to capture the time stamp for each patient; however, it slows the simulation.

In addition, the DES model has the following assumptions:

1. Patient discharge process is assumed to have a zero processing time, since no data is available for it and it was not captured in the SysML based model. Discharge activities include completing registration/paperwork, and moving patients outside of the ED.

2. All ED nurses, CTs and physicians are assumed to have the same efficiency and speed.

3. ED patients might wait for an available bed anywhere at the ED (e.g. waiting inside the room, in the hallway or at the front assessment area); therefore, patients waiting inside treatment buffers represent all patients waiting for an available bed at the assigned rooms.

4. The three stages of care inside each treatment room are assumed to follow a sequential order: CT care, then nursing care, and then physician treatment.

5. Other treatment processes (e.g. X-ray, lab test or MRI) are not captured in the model, and are assumed to happen while the patient is occupying his room.

6. Only three types of clinicians were captured in the simulation model, and medical equipment were not captured.

7. patients LWBS output was not calculated using the model, since no data is available for those patients and they were not captured in the SysML based model.

	string 0	time 1	time 2	time 3
string	Patient	Entrance_Time	Exit_Time	DT
1	.MUs.Patient:1	5:00.0000	1:05:11.0616	1:00:11.0616
2	.MUs.Patient:2	6:00.0000	1:12:02.5010	1:06:02.5010
3	.MUs.Patient:3	41:00.0000	3:45:18.9513	3:04:18.9513
4	.MUs.Patient:4	52:00.0000	1:13:42.2651	21:42.2651
5	.MUs.Patient:5	58:00.0000	1:53:43.0674	55:43.0674
6	.MUs.Patient:6	59:00.0000	1:59:01.4879	1:00:01.4879
7	.MUs.Patient:7	1:08:00.0000	4:49:47.8392	3:41:47.8392
8	.MUs.Patient:8	1:32:00.0000	2:57:25.6685	1:25:25.6685
9	.MUs.Patient:9	1:37:00.0000	3:20:39.8965	1:43:39.8965
10	.MUs.Patient:10	1:49:00.0000	3:12:23.2108	1:23:23.2108
11	.MUs.Patient:11	1:51:00.0000	11:06:15.5043	9:15:15.5043
12	.MUs.Patient:12	1:54:00.0000	3:31:47.4054	1:37:47.4054
13	.MUs.Patient:13	1:57:00.0000	3:06:08.0525	1:09:08.0525
14	.MUs.Patient:14	2:02:00.0000	3:27:22.1889	1:25:22.1889
15	.MUs.Patient:15	2:05:00.0000	11:26:46.1148	9:21:46.1148
16	.MUs.Patient:16	2:07:00.0000	3:27:41.3544	1:20:41.3544
17	.MUs.Patient:17	2:08:00.0000	18:13:15.2489	16:05:15.2489
18	.MUs.Patient:18	2:24:00.0000	3:14:16.3811	50:16.3811
19	.MUs.Patient:19	2:28:00.0000	3:55:46.4806	1:27:46.4806
20	.MUs.Patient:20	2:32:00.0000	4:24:36.2378	1:52:36.2378
21	.MUs.Patient:21	2:39:00.0000	4:41:58.6868	2:02:58.6868

Fig. 3.20.: LOS of discharging patients, recorded in a table file while the simulation is running.

4. VERIFICATION AND VALIDATION

4.1 Model Verification

Research team members including a physician from the ED participated in the verification and validation process of the ED general model through characterization and description of the patient flow process using the process flow model in Figure 3.8. Model verification methods are applied on both simulation model A and B to ensure that the formal representation of the computerized model is accurate for both. Simulation models were developed part by part. Data were gathered over two-years' period and model's logic was built manually using Tecnomatix existing functionalities, which have proven to be effective for modeling the healthcare operation [43].

The following four methods were applied for verification:

1. Inspection of the simulation's logic using walkthroughs, slow simulation runs and test runs (inspection).

2. Performing consistency checks on some of the model output parameters (analysis).

3. Running extreme test scenarios to test the change in the model's output in corresponding to different inputs under a set of assumptions and initial conditions (examination).

4. Testing the variation in the model's output using multiple simulation runs (analysis). All these verification methods involved reprogramming some of the model's components [36].

We focused on verifying the resource model (Model B); however, some of the verification methods were applied to Model A as well. We used graphs and plots to demonstrate the results, in order to make it easier for verification.

First, both simulation models were inspected using slow simulation runs and animation of patient flow. We tracked the patient flow process through the main frame and the sub-models. The model was animated to show different states of the flow process for patients and clinicians. The following were observed during the walkthroughs: 1. Patient being served by a clinician, 2. Patient waiting for another patient being served, 3. Patient waiting in his room for a clinician to serve him. 4. Room being Idle, 5. Room being filled by a patient, 6. Room being not in operation, 7. Clinician being idle, 8. Clinician serving multiple patients and 9. Clinician serving the same patient more than once. Figure 4.1 shows a snapshot for the treatment process at 6:30 am, Sunday at Intake. Figure 4.1 shows an animation of the patient flow process, showing a patient being served by a CT at the first stage of treatment process, and another one being served by a nurse at the second stage. It shows a patient waiting in the queue for another patient being served by a physician, in order to occupy his room once the current patient leaves. To facilitate the verification process while the simulation is running, patients waiting are animated in yellow color, and patients currently receiving treatment are animated in blue color. All human resources are animated in different colors as well. Similar walk-troughs have been conducted through the simulation model for the other treatment sub-models at different times of the day and different days of the week.

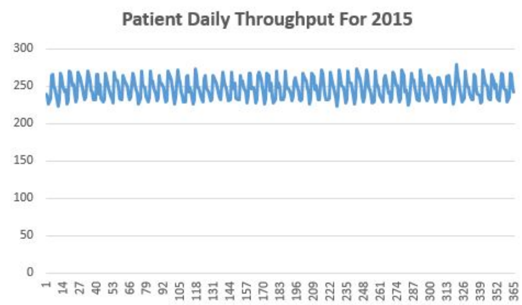
Fig. 4.1.: Treatment process walk-through using animation of patient flow while running the simulation.

In addition, model data inputs were also inspected against the process input requirements that has been developed at an earlier stage of the project. Each of the key decision points in the process flow model were verified with the help of our research team using excel templates (shown in the appendices). Key probability distribution numbers were identified and verified, which represent the routing probabilities in the model.

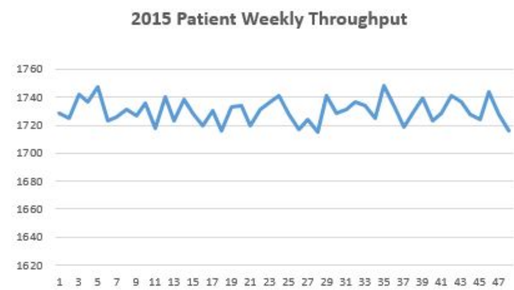
Simulation was also examined by performing consistency checks on some of the output measures. Different output parameters were tracked for each patient such as LOS as shown in Figure 3.26. We relied on a qualitative approach for this test to ensure that the output behavior of the model falls within a ”reasonable” range. Four different testing cases were applied on both model A and model B, and used either for testing the model, or testing the boundary conditions of the ED in the form of extreme case scenarios. Some of the testing cases are applied only on Model B.

The first testing case is varying the input data for both models, such that the average LOS and patient throughput were calculated daily, weekly, biweekly and monthly to show that the model output is consistent. It is observed that the results are consistent for both models. It is also observed that the results from both models are comparable, where data variations from both are minor. Simulation was run and the output data were plotted using excel. Figure 4.2 shows patient throughput results of model A for 2015. Figure 4.3 shows patient throughput data of model B for 2015. It is shown that the throughput data for each time frame follow similar trends; where the maximum observed variation between the upper and lower limits in the graphs was 41 patients only, while monthly data showed a maximum variation of 75 patients between the upper and lower limits in the plot. Similar trends have been observed in the real system. Similar results were observed for 2014 and 2016 data.

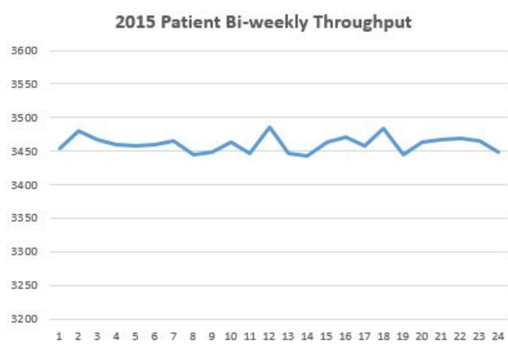
The second testing case is testing an extreme condition by doubling the rate of patients arriving to the ED at 2015. The aim is to test the boundary conditions of the model and the actual ED system. This test is applied assuming all model’s variables are the same regarding of the extreme condition. Model B was used to run this test,



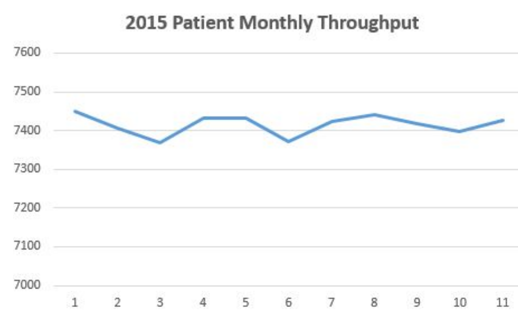
(a) Patient daily throughput of Model A for 2015.



(b) Patient weekly throughput of Model A for 2015.

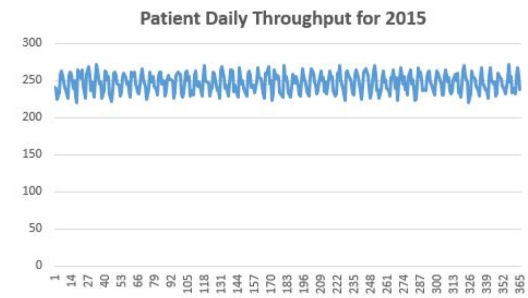


(c) Patient bi-weekly throughput of Model A for 2015.

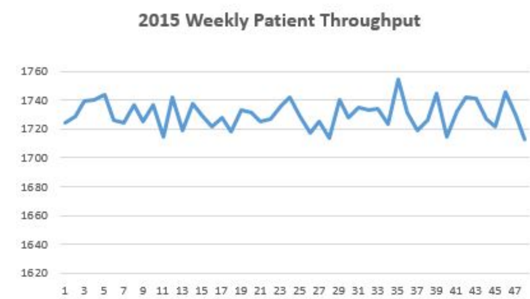


(d) Patient monthly throughput of Model A for 2015.

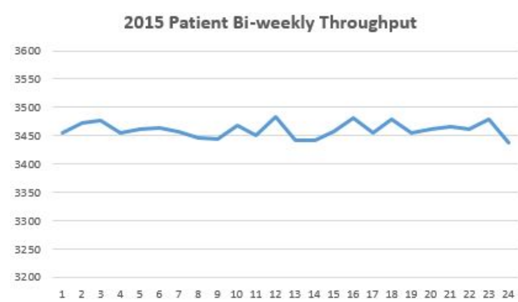
Fig. 4.2.: Consistency check of patient throughput data of Model A for 2015.



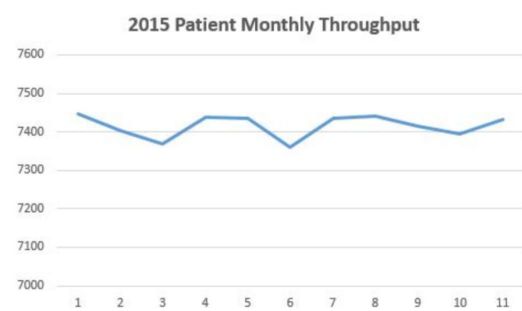
(a) Patient daily throughput of Model B for 2015.



(b) Patient weekly throughput of Model B for 2015.



(c) Patient bi-weekly throughput of Model B for 2015.



(d) Patient monthly throughput of Model B for 2015.

Fig. 4.3.: Consistency check of patient throughput data of Model B for 2015.

and the average LOS was used as a performance metric. Table 4.2 shows the results' comparison between normal and extreme condition scenarios for both discharged and admitted patients. It is observed that patients coming to the ED are blocked in the waiting room (buffer) for a very long time until a room becomes available at Intake or another treatment unit. Results show that the LOS will increase dramatically when doubling the number of patients on 2015 as shown in Table 4.1, to exceed one day for both admitted and discharged patients. Based on the results, a more realistic case is identified and communicated with the ED, which is the third case.

Table 4.1: Checking the boundary of the model using an extreme case of doubling the rate of arrivals on 2015

Scenario	Discharged Patients' LOS	Admitted Patients' LOS
Current State	3:20:59	6:07:42
Extreme Case	1 Day and 3 hrs.	1 Day and 23 hrs.

The third testing case is testing the same extreme condition over a specific period during the day (surge), where the number of patients arriving to the ED was doubled between 9 AM and 12 PM on 2/1/2014. Figure 4.4 shows the results from both extreme and normal scenarios for Model B. The forth testing case is also an extreme condition, which is applied by tripling the number of patients during the same time frame. Figure 4.5 shows the results after tripling the number of arriving patients for Model B. The x-axis represents the time of the day starting at 12 AM on 2/1/2014, and the y-axis represents the average LOS in hours. It is observed from Figure 4.4 that patients' LOS starts increasing after 1 PM and returns back to its original value at 3 AM in the morning. Figure 4.5 shows that the model reacts to tripling the number of patients; such that, the LOS starts increasing after 1 PM to reach 7 hours at its peak, then it decreases again to go back to normal at 5 AM in the next day. All these extreme cases are applied on the generic population of patients, and assume that the ED will use its existing resources (all model variables are the same).

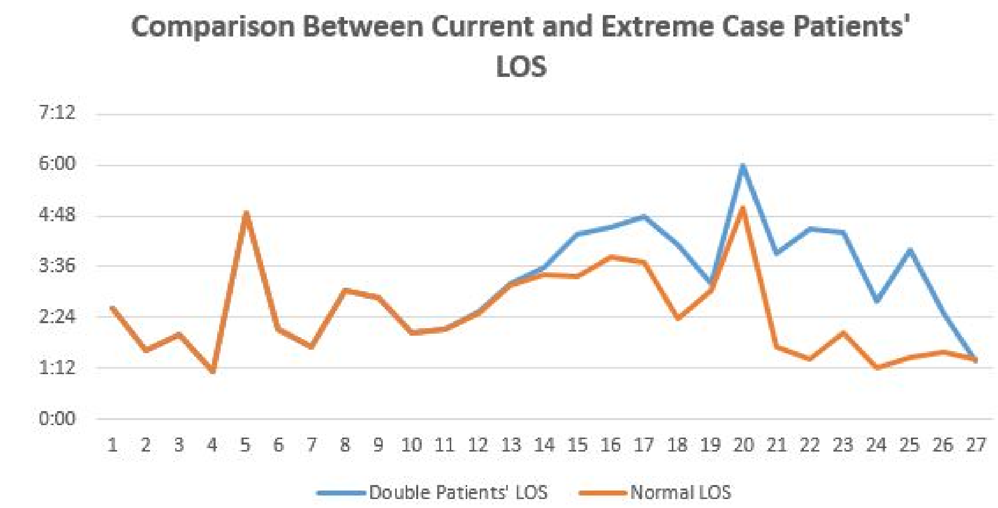


Fig. 4.4.: Comparison between the current LOS and the LOS after doubling the number of patients between 9 AM and 12 PM on 2/1/2014. The graph shows LOS behavior over two days' period.

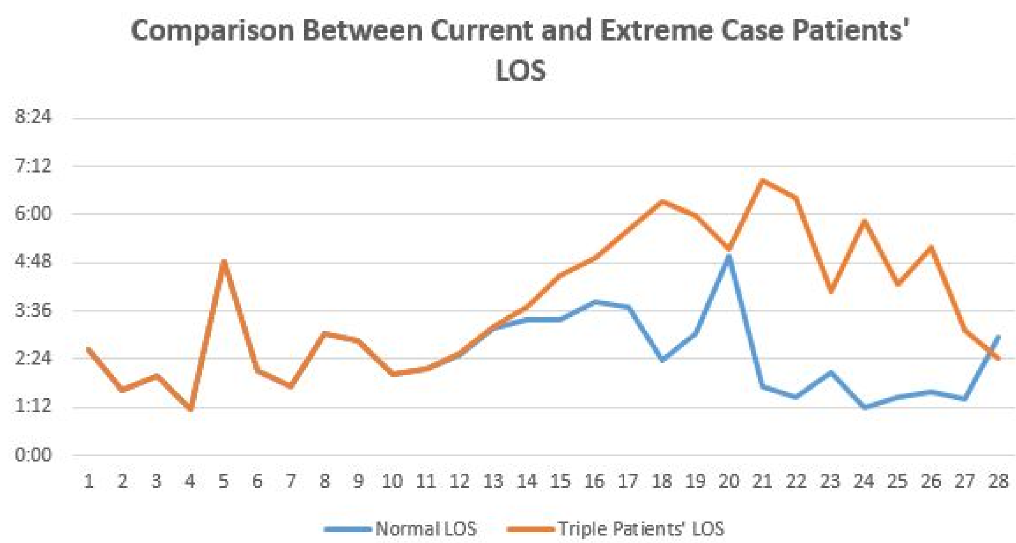


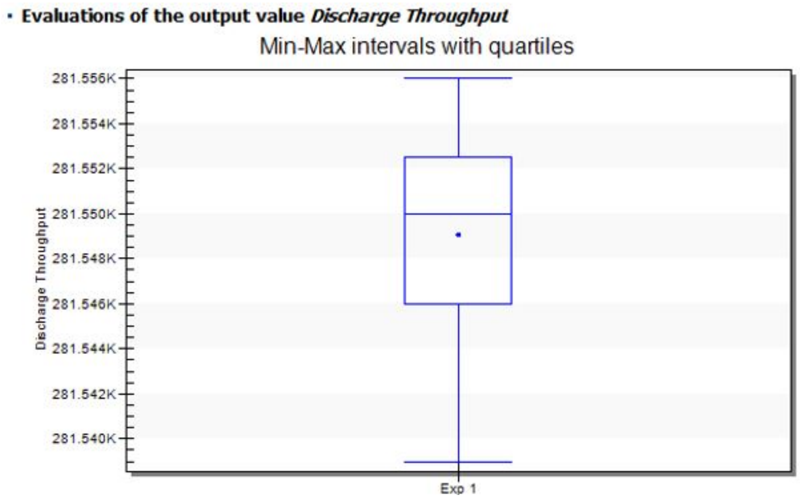
Fig. 4.5.: Comparison between the current LOS and the LOS after tripling the number of patients between 9 AM and 12 PM on 2/1/2014. The graph shows LOS behavior over two days' period.

The model output variation was tested by running the simulation 100 times using "ExperimentManager" tool in Tecnomatix for both models. Figure 4.6 shows the resulting output interval of Model B after 100 simulation runs. Figure 4.7 shows the resulting output interval of Model A after 100 simulation runs. Both plots show that the output is consistent with minor variations. It is observed that the variation is minimum for both models, where Model A has a standard deviation of 2.16 in patient throughput and 13.5 seconds in the average LOS, while Model B has a standard deviation of 4.3 in patient throughput and 1.8 minute in the average LOS.

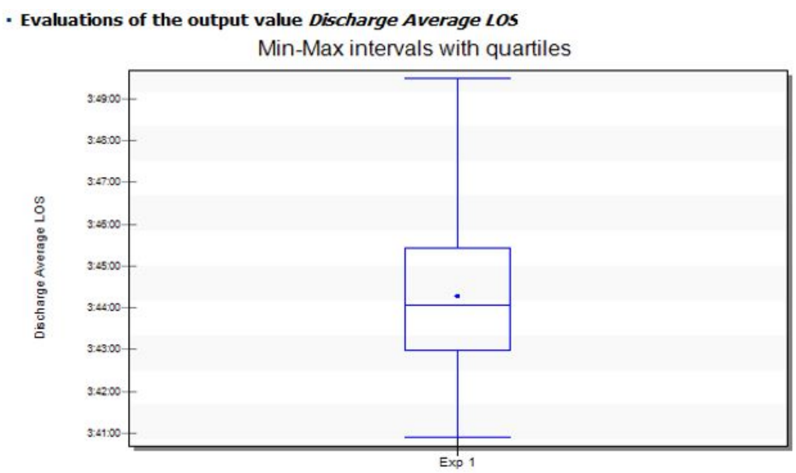
4.2 Model Validation

Model validation is applied validate the model's assumptions and ensure the model approximates the real system's behavior. Results from verification testing cases are used for validating the model with the help of a simulation expert and by using outputs from the actual ED system (Data from Epic). We focused on validating Model B, which was used later in the analysis. Only one validation method is applied to Model A. Validation methods applied are: 1. Comparing model's output data with Epic and Picasso data, 2. Comparing the model's behavior with another model's output trends, 3. Validation with a simulation expert and with the ED, and 4. Validation by observing the real ED system (observation) [43].

The first validation method is validating the model's output behavior using ED output data (Epic and Picasso). First, simulation's output was compared with Epic data using three different metrics: patient throughput, average LOS, time between arriving to the ED and firs ED room assignment (Time between Door to Room). The output results were estimated according to the last patient room except for the time between door to room. The first validation method is also applied on Model A, where average LOS values and patient throughput data were compared. Table 4.2 shows a comparison between the output results of Model B and Epic data for model

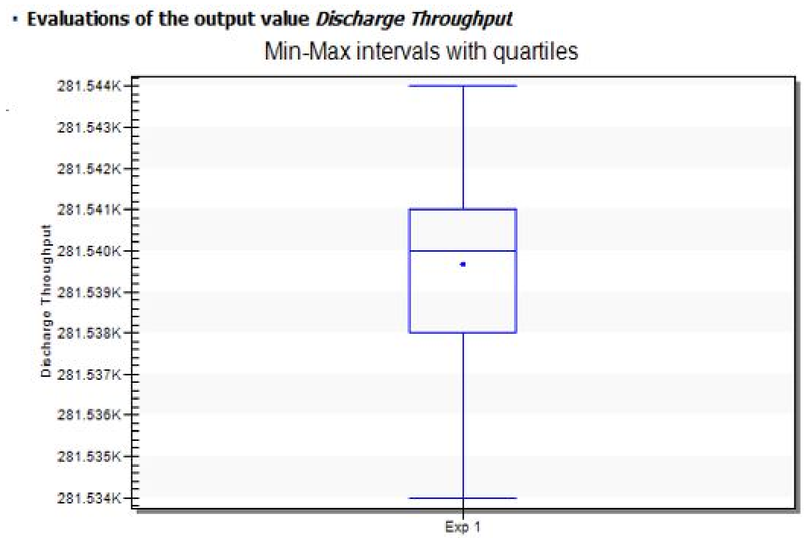


(a) Demonstration of patient throughput output interval after 100 simulation runs.

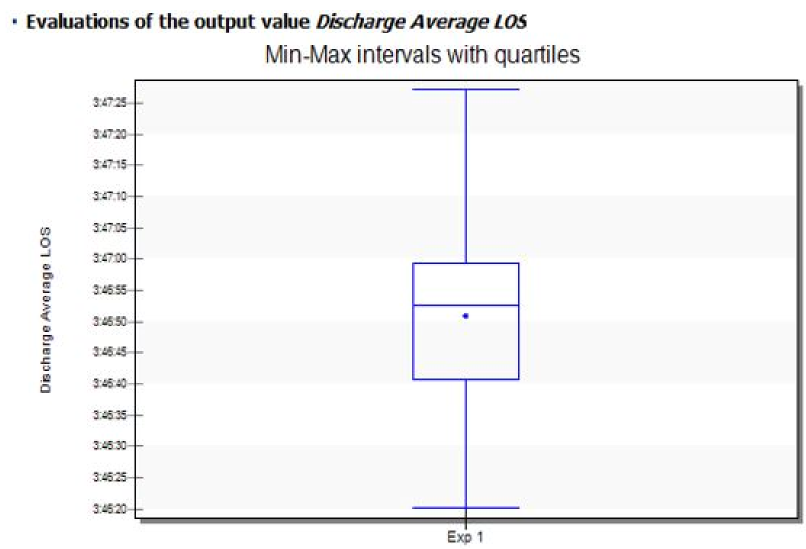


(b) Demonstration of patients' average LOS output interval after 100 simulation runs.

Fig. 4.6.: Simulation output intervals for Model B after 100 runs, including mean, maximum and minimum values.



(a) Demonstration of patient throughput output interval after 100 simulation runs.



(b) Demonstration of patients' average LOS output interval after 100 simulation runs.

Fig. 4.7.: Simulation output intervals for Model A after 100 runs, including mean, maximum and minimum values.

validation. Table 4.3 shows a comparison between the output results of Model A and Epic data.

It is observed that the percentage error between the average patient throughput data, Door to first provider output data and average LOS output data is minor for Model B (less than 1% in patient throughput and 3% in LOS and door to first provider); however, when the data is divided according to last patients' room, a larger percentage of error is observed because we are only relying on the sample we collected through observation for building the model. Besides, we used only four months of ED (Epic) data for validation. A larger variation in the average LOS for LA patients is observed; because we didn't collect data for patients who occupy the LA room for a long time, and sometimes for one day or more (e.g. Intoxicated patients).

It is also observed that there is a minor variation in Intake patients' results; whom they account for more than 70% of total ED patients. Patients visiting the other three units combined account for less than 30% only. Results from the simulation model show an average value for monthly patient throughput of 7618.2, an average LOS value of 3.8 hours and an average time between door and first provider assignment of 50.86 minutes for all patients. Epic data shows an average monthly patient throughput of 7567.9, average LOS of 3.9 hours and average door to first provider time of 52.19 minutes for all patients.

Model A is observed to have the exact same values for patient throughput numbers; however, it has slightly lower values for the average LOS with less percentage of error for LA patients. Model A is determined to be only valid for measuring the high-level room utilization data, which are demonstrated in the results section. A more detailed statistical analysis was not applied due to the limitation in the current ED data.

The second validation method is based on comparing the output trends over the day with ED (Picasso) data; since Picasso had captured the average patients' LOS every one hour during the day, which was not captured by Epic. An algorithm was implemented using Tecnomatix that enables the simulation model to calculate the average LOS every one hour. Figure 4.8 shows the results from both the simulation

Table 4.2: Validation of Simulation Model B results using Epic data

Patient Type	Simulation Output	EPIC Output	% Error
Average Patient Monthly Throughput			
Intake	4008.92	3632.64	10.36%
LA	2044.64	2470.57	17.24%
HA	1407.36	1246.7	12.89%
Shock	157.28	218	27.85%
Average	**7618.2**	**7567.9‘**	**0.66%**
Average LOS			
Intake	2.78 hrs.	2.67 hrs.	4.12%
LA	4.07 hrs.	5.33 hrs.	23.64%
HA	5.84 hrs.	6.0 hrs.	2.67%
Shock	5.07 hrs.	4.41 hrs.	14.97%
Average	**3.8 hrs.**	**3.9 hrs.**	**2.56%**
Average Door to Room			
Intake	31.17 mins.	32 mins.	2.59%
LA	11.12 mins.	10.75 mins.	3.44%
HA	4.7 mins.	4.65 mins.	1.8%
Shock	2.21 mins.	2.67 mins.	17.23%
Average	**24.76 mins.**	**25.36 mins.**	**2.37%**

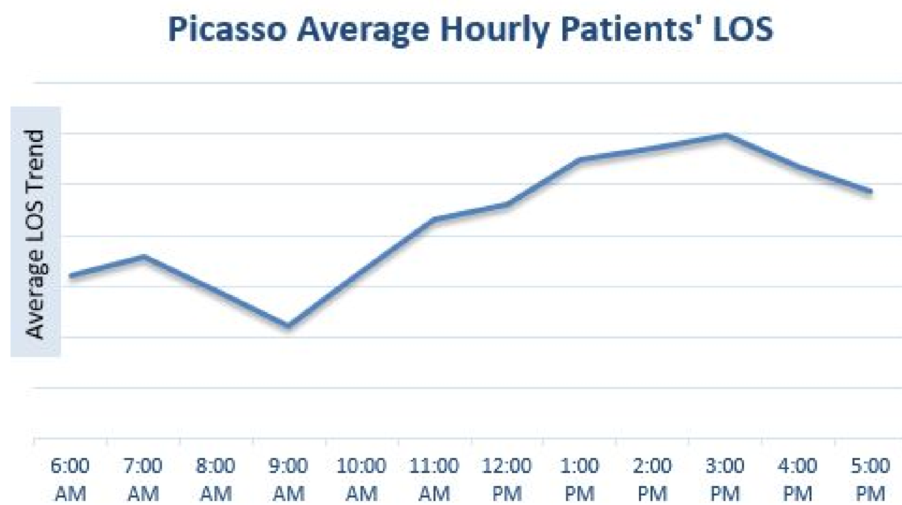
Table 4.3: Validation of Simulation Model A results using Epic data

Patient Type	**Simulation Output**	**EPIC Output**	**% Error**
Average Patient Monthly Throughput			
Intake	4008.92	3632.64	10.36%
LA	2044.64	2470.57	17.24%
HA	1407.36	1246.7	12.89%
Shock	157.28	218	27.85%
Average	**7618.2**	**7567.9‘**	**0.66%**
Average LOS			
Intake	2.43 hrs.	2.67 hrs.	9.88%
LA	4.78 hrs.	5.33 hrs.	10.32%
HA	5.37 hrs.	6.0 hrs.	11.73%
Shock	5.05 hrs.	4.41 hrs.	14.51%
Average	**3.69 hrs.**	**3.9 hrs.**	**5.38%**

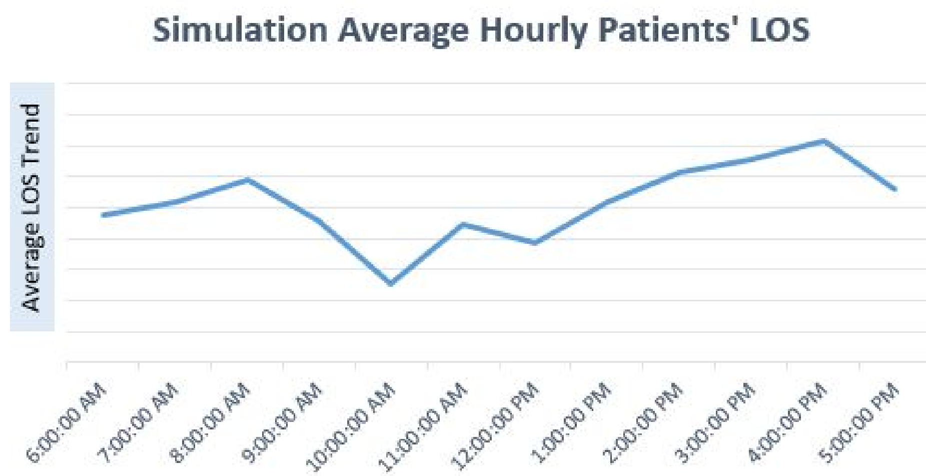
model and ED data analyzed from Picasso. The x-axis represents the time of the day, and the y-axis represents the trend of the average LOS during the day. The results capture the average LOS between 6:00 AM and 6:00 PM for both graphs, where both were observed to follow the same trend during the day. It is observed from both graphs that the LOS reaches its peak value between 3 PM and 4 PM, and starts decreasing again until it reaches its minimum value between 9 AM and 11 AM for both graphs.

The model output trend was also compared to another model (case study) output trend. We compared human resource utilization rates and the average LOS from the present model with Lisa Patvivatsiri, (2006) model from the literature. The output from the current system is showing similar trends for patients' LOS, room utilization rates and human resources utilization rates; which range between 14% and 75.95% [16].

On the other side, the MBSE framework and the SysML based model were validated with the help of the research team and an ED physician, whom she validated the model assumptions one by one by going through the generic process model. Data used for building the model were also validated; although, we faced many challenges regarding data collection and analysis. Data has been collected over two years period using different sources: observation, interviews, databases (Epic and Picasso) and documents. Models were developed through many iterations, and multiple data sources were used in building the models to ensure the assumptions behind the data are accurate. Data were collected such that, it can be used for different purposes either for building the models or for validation. Procedures and data protocols were used to collect and maintain the data.



(a) Hourly LOS trend from Picasso EMR system.



(b) Hourly LOS trend from the Simulation model.

Fig. 4.8.: Comparison between hourly trend of Simulation and Picasso LOS Data over the day.

5. RESULTS AND DISCUSSION

This chapter discusses the results of the MBSE framework and the DES model. Each MBSE diagram we used in the development of the simulation model is presented and discussed separately. The results from both simulation models are presented. The results focus on measuring physical and human resources utilization rates. In addition, the results from the different "what-if" scenarios are presented, which focus on optimizing resource allocation at the main treatment units.

5.1 Discussion of The MBSE Model

This section discusses the resulting MBSE views, implemented using Cameo and other modeling tools. In general, the selection of the current MBSE approach depends on the nature of the problem being addressed; therefore, a simplified pathway has been followed to solve the problem. The current MBSE approach helped us achieve the following:

1. Definition of stakeholder needs and requirements. 2. Definition of the use-cases. 3. Functional analysis of the ED work-flow. 4. Behavioral modeling of the ED work-flow. 5. Structural decomposition of the ED work-flow. 6. Simulation of the ED process using DES.

5.1.1 ED Stakeholder Needs Identification

The ED general model requirements are put together using the IPO diagram. Figure 5.1 shows the definition of stakeholder needs using the IPO diagram as developed by INCOSE. The diagram shows a summary of the requirements gathering phase of the project including inputs, activities and outputs. This IPO model helped our research team to define project controls and to have a general strategy for implementation, while considering stakeholder needs through the entire project life-cycle. The process of stakeholder needs identification started by conducting initial meetings with ED stakeholders and gathering information from them including information about their process documents, constraints, alternative solution classes, policies, regulations and problem statement. Groups of actions were taken, followed by a group of activities conducted to meet the project requirements in general as well as other requirements including data storage, software, process, training, ED observation and others. The outcomes of this requirements gathering phase include the implementation of a project charter document that defines problem statement, solution strategy, list of tasks, team members, durations, time-lines, milestones, risks, mitigation plans and deliverables. In addition, initial frameworks and models were developed to define a high-level domain of the ED work-flow including function, activity and sequence models.

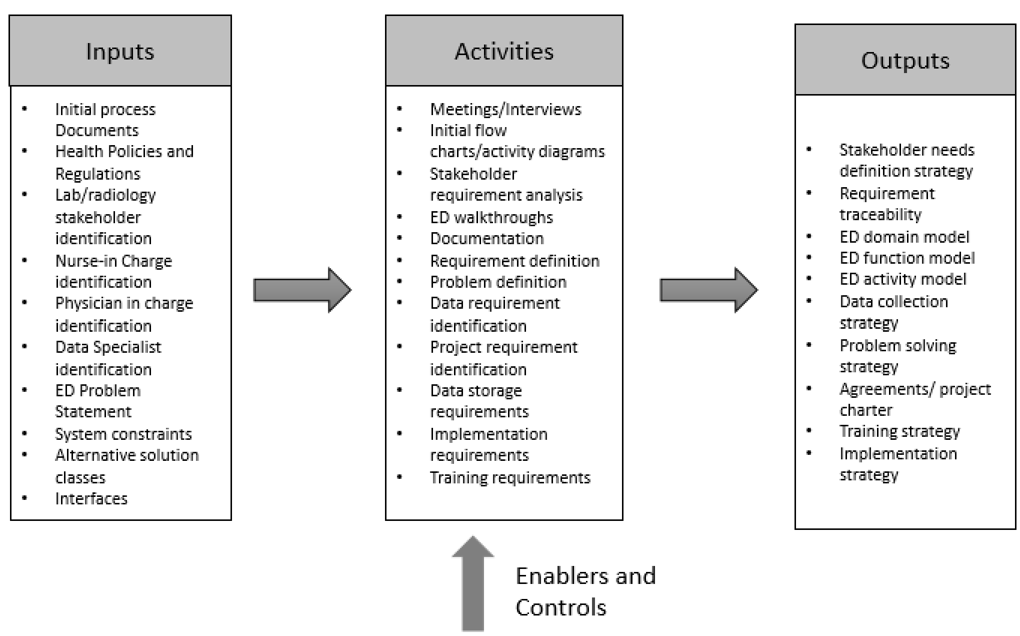


Fig. 5.1.: IPO diagram defining stakeholders' need in the form of inputs, activities and outputs [7].

5.1.2 ED Use-cases Definition

Based on the application of stakeholder requirements, multiple use-case scenarios were defined for ED patients and human resources. Figure 5.2 shows the first use-case model that demonstrates the objective of the current work as modeling the work-flow of the generic population of patients. Two use-cases are identified for patients who are considered the system actors, the first one represents the generic work-flow at the ED, and the second one represents the treatment sub-flow. The two use-cases are connected to a group of activity models. Another use-case diagram is implemented to define the use-cases for ED clinicians.

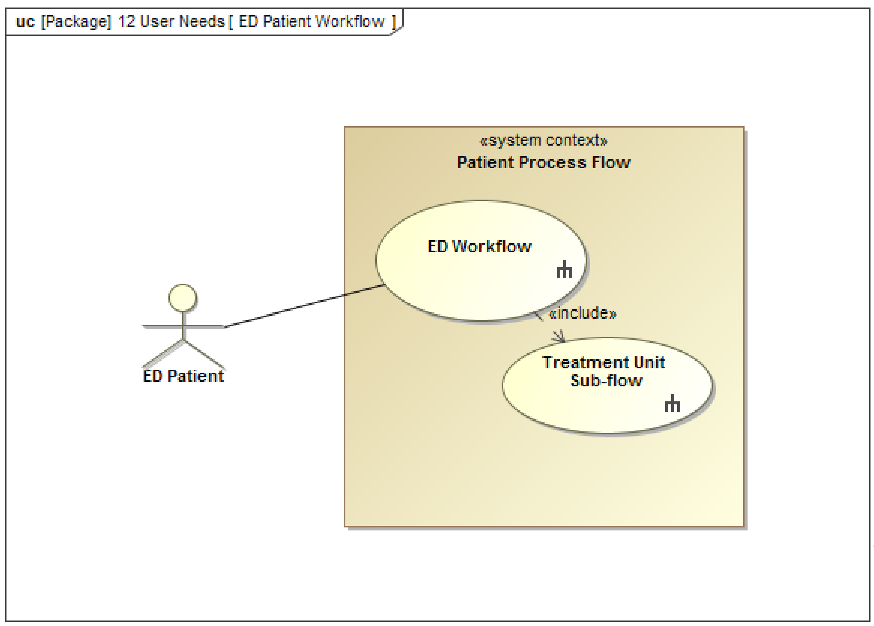


Fig. 5.2.: SysML use-case diagram defining patient use-cases.

5.1.3 ED Functional Analysis

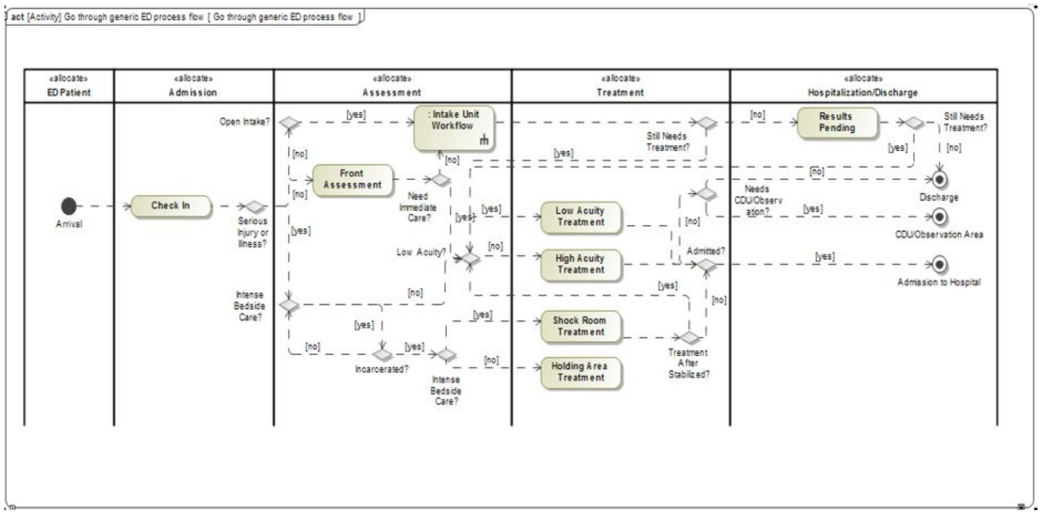
Multiple views of the ED work-flow were implemented using SysML activity diagrams to demonstrate the generic patient flow process and sub-flow processes. Figure 5.3 demonstrates the generic work-flow model in Cameo, which shows the four steps in patient's flow (admission, assessment, treatment and hospitalization/discharge), are all allocated to the activity diagram. The sub-flow model shown in the Figure 5.3 is applied to all four units inside the ED: Intake, LA, HA and Shock. It describes the treatment process in the form of a queuing model with three stages of care: CT treatment, registered nurse treatment and attending physician treatment. Those activity models were used to develop time studies and data collection grids to define data inputs and requirements and provide mapping of the process flow.

5.1.4 ED Structural Decomposition

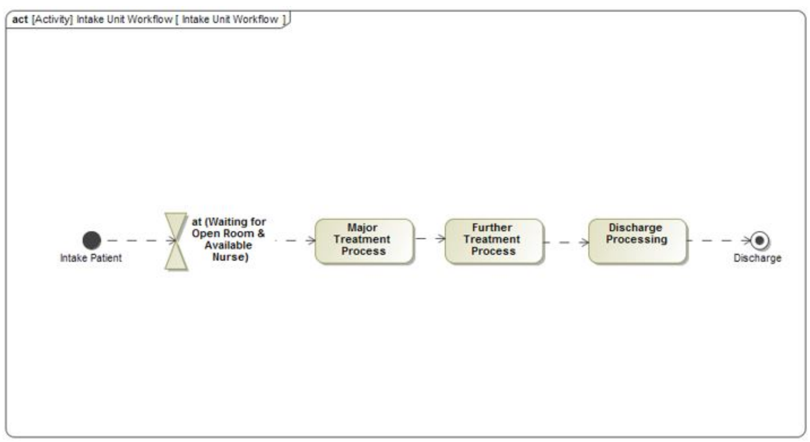
The structural model is implemented using SysML BDD diagram to clearly demonstrate the definitions and functions of the modeled system of interest and its elements. This structural diagram helped in the development of the simulation model's by decomposing the system into components. It has three different types of blocks: system block, interface block and block. As demonstrated in Figure 5.4, the system of interest (patient work-flow model) is decomposed it into six different blocks (system components). Each component is described using different types of properties: flow properties, value properties, constraints and parts. Generalization and association relationships were used in connecting the different elements of the diagram with each other and with the system of interest.

5.1.5 ED Model Behavioral

The ED work-flow STM diagram was implemented to describe the component behavior of the patient flow process. The STM diagram was used by our research team as a blueprint of the simulation model's logic. The diagram is divided into four different states: admission, assessment, treatment and discharge. This diagram is used to call a number of other activity diagrams at each state to describe the function of the flow. An example is the treatment process which has three different states, where a patient starts the process only if he got assigned to a bed (entry state). After



(a) Generic process activity diagram.



(b) Treatment process activity diagram.

Fig. 5.3.: SysML activity models describing the generic patient flow and treatment sub-flow.

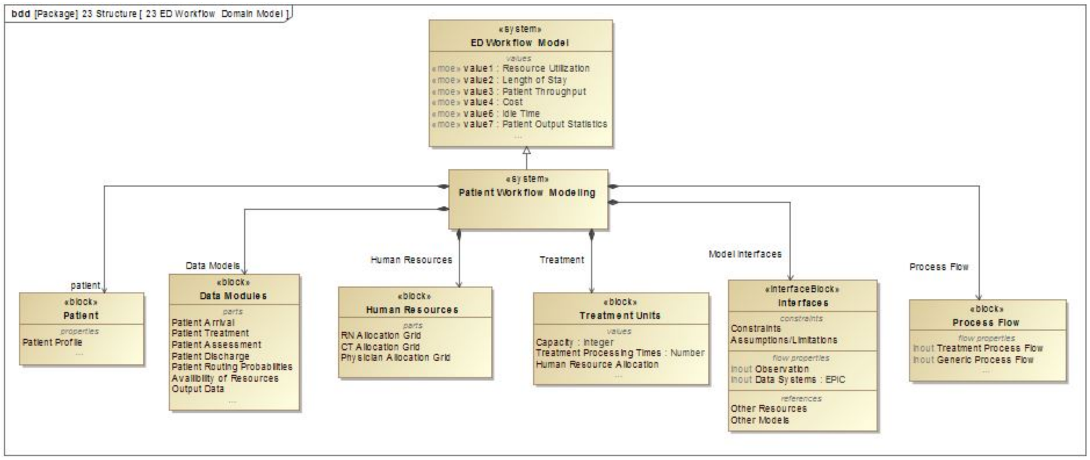


Fig. 5.4.: SysML BDD diagram defining work-flow model structure.

that, clinicians process his treatment through multiple stages (do state); and finally, the discharge nurse or CT will process his discharge or might send him to another unit in case he needs further treatment (exit state). Those states are defined at the treatment block, which is connected to the other blocks through different signals such as "send patient home" signal which represents discharged patient as demonstrated in Figure 5.5. Each state is described by different functions and different activity models. Figure F.8. in the appendices section is another model that demonstrates the simulation model's behavior in more detail.

5.2 Discussion of The DES Model Results

The MBSE integration between the conceptual model and the Tecnomatix model was achieved manually. The resulting data were analyzed and a group of modification scenarios were formulated to optimize the ED process. Figure 5.6 shows how the mapping process was achieved between SysML activity diagrams, data grids and the simulation platform.

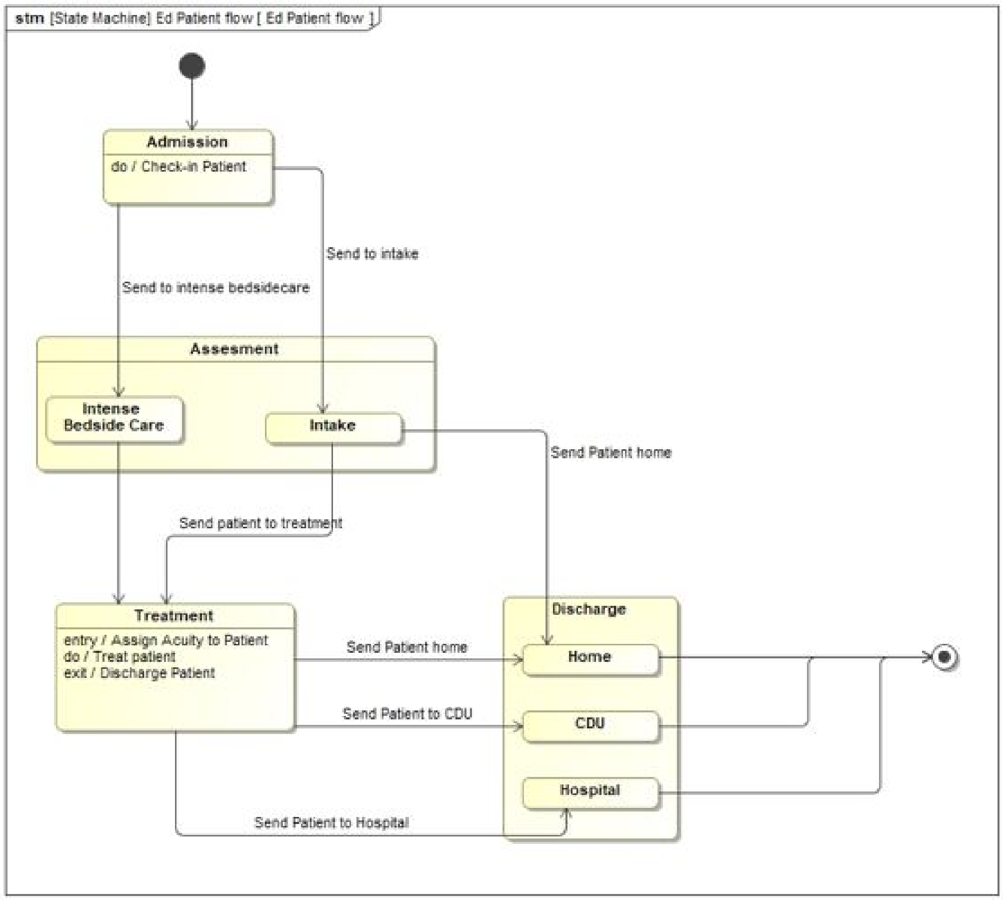


Fig. 5.5.: SysML STM diagram describing model behavior.

5.2.1 Time-in-Motion Model Results

We used the time-in-motion model in estimating the high-level room utilization data, without taking into consideration the interaction between human resources and patients. Figure 5.7 shows a graphical representation of the results from the time-in-motion model in the form of resource utilization charts for each one of the four treatment units respectively; showing percentages of patients occupancy at each pod, non-operating time and idle time at each. We can observe from the charts that the utilization rates of pods at Intake - without the non-operating time - is close to 97 %; while it ranges between 75 and 90 percents for the other units, where the idle time is observed to be large for LA. Table 5.1 demonstrates the numerical data for

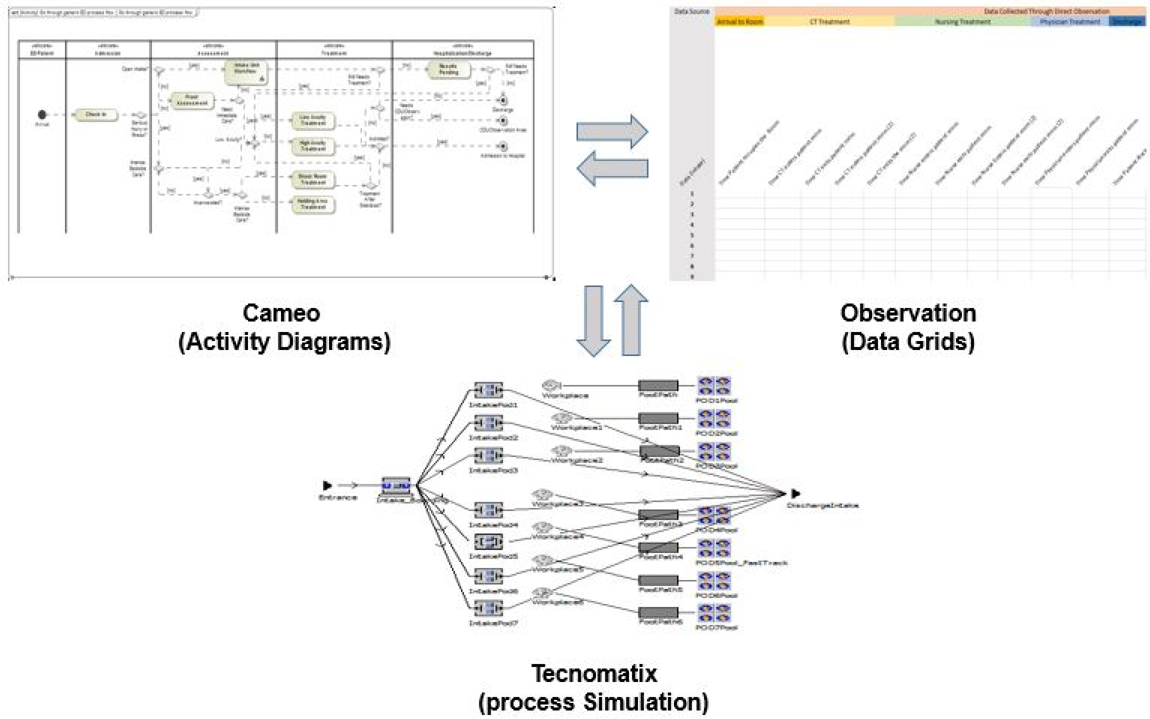
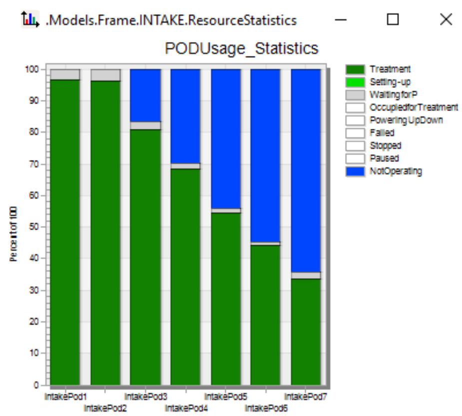


Fig. 5.6.: Demonstration of the mapping Process between Cameo activity models, data grids and Tecnomatix process simulation.

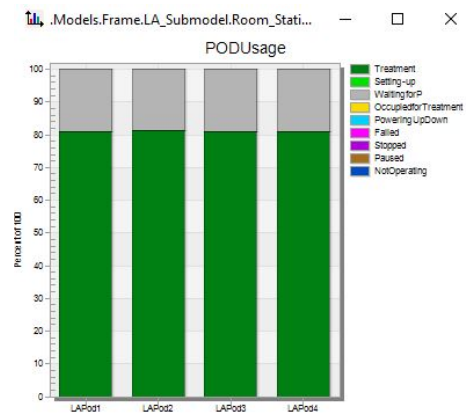
pod utilization rates. This data is used to show the capacity of the ED by estimating the portion of time pods are occupied by patients. It is observed from the data that Intake Pods are occupied more than 95% of the time while they are in operation, which causes patients to have long waiting times. Charts also show a higher occupancy rate for HA pods compared to LA and Shock ones. A high pod utilization rate doesn't mean that all rooms within the pod are utilized; therefore, room utilization rates are expected to have lower values, especially for LA unit which has six rooms for each pod.

5.2.2 Resource Model Results

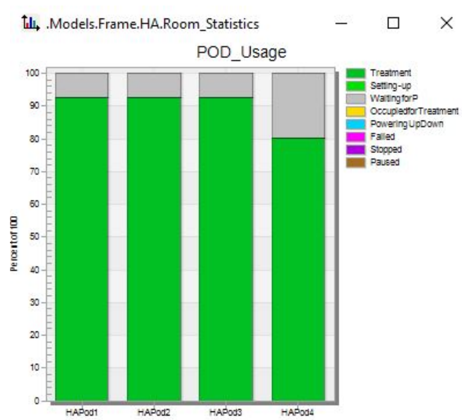
Human resource utilization data were estimated by the resource model. These data represent the percentages of time spent by each human resource inside patients'



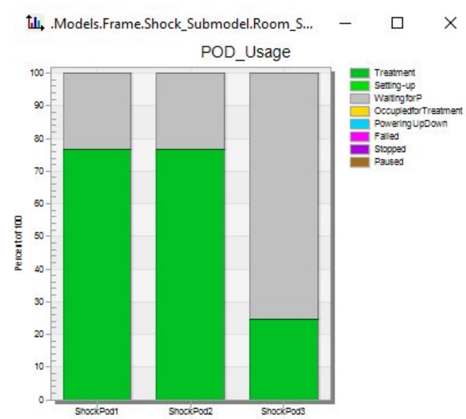
(a) Intake pods utilization chart.



(b) LA pods utilization chart.



(c) HA pods utilization chart.



(d) Shock room utilization chart.

Fig. 5.7.: Room usage charts for Intake, LA, HA and Shock room respectively, showing patient occupancy rate in green, room idle time in gray and non-operating time in blue.

Table 5.1: Physical resources statistics as estimated by Model A

Treatment Pod	Occupancy Rate	Non-operating Time	Idle Time
Intake Pod 1	96.56%	0%	3.44%
Intake Pod 2	96.41%	0%	3.59%
Intake Pod 3	80.81%	16.67%	2.52%
Intake Pod 4	68.32%	29.75%	1.93%
Intake Pod 5	54.41%	44.04%	1.55%
Intake Pod 6	44.05%	54.75%	1.20%
Intake Pod 7	33.45%	64.25%	2.31%
LA Pod 1	79.59%	0%	20.41%
LA Pod 2	79.72%	0%	20.28%
LA Pod 3	79.59%	0%	20.21%
LA Pod 4	79.66%	0%	20.34%
HA Pod 1	87.6%	0%	12.4%
HA Pod 2	87.73%	0%	12.27%
HA Pod 3	87.82%	0%	12.18%
HA Pod 4	74.59%	16.67%	8.74%
Shock Pod 1	76.77%	0%	23.23%
Shock Pod 2	76.61%	0%	23.39%
Shock Pod 3	24.46%	66.67%	8.87%

rooms based on applying the queuing theory, where patients wait inside their rooms until a clinician is available to serve them. The sequence of this queuing process is shown in Figure 5.8. For each activity in that diagram, a loop might be added, where care providers might visit the patient inside his room more than once. Table 5.2 shows the percentage of time spent by each clinician inside patients' rooms after running the model for three years.

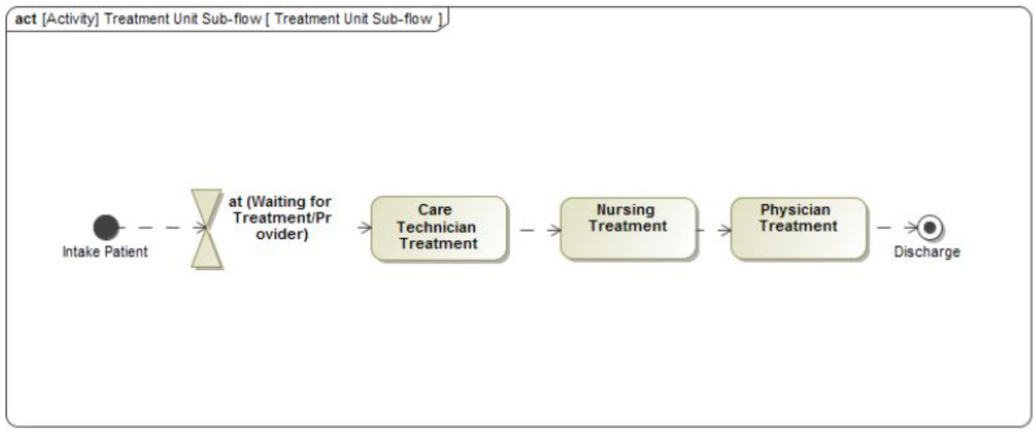


Fig. 5.8.: SysML Activity Diagram, showing the process sequence of the patient care process inside each treatment unit.

It is observed from Table 5.2 that the percentage of time physicians spend inside patients' rooms is relatively higher than other human resources, recorded at 75.16% for physicians at LA-Intake and recorded at 79.59% for physicians at HA-Shock; since physicians serve a large number of patients at the same time (up to 45 patients per shift). Utilization rates recorded for CTs are considered to be the lowest, where CTs at LA and HA spend 16% and 21% of the time inside patients' rooms; however, Intake CT spend 48.9% of the time inside patients' rooms due to the high occupancy rate at Intake compared to the other units.

Some of Tecnomatix output reports for both model A and model B are shown in the appendices.

Table 5.2: Percentage of time spent by CTs, registered nurses (RNs) and attending physicians inside patients' rooms (contact time) during their shifts, as estimated by Model B.

HR Type	Utilization Rate
Intake CT	48.9%
Intake RN	44.01%
LA CT	20.82%
LA RN	40.35%
HA CT	16.31%
HA RN	36.94%
Shock RN	32.23%
Intake_LA PHYS.	75.16%
HA_Shock PHYS.	79.59%
Fast_Track PHYS.	37.18%

5.3 Modification Scenarios

Information driven from the MBSE framework and the resulting data from both models were analyzed and formulated to develop a group of "what-if" scenarios for ED process improvement. Results from the resource model show a large workload for physicians at the four units, since each physician is assigned to two treatment units at the same time. Results also show high room utilization rates at Intake, which cause patients to wait for more than 30 minutes on an average before getting assigned to an Intake room. Results show a high occupancy rate for HA unit as well. The problem is formulate such that, the objective function is to minimize the average LOS and the average time between door to room. The first constraint to our problem is a cost constraint, which represents the hiring budget for adding new resources to the process. The second constraint is an improvement constraint, which requires a minimum of 10% improvement in the average LOS and the average time between door to room. The third constraint is related to the clinical value, where the average LOS shall not be less than 2 hours. Decision variables are the resources amounts and the shift times. Two different types of what-if scenarios were implemented using the resource model, the first one is based on optimizing existing ED resources (added cost = 0) and the second one is adding more human resources to the current process [44] [45].

5.3.1 Optimization of Existing ED Resources

Four different case studies were applied to optimize the current resources without adding more costs. The first case study we applied was moving resources between LA and Intake. First, we tried re-assigning one pod from LA to Intake, and re-assigning the LA nurses working in that pod to Intake without changing the Nurse to room ratio; such that, three rooms were added to Intake and six rooms were removed from LA. Two performance measures were compared: the average LOS and the time between door to intake room. Results show a slight improvement in the average LOS and door to room time as demonstrated in Table 5.3.

Table 5.3: Results of the first what-if scenario (Case study 1) compared to the current model

Performance Metric	**Current Model**	**Case Study 1**
Average LOS	3.8 hrs.	3.7 hrs.
Door to Intake Room	31.17 mins.	30.4 mins.

Second, we re-assigned one pod from LA to Intake and changed the nurse to patient ratio at Intake from 1/3 to 1/4, except for Intake pod 7 which remains at 1/2, such that, all six rooms were allocated to Intake from LA. After increasing the nurse to patient ratio at Intake, we tested replacing the nurses from the removed pod at LA with one physician serving at Intake/LA between 9 AM to 6 PM (peak time). This optimization scenario shows a possible reduction in the average LOS from 3.8 hours to 3.25 hours, and a possible 7 minutes reduction in the average time between door to Intake room as demonstrated in Table 5.4. Both first and second case studies have an additional cost = 0; therefore, both meet the cost constraint. Only case study two meets the improvement constraint; therefore, it is determined to be the optimum solution for Intake patients. It is also observed that by applying the second case study, the percentage of time clinicians spend with patients will be optimized as demonstrated in Table 5.5. The table shows an increased utilization rates for Intake/LA CTs, RNs and fast-track physicians. It also shows a reduced utilization rate for Intake/LA physicians'. Both case studies show that the current number of physicians has the highest impact on the problem.

Table 5.4: Results of the second what-if scenario (Case study 2) compared to the current model

Performance Metric	**Current Model**	**Case Study 2**
Average LOS	3.8 hrs.	3.25 hrs.
Door to Intake Room	31.17 mins.	23.2 mins.

Table 5.5: Comparison between current and optimum human resource utilization rates from case study 2.

HR	Current Utilization	Optimum Utilization
Intake CT	48.9%	59.74%
Intake RN	44.01%	47.4%
LA CT	20.82%	25.31%
LA RN	40.35%	45.96%
Intake/LA PHYS.	75.16%	74.56%
Fast-Track PHYS.	37.18%	44.23%

The third case study is based on moving resources between LA and HA. We tested re-assigning one pod from LA to HA without changing the Nurse to room ratio; such that, four rooms were added to HA and six rooms were removed from LA. Two performance measures were compared: the average LOS and the time between Door to HA room. Results are demonstrated in Table 5.6, which shows a 30-minutes reduction in the average LOS.

In addition, we tested changing the nurse to patient ratio at HA from 1/4 to 1/5, and adding one physician serving at HA/Shock between 9 AM to 6 PM (peak time) instead. Results from this case study (forth case) are demonstrated in Table 5.7, which shows a slight improvement in LOS compared to results from Table 5.7. Case study four is determined as the optimum solution for HA patients; since it meets the two constraints. Table 5.8 shows the new human resources utilization rates based on applying case study four. Table 5.9 shows a comparison between the current state, case study 1 and case study 2. Table 5.10 shows a comparison between the current state, case study 3 and case study 4.

Table 5.6: Results of the third what-if scenario (Case study 3) compared to the current state

Performance Metric	**Current Model**	**Case Study 3**
Average LOS	3.8 hrs.	3.3 hrs.
Door to HA Room	4.7 mins.	4.55 mins.

Table 5.7: Results of the forth what-if scenario (Case study 4) compared to the current state

Performance Metric	**Current Model**	**Case Study 4**
Average LOS	3.8 hrs.	3.25 hrs.
Door to HA Room	4.7 mins.	3.78 mins.

Table 5.8: Comparison between the current and optimum human resource utilization rates from case study 4

HR	Current Utilization	Optimum Utilization
HA CT	16.31%	17.14%
HA RN	36.94%	42.08%
LA CT	20.82%	25.31%
LA RN	40.35%	45.96%
HA/Shock PHYS.	79.59%	65.97%

Table 5.9: Comparison between the current state, case study 1 and case study 2 (optimum)

Point of Comparison	Current State	Case Study 1	Case Study 2
Average LOS	3.8 hrs.	3.7 hrs.	**3.25 hrs.**
Door to Intake Room	31.17 mins.	30.4 mins.	**23.2 mins.**
Added/Removed INT RNs	0	+2 RNs	**0**
Added/Removed LA RNs	0	-2 RNs	**-2 RNs**
Added/Removed Physicians	0	0	**+1 Physician**
Number of Intake Rooms	20	23	**26**
Number of LA Rooms	24	18	**18**
Intake N/P Ratio	1 to 3	1 to 3	**1 to 4**

5.3.2 Allocating More Resources to The ED

Based on the results from the first four case studies, other case studies were introduced and communicated with the ED based on adding more physicians to the current model. The average LOS was used as a performance metric in this test. First, five different experiments were tested on the physicians at HA/Shock, where we tested adding from one to five physicians serving at both units. An experiment

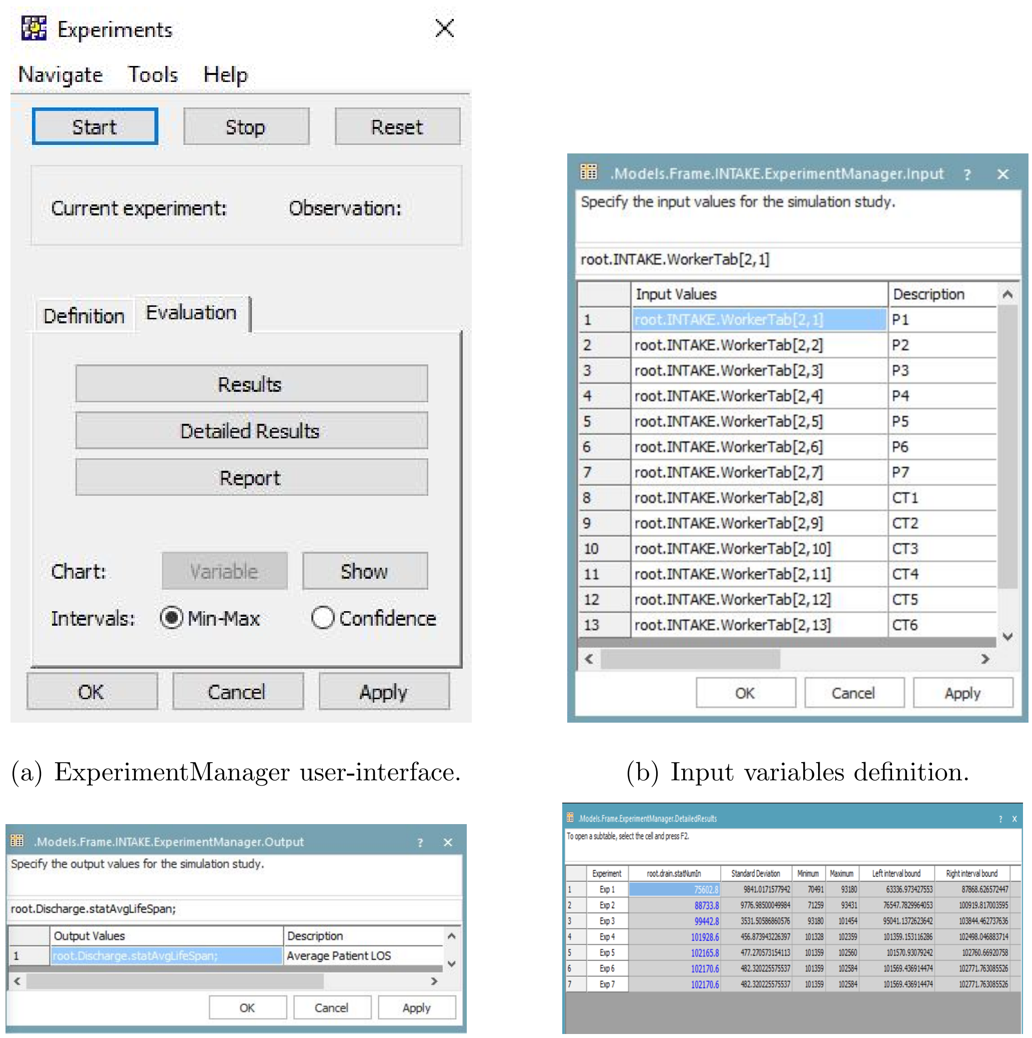
Table 5.10: Comparison between the current state, case study 3 and case study 4 (optimum)

Point of Comparison	**Current State**	**Case Study 3**	**Case Study 4**
Average LOS	3.8 hrs.	3.3 hrs.	**3.25 hrs.**
Door to HA Room	4.7 mins.	4.55 mins.	**3.78 mins.**
Added/Removed HA RNs	0	+2 RNs	**0**
Added/Removed LA RNs	0	-2 RNs	**-2 RNs**
Added/Removed Physicians	0	0	**+1 Physician**
Number of HA Rooms	16	20	**20**
Number of LA Rooms	24	18	**18**
HA N/P Ratio	1 to 4	1 to 4	**1 to 5**

number from two to six demonstrates each added physician, while experiment one represents the current state. We started by adding one physician at the peak-time, then adding more physicians one by one to the remaining shifts. Similarly, we tested adding physicians from one to five at Intake/LA. In addition, we tested adding one to five CTs at Intake as a lower cost alternative to adding physicians. A cost constraint of $1,000,000 was identified as the maximum cost for hiring new resources.

A tool in Tecnomatix namely, "ExperimentManager" was used to conduct all the experiments that involve adding resource to the ED due to the sensitivity of the problem. The paired t-test was used by this tool for testing the null hypothesis to design our experiments. This test was used because the simulation was run for multiple times for each experiment. The observed statistical significance values (p-values) were analyzed and traditionally determined as 0.05, where values less than 0.05 are considered as statistically significant. Figure 5.9 shows the sequence of conducting experiments using experiment manager tool. The p-values from the outputs of each test are shown in the appendices.

Resulting graphs were plotted using "ExperimentManager" tool to show the optimum LOS value for each case study. Figure 5.10 shows the results of sensitivity analysis on HA/Shock physicians, including statistics on the output values. Figure 5.11 shows the results of sensitivity analysis on Intake/LA physicians. Figure 5.12 shows the results of sensitivity analysis on Intake CTs. Figure 5.13 shows the results after combining all optimum scenarios for adding physicians. The x-axis in all



(a) ExperimentManager user-interface.

(b) Input variables definition.

(c) Output variables definition.

(d) ExperimentManager evaluation report.

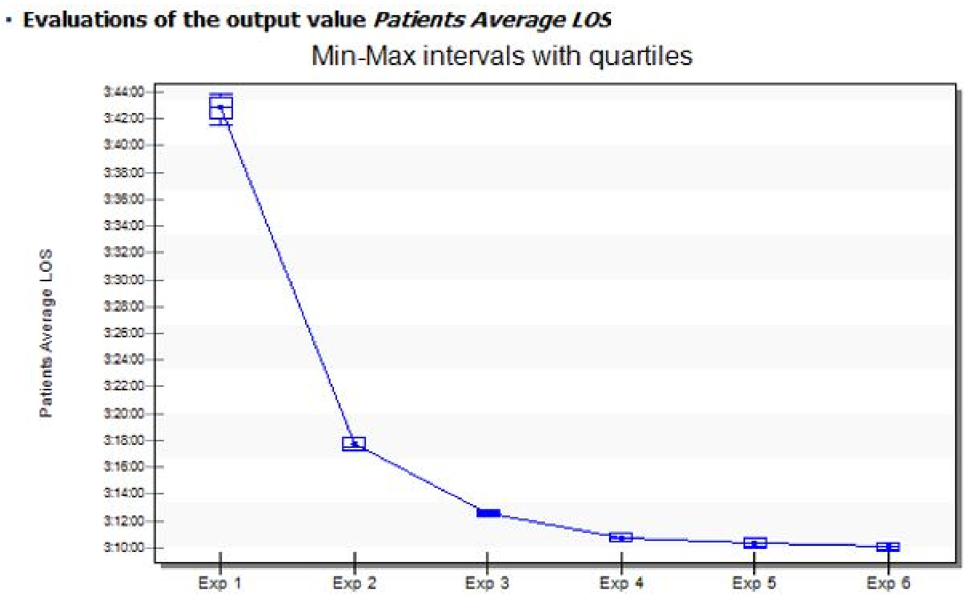
Fig. 5.9.: Sequence of using ExperimentManager tool in Plant Simulation.

plots represents the experiment number as described earlier. The y-axis in all plots represents the average LOS in hours. It is concluded that the average LOS can be reduced up to 3.18 hours when adding three physicians at HA/Shock, and to 3.13 hours when adding four physicians at Intake/LA. Adding CTs at Intake might result in improving the average LOS by 5 minutes only as shown in Figure 5.12; therefore it doesn't meet the improvement constraint.

A combination between all optimum scenarios results in an optimum average LOS of 2.43 hours as shown in experiment five in Figure 5.13; however, experiment three shown in Figure 5.13 is identified as the optimum solution because it meets the cost constraint. The optimum LOS is identified as 2.83 hours, which is considered as a 25.53% reduction in the average LOS for ED patient. The optimum scenario will result in adding four physicians; therefore, the percentages of time physicians spend inside patients' rooms are reduced at the four units based on the new simulation results. The annual cost is also increased by $960,000, assuming each physician will make an annual salary of $240,00 per year (as estimated by the ED). Table 5.11 shows a comparison between the current and the new human resource utilization rates for Intake CTs, Intake/LA Physicians and HA/Shock Physicians; showing a reduction of approximately 20% in the percentages of time spent inside patients' rooms based on applying the optimum scenario [44].

Table 5.11: Comparison between the current and new human resource utilization rates based on applying the optimum scenario

HR	**Current Utilization**	**Optimum Utilization**
INT CT	48.9%	42.14%
INT_LA PHYS	75.16%	57.27%
HA_SHOCK PHYS	79.59%	64.39%



(a) Plot of sensitivity analysis results on physicians at HA/Shock, showing the optimum solution as adding three physicians through the different shifts, which results in an average LOS of 3:10 hours.

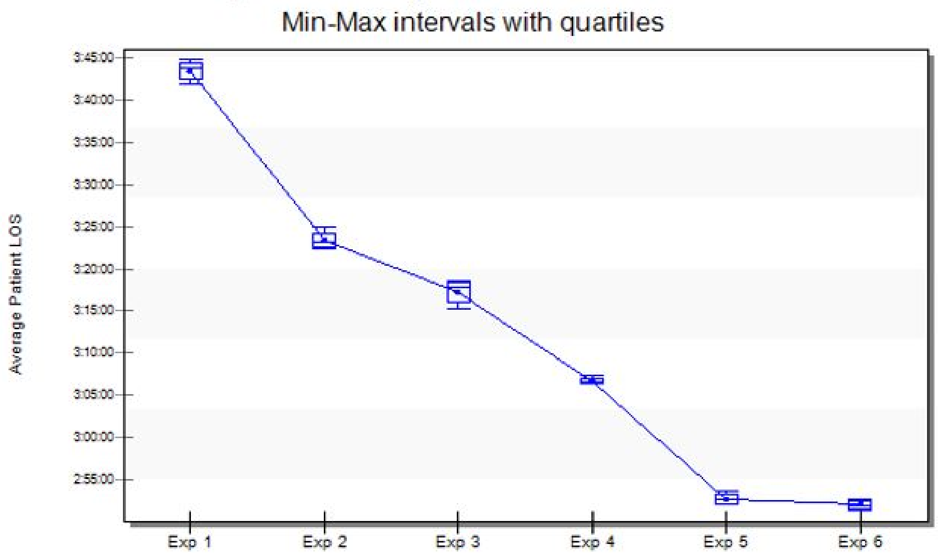
Output value *Patients Average LOS*

	Mean value	Standard Deviation	Minimum	Maximum	Left interval bound	Right interval bound
Exp 1	3:42:51.2744	55.4423	3:41:28.9672	3:43:49.9383	3:41:42.1712	3:44:00.3776
Exp 2	3:17:41.4816	28.4625	3:17:13.3516	3:18:14.7905	3:17:06.0060	3:18:16.9572
Exp 3	3:12:34.5362	11.9432	3:12:15.9410	3:12:47.6492	3:12:19.6502	3:12:49.4222
Exp 4	3:10:45.7982	16.5133	3:10:28.7441	3:11:07.5165	3:10:25.2161	3:11:06.3803
Exp 5	3:10:23.6310	17.0655	3:10:00.6991	3:10:43.1016	3:10:02.3607	3:10:44.9014
Exp 6	3:10:06.0997	15.5990	3:09:46.4497	3:10:24.0829	3:09:46.6571	3:10:25.5422

(b) Experiment statistics after five simulation runs.

Fig. 5.10.: Sensitivity to number of physicians at HA/Shock.

• **Evaluations of the output value *Average Patient LOS***



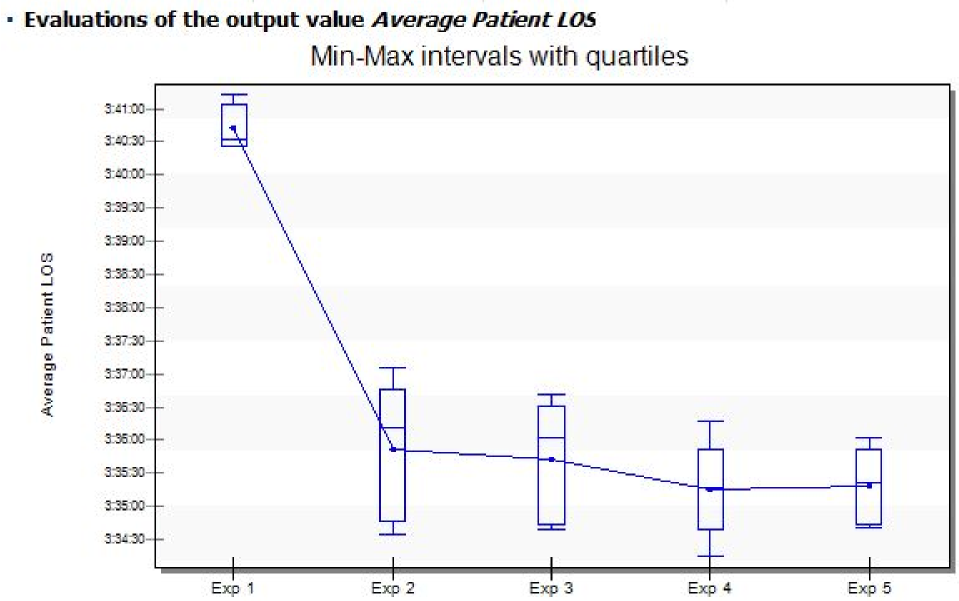
(a) Plot of sensitivity analysis results on physicians at Intake/LA, showing the optimum solution as adding four physicians through the different shifts, which results in an average LOS of 2:52 hours.

Output value *Average Patient LOS*

	Mean value	Standard Deviation	Minimum	Maximum	Left interval bound	Right interval bound
Exp 1	3:43:34.4524	1:05.0363	3:41:52.3807	3:44:47.0331	3:42:13.3913	3:44:55.5135
Exp 2	3:23:22.7185	58.4716	3:22:31.0219	3:24:59.5442	3:22:09.8396	3:24:35.5974
Exp 3	3:17:17.3577	1:20.3680	3:15:15.3782	3:18:39.1329	3:15:37.1872	3:18:57.5281
Exp 4	3:06:38.8923	25.2148	3:06:19.4052	3:07:21.4689	3:06:07.4646	3:07:10.3200
Exp 5	2:52:39.6154	36.8939	2:52:04.8010	2:53:38.1918	2:51:53.6310	2:53:25.5999
Exp 6	2:51:58.2653	33.2121	2:51:21.7695	2:52:43.6553	2:51:16.8698	2:52:39.6607

(b) Experiment statistics after five simulation runs.

Fig. 5.11.: Sensitivity to number of physicians at Intake/LA.



(a) Plot of sensitivity analysis results on CTs at Intake, showing the optimum value as adding one more CT, which results in an average LOS of 3:35 hours.

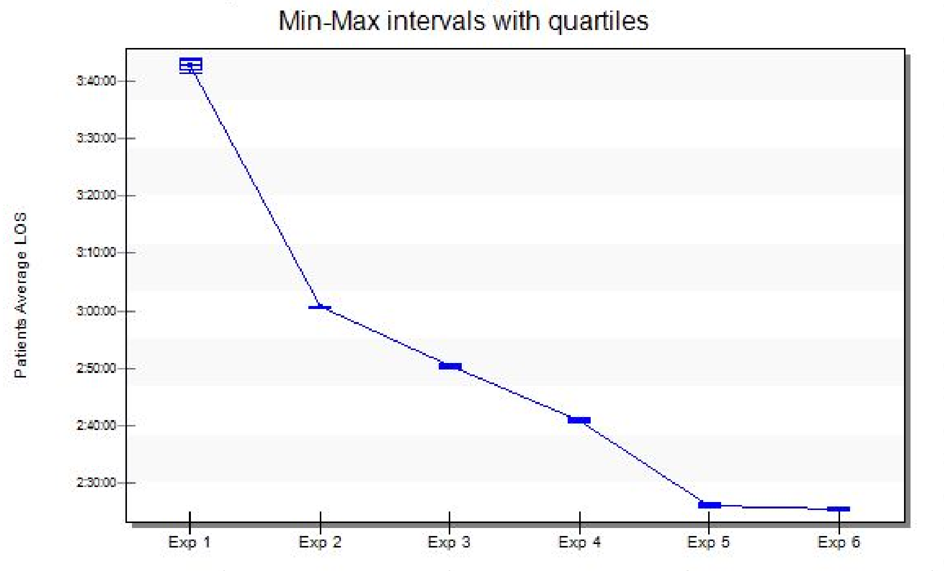
Output value *Average Patient LOS*

	Mean value	Standard Deviation	Minimum	Maximum	Left interval bound	Right interval bound
Exp 1	3:40:42.4716	20.8596	3:40:25.5194	3:41:12.2691	3:40:16.4722	3:41:08.4710
Exp 2	3:35:51.3204	1:02.8628	3:34:35.2768	3:37:05.3614	3:34:32.9683	3:37:09.6725
Exp 3	3:35:42.3082	55.1870	3:34:39.1015	3:36:41.3312	3:34:33.5232	3:36:51.0933
Exp 4	3:35:15.4607	43.7670	3:34:15.7058	3:36:16.8791	3:34:20.9095	3:36:10.0118
Exp 5	3:35:18.0864	35.0565	3:34:39.9943	3:36:02.4122	3:34:34.3920	3:36:01.7807

(b) Experiment statistics after five simulation runs.

Fig. 5.12.: Sensitivity to number of CTs at Intake/LA.

▪ **Evaluations of the output value *Patients Average LOS***



(a) Plot of sensitivity analysis results on physicians at all four units, showing the optimum value as adding four more physicians at Intake/LA and HA/Shock, which results in an average LOS of 2:50 hours (optimum solution identified).

Output value *Patients Average LOS*

	Mean value	Standard Deviation	Minimum	Maximum	Left interval bound	Right interval bound
Exp 1	3:42:51.2744	55.4423	3:41:28.9672	3:43:49.9383	3:41:42.1712	3:44:00.3776
Exp 2	3:00:41.5329	6.8132	3:00:32.7364	3:00:51.7127	3:00:33.0410	3:00:50.0249
Exp 3	2:50:28.6641	18.3370	2:50:03.8814	2:50:50.9712	2:50:05.8089	2:50:51.5193
Exp 4	2:40:55.8690	19.2233	2:40:34.6774	2:41:27.2781	2:40:31.9092	2:41:19.8289
Exp 5	2:26:09.6941	17.3422	2:25:44.7553	2:26:31.2999	2:25:48.0789	2:26:31.3094
Exp 6	2:25:30.4010	12.8297	2:25:18.3676	2:25:44.5770	2:25:14.4100	2:25:46.3919

(b) Experiment statistics after five simulation runs.

Fig. 5.13.: Sensitivity to number of physicians at Intake/LA and HA/Shock combined.

6. CONCLUSION AND FUTURE WORK

The conclusions of the current research project can be summarized as follows:

1. A model-based systems engineering approach is applied to build a patient flow systems model all the way from stakeholder needs to simulation of the ED process. The four pillars of systems engineering were modeled with an emphasis given to modeling the behavior of the system. This approach has been applied to Eskenazi ED, and can be generalized and applied to other EDs as well. The resulting MBSE framework provided the following: a. Better understanding of the system and its requirements, b. Identification of simulation inputs, outputs and key decision points, c. Mapping of the process flow, d. Documentation of the system in the form of a group of models, e. Communication tool, and f. Verification and validation tool.

2. Two different simulation models were implemented to model and simulate the ED work-flow using a commercial DES tool: Tecnomatix 13.0. Multiple methods and testing cases were implemented to verify and validate the two models. The validity of the models was determined by comparing the results with an alternative output data from the ED.

3. The Time-in-motion model was used to predict the high-level room and patient data, and the resource model was used to predict human resource utilization data. The resource model was used in formulating and running a group of "what-if" scenarios that offer multiple strategies for resource allocation optimization.

4. Four case studies were implemented to optimize existing ED resources. Case study two was applied on Intake patients, and shows a potential reduction in the average LOS from 3.8 hours to 3.25 hours, and a potential reduction in the time between door to Intake room from 31.7 minutes to 23.2 minutes. Case study four was applied on HA patients, and shows a potential reduction in the average LOS from 3.8 hours to 3.25 hours.

5. Three case studies were implemented to optimize resource allocation by adding more physicians to Intake, LA, HA and Shock room, and by adding more CTs to Intake. A combination between all of the three case studies resulted in reducing the average LOS by more than 25%, and reducing the time spent by physicians inside patients' rooms by more than 20%.

Future work will focus on using the systems modeling efforts and expanding our model to include the two use-cases (phase II of the project). The first use-case will be applied on patients with acute exacerbations of chronic obstructive pulmonary disease (COPD). Those patients often present in significant respiratory distress; therefore, they require emergency care.

The second use-case will be applied to patients who present with mental illness, and require medical evaluation for acute injury or toxicities requiring intervention, followed by evaluation by psychiatric services. Those patients are presented as acutely intoxicated. We are currently in the process of collecting the required data and modeling the workflow of those patients with the help of medical students and our research team members. This activity requires the breakdown of the system-level views into more detailed structures describing staffing requirements for those patients and the cost associated with their care.

The simulation model has proven to be a valid decision-making tool that can be used by the ED in making resource planning decisions; however, it has the following limitations:

1. The model did not consider some design variables which impact the process and need to be considered in the future such as student nurses and physicians, whom they help registered nurses and attending physicians in treating patients; therefore, adding those resources to the model in the future will provide a better understanding of the current resource utilization at the ED.

2. Fewer data points were collected for LA, HA and Shock patients compared to Intake patients. The current model didn't capture patients who stay inside those units for a long time, and sometimes for one day or more. This is due to the limitations

in the current data collection methods applied. It is recommended in the future to use data collected through the ED systems over using time studies and manual data collection approaches, although this might seem difficult due to the limited access to patient data.

3. Output data for patients left without being seen (LWBS) was not calculated using the model, since no data were available for them and those patients were not captured in the generic process flow model. It is recommend considering those patients as a separate case study in the future.

5. Human Resource utilization rates are assumed to be the percentage of time spent by an ED clinician to serve a number of patients inside their rooms. The time physicians, CTs and nurses spend inside their workstations or doing other tasks is not estimated by the model, which is recommended to be considered in the future.

6. Other DES validation methods are used in similar case studies and were not included in the current model. Those validation methods include validation using mathematical and operations research models such as the M/M/C queuing model [46]. In addition, model validation should be applied on recent changes in the ED process, and using real-time data from the ED, which is not currently available.

7. It is assumed that all human resources will reserve the exact same functions; however, CTs might replace nurses in some tasks and vice versa. A more detailed functional analysis of ED resources needs to be conducted in the future.

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APPENDICES

A. ED PLAN VIEW MODEL

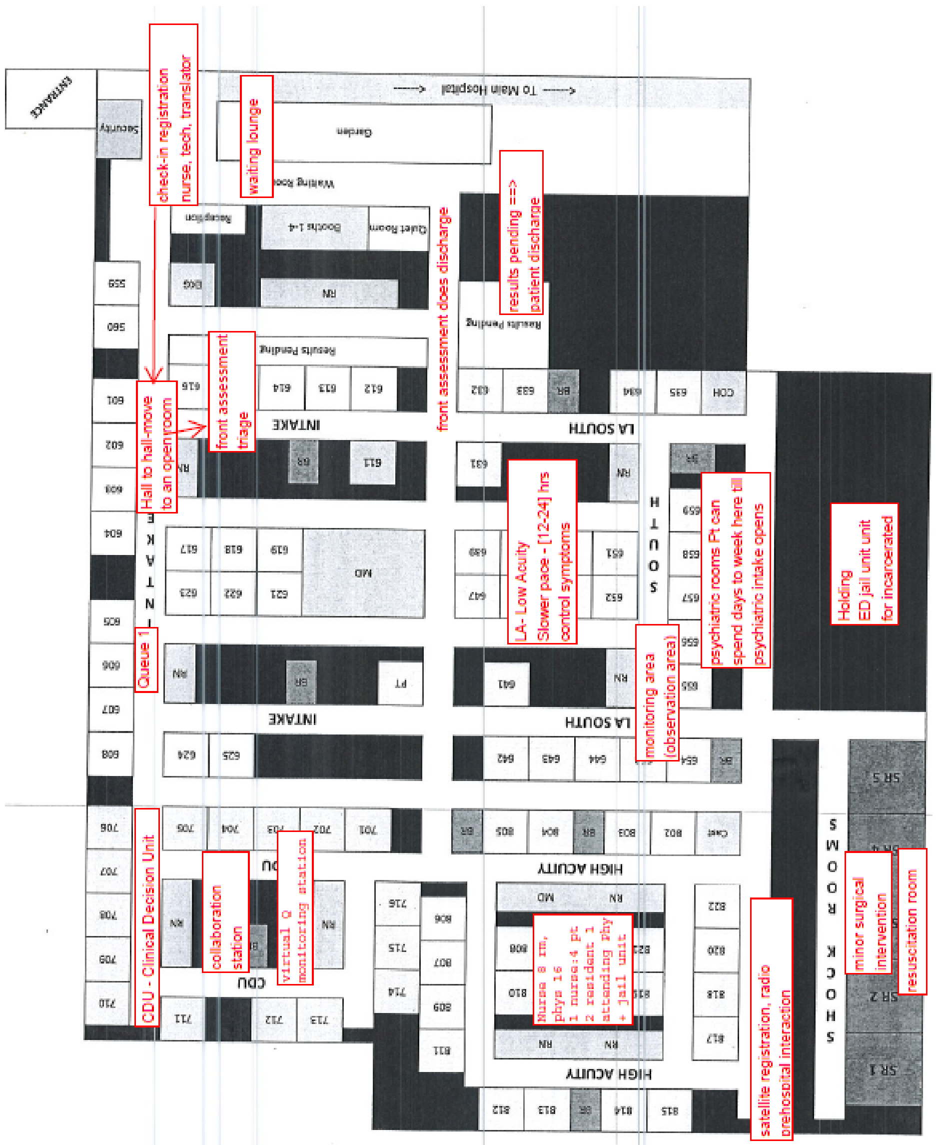


Fig. A.1.: Plan view model of the ED with labels.

B. TIME STUDY TEMPLATES

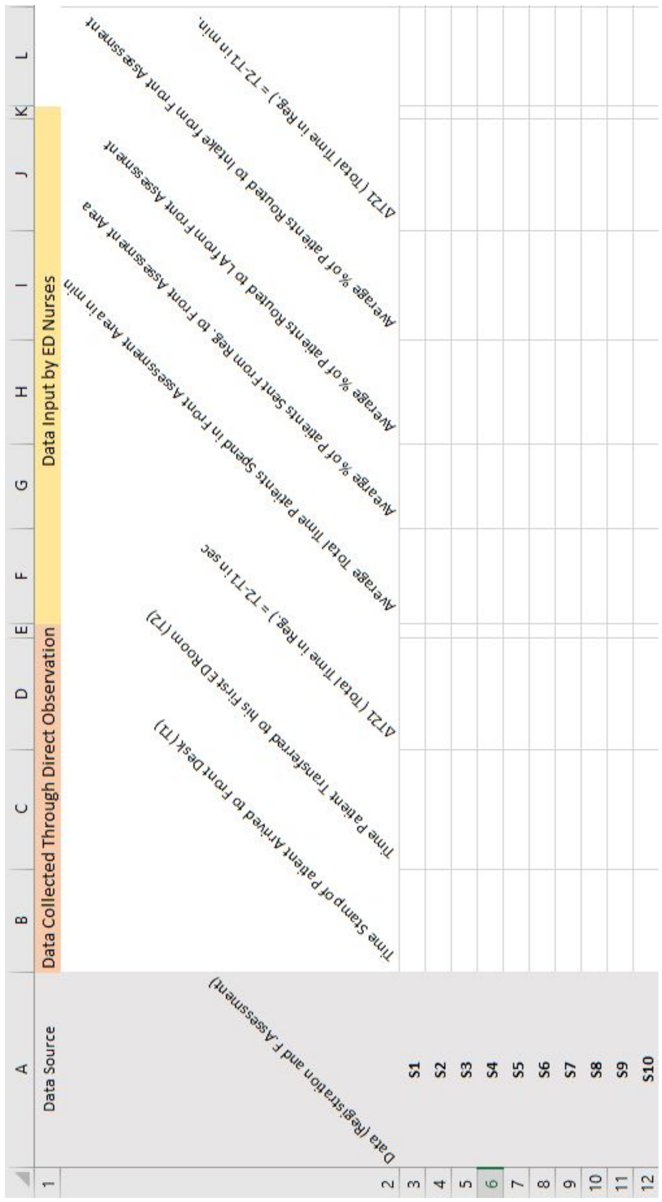


Fig. B.1.: Time study template used to record patient data at the registration desk.

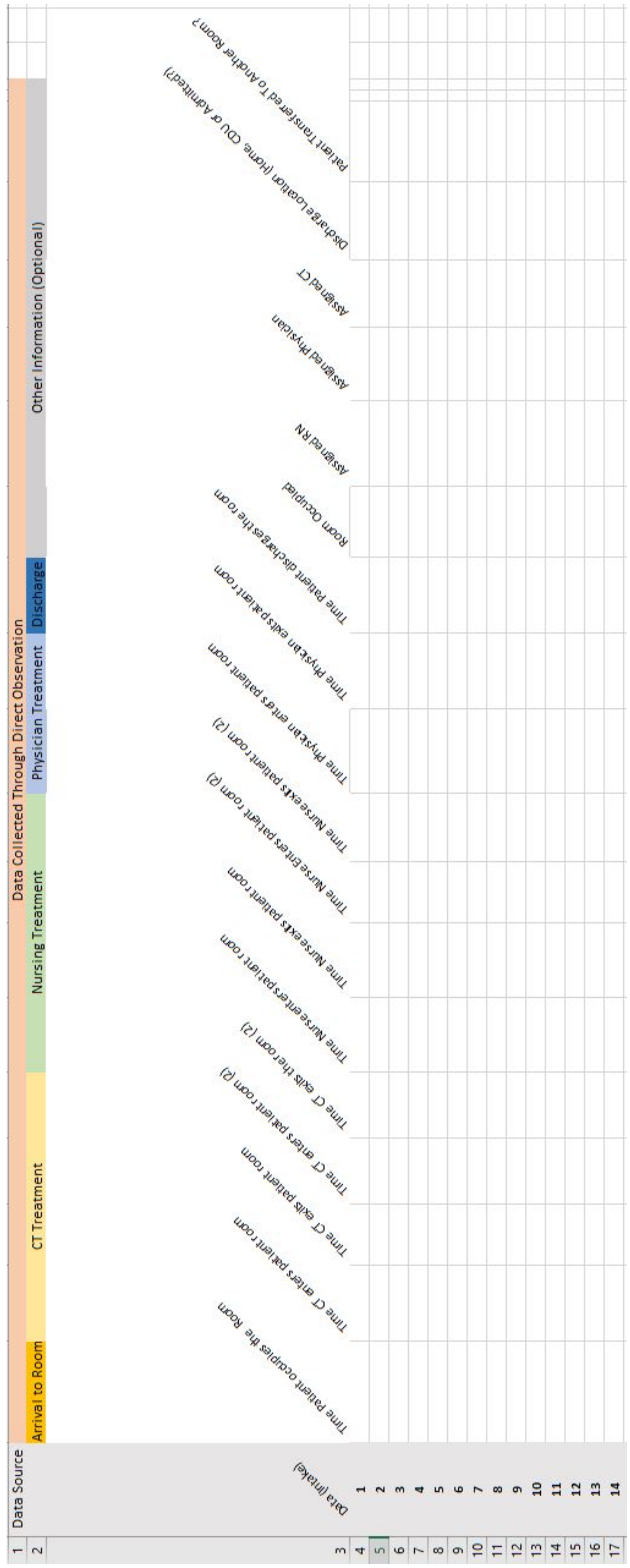


Fig. B.2.: Time study template used to record patient data inside the treatment units.

C. TECNOMATIX MODEL OBJECTS

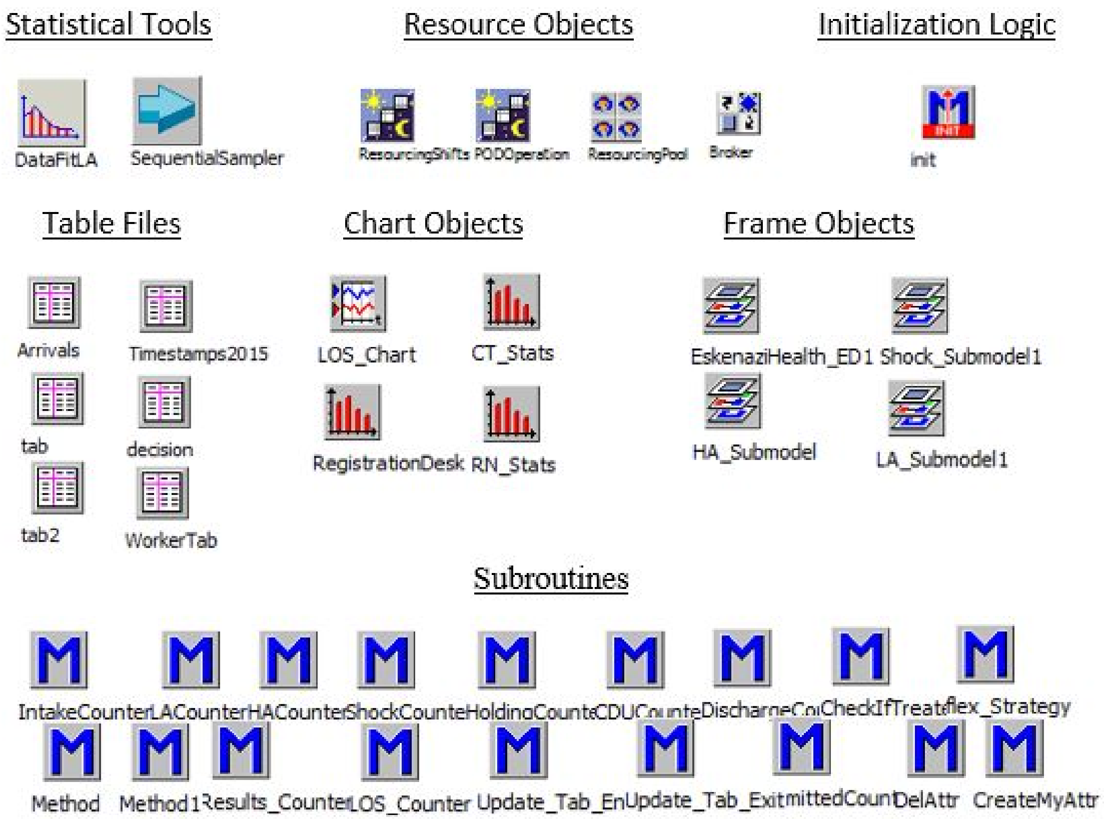


Fig. C.1.: Tecnomatix objects used by the simulation model.

Statistical Tools: Tools used for data fitting and output sampling.

Resource Objects: Objects and tools used to input ED resourcing grids.

Initialization Logic: Sub-routine used to set-up the initial conditions of the model.

Table Files: Files containing model input and output data.

Chart Objects: Represent charts that track some of the model variables (e.g LOS and number of patients) while the simulation is running.

Frame Objects: Represent the main model and sub-models for the treatment units.

Sub-routines: Programs which Tecnomatix execute while the simulation is running.

D. ED DATA

Care Area	Disposition	Door to Room	Room to Initial Assmt Star	Door to 1st Prov Assig	Room to 1st Prov Orde	Door to Dispo	Dispo to Admi	Dispo to Depar	LOS	Number of Patients
ESK HOLDING ROOM [1601005]	Admit	10.88	23.8	32.38		277.08	227.71	227.71	585.12	40
ESK HOLDING ROOM [1601005]	Admit	5.33	4.58	23		207.16	144.63	176	402	23
ESK HOLDING ROOM [1601005]	Admit	3	27.67	20.02		242.03	222.01	235.45	561.28	24
ESK HOLDING ROOM [1601005]	Admit	7.18	20.98	20.4	16.48	282.82	293.38	315.12	636.5	32
ESK HOLDING ROOM [1601005]	Discharge	9.34	15.34	30.89		319.8		51.72	387	293
ESK HOLDING ROOM [1601005]	Discharge	7.9	8.37	21.08		265.83		50.03	348	226
ESK HOLDING ROOM [1601005]	Discharge	6.23	7.48	23.2		285.28		49.58	351	243
ESK HOLDING ROOM [1601005]	Discharge	6.61	13.41	23.44	30.45	269.67	35.65	42.5	342	305

Fig. D.1.: ED throughput summary from Epic (From October 1st, 2016 through February 1st, 2017).

Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
05/01 EZ 7a-3p J.Acciani EZ 7a-3p A.Beckman EZ 9a-5p L.Rood EZ 12p-8p L.Schafer EZ 3p-11p M.Rutz EZ 3p-11p K.Brucker EZ 5p-1a H.Minnigan EZ 11p-7a M.Kuchinski EZ 11p-7a D.Rusk	05/02 EZ 7a-3p T.Stepsis EZ 7a-3p C.Hobgood EZ 8a-4p A.Leflore EZ 9a-5p A.Humbert EZ 12p-8p C.Stehman EZ 3p-11p K.Brucker EZ 3p-11p L.Schafer EZ 4p-12a H.Minnigan EZ 5p-1a A.Mitchell EZ 11p-7a D.Rusk EZ 11p-7a M.Kuchinski	05/03 EZ 7a-3p F.Russell EZ 7a-3p A.Leflore EZ 8a-4p L.Rood EZ 9a-5p L.Coy EZ 12p-8p J.Jones EZ 3p-11p A.Humbert EZ 3p-11p C.Stehman EZ 4p-12a M.Rutz EZ 5p-1a M.Doehring EZ 11p-7a M.Kuchinski EZ 11p-7a B.Sloan	05/04 EZ 7a-3p A.Leflore EZ 7a-3p L.Rood EZ 8a-4p L.Coy EZ 9a-5p F.Russell EZ 12p-8p J.Acciani EZ 3p-11p M.Rutz EZ 3p-11p H.Minnigan EZ 4p-12a T.Stepsis EZ 5p-1a D.Beam EZ 11p-7a B.Sloan EZ 11p-7a A.Mitchell	05/05 EZ 7a-3p C.Stehman EZ 7a-3p M.Rutz EZ 8a-4p K.Brucker EZ 9a-5p C.Miramonti EZ 3p-11p E.Weinstein EZ 3p-11p H.Minnigan EZ 4p-12a J.Finnell EZ 5p-1a D.O'Donnell EZ 11p-7a A.Mitchell EZ 11p-7a B.Sloan	05/06 EZ 7a-3p J.Turner EZ 7a-3p A.Humbert EZ 8a-4p M.Kuchinski EZ 9a-5p C.Stehman EZ 3p-11p H.Minnigan EZ 3p-11p J.Finnell EZ 4p-12a P.Pang EZ 5p-1a H.Fleming EZ 11p-7a J.Acciani EZ 11p-7a T.Stepsis	05/07 EZ 7a-3p M.Doehring EZ 7a-3p M.Rutz EZ 9a-5p F.Russell EZ 12p-8p V.Palmer-Smi EZ 3p-11p P.Musey EZ 3p-11p J.Turner EZ 5p-1a J.Jones EZ 11p-7a T.Stepsis EZ 11p-7a J.Acciani
05/08 EZ 7a-3p C.Stehman EZ 7a-3p F.Russell EZ 9a-5p J.Finnell EZ 12p-8p M.Doehring EZ 3p-11p J.Turner EZ 3p-11p J.Jones EZ 5p-1a M.Rutz EZ 11p-7a M.Kuchinski EZ 11p-7a D.Rusk	05/09 EZ 7a-3p J.Finnell EZ 7a-3p C.Stehman EZ 8a-4p V.Palmer-Smi EZ 9a-5p A.Leflore EZ 12p-8p H.Minnigan EZ 3p-11p P.Musey EZ 3p-11p A.Beckman EZ 4p-12a L.Rood EZ 5p-1a F.Messina EZ 11p-7a D.Rusk EZ 11p-7a M.Kuchinski	05/10 EZ 7a-3p M.Rutz EZ 7a-3p L.Coy EZ 8a-4p C.Weaver EZ 9a-5p A.Leflore EZ 12p-8p J.Kindrat EZ 3p-11p L.Rood EZ 3p-11p J.Finnell EZ 4p-12a A.Beckman EZ 5p-1a J.Turner EZ 11p-7a M.Kuchinski EZ 11p-7a D.Rusk	05/11 EZ 7a-3p C.Miramonti EZ 7a-3p V.Palmer-Smi EZ 8a-4p L.Schafer EZ 9a-5p T.Stepsis EZ 12p-8p A.Mitchell EZ 3p-11p H.Minnigan EZ 3p-11p J.Kindrat EZ 4p-12a M.Doehring EZ 5p-1a A.Leflore EZ 11p-7a B.Sloan EZ 11p-7a M.Kuchinski	05/12 EZ 7a-3p A.Beckman EZ 7a-3p J.Turner EZ 8a-4p J.Finnell EZ 9a-5p L.Schafer EZ 3p-11p C.Weaver EZ 3p-11p H.Minnigan EZ 4p-12a J.Kindrat EZ 5p-1a T.Stepsis EZ 11p-7a L.Rood EZ 11p-7a B.Sloan	05/13 EZ 7a-3p E.Weinstein EZ 7a-3p A.Beckman EZ 8a-4p A.Leflore EZ 9a-5p R.Fisher EZ 3p-11p P.Pang EZ 3p-11p L.Schafer EZ 4p-12a J.Turner EZ 5p-1a J.Finnell EZ 11p-7a D.Cooper EZ 11p-7a L.Rood	05/14 EZ 7a-3p J.Jones EZ 7a-3p R.Fisher EZ 9a-5p A.Beckman EZ 12p-8p D.O'Donnell EZ 3p-11p L.Schafer EZ 3p-11p A.Leflore EZ 5p-1a C.Stehman EZ 11p-7a E.Weinstein EZ 11p-7a D.Cooper

Fig. D.2.: Sample of Physicians schedules during the first two weeks of May.

E. DATA FITTING RESULTS

	string 0	real 1	real 2	boolean 3	real 4	real 5	boolean 6	real 7	real 8	boolean 9	real 10	real 11
string	Distribution	Chi statistic	Chi value	Result Chi	KS statistic	KS value	Result KS	AD statistic	AD value	Result AD	Parameter1	Parameter2
1	Gamma	0.7469	7.8041	true	0.4773	1.3580	true	0.2378	2.4920	true	4.8593822...	1157.3128...
2	Lognorm	1.3022	7.8041	true	0.5398	1.3580	true	0.1609	2.4920	true	5640.0629...	2787.7650...
3	Erlang	1.6384	7.8041	true	0.6797	1.3580	true	0.4695	2.4920	true	5786.5641...	2587.8301...
4	Paralogistic	2.4444	9.4802	true	0.4996	1.3580	true	0.2809	2.4920	true	2.8215326...	8296.3893...
5	Loglogistic	2.4444	9.4802	true	0.6938	1.3580	true	0.7184	2.4920	true	5144.0674...	4.3338132...
6	Weibull	4.2222	9.4802	true	0.7502	1.3580	true	0.6806	2.4920	true	2.2791937...	6370.2663...
7	Laplace	4.8889	9.4802	true	0.7365	1.3580	true	0.8044	2.4920	true	5280	2802.8141...
8	Normal	4.9035	9.4802	true	0.9588	1.3580	true	1.2763	2.4920	true	5623.8253...	2628.2352...
9	Logistic	5.1111	9.4802	true	0.9385	1.3580	true	1.2005	2.4920	true	5623.8253...	2649.3458...
10	Triangle	5.5556	7.8041	true	1.0064	1.3580	true	3.6750	2.4920	false	3420	1620
11	Pareto	12.4444	9.4802	false	1.5416	1.3580	false	14.0450	2.4920	false	1.8524417...	2955.7130...
12	Frechet	15.7778	9.4802	false	8.0711	1.3580	false	198.7766	2.4920	false	3.7277322...	4497.2879...
13	Uniform	25.1111	9.4802	false	2.4955	1.3580	false	11.4585	2.4920	false	1620	13020
14	Cauchy	34.3094	7.8041	false	2.8184	1.3580	false	16.7859	2.4920	false	3420	1455
15	Negexp	37.1111	11.0650	false	2.4910	1.3580	false	8.9379	2.4920	false	5623.8253...	
16	Gumbel	100.0000			0.3953	1.3580	true	0.1842	2.4920	true	5623.8253...	2649.3458...

Fig. E.1.: Data fitting results for Intake Patients, obtained from the "DataFit" tool in Tecnomatix. Data is for Model A.

	string 0	real 1	real 2	boolean 3	real 4	real 5	boolean 6	real 7	real 8	boolean 9	real 10	real 11
string	Distribution	Chi statistic	Chi value	Result Chi	KS statistic	KS value	Result KS	AD statistic	AD value	Result AD	Parameter1	Parameter2
1	Cauchy				1.6994	1.3580	false	5.2226	2.4920	false	2940	1335
2	Erlang				0.6369	1.3580	true	0.3917	2.4920	true	6773.0974...	3910.4496...
3	Frechet				2.8070	1.3580	false	29.1610	2.4920	false	3.1584549...	5918.4511...
4	Gamma				0.4523	1.3580	true	0.2293	2.4920	true	3.4738273...	2257.6991...
5	Gumbel				0.4286	1.3580	true	0.2212	2.4920	true	7842.8571...	4842.1541...
6	Laplace				0.5851	1.3580	true	0.3537	2.4920	true	7620	4654.7829...
7	Logistic				0.6286	1.3580	true	0.3851	2.4920	true	7842.8571...	4842.1541...
8	Loglogistic				0.5425	1.3580	true	0.2810	2.4920	true	6857.8711...	3.5487862...
9	Lognorm				0.4486	1.3580	true	0.1892	2.4920	true	7829.4450...	4614.4392...
10	Negexp				0.8776	1.3580	true	0.7833	2.4920	true	7842.8571...	
11	Normal				0.6273	1.3580	true	0.4315	2.4920	true	7842.8571...	4482.9636...
12	Paralogistic				0.3918	1.3580	true	0.1938	2.4920	true	2.3135199...	10897.689...
13	Pareto				0.6956	1.3580	true	1.4842	2.4920	true	1.4494689...	3499.0205...
14	Triangle				0.4842	1.3580	true	1.2097	2.4920	true	2940	2940
15	Uniform				1.0695	1.3580	true	2.6305	2.4920	false	2940	17340
16	Weibull				0.4998	1.3580	true	0.2700	2.4920	true	1.8871560...	8899.5020...

Fig. E.2.: Data fitting results for LA Patients, obtained from the "DataFit" tool in Tecnomatix. Data is for Model A.

	string 0	real 1	real 2	boolean 3	real 4	real 5	boolean 6	real 7	real 8	boolean 9	real 10	real 11
string	Distribution	Chi statistic	Chi value	Result Chi	KS statistic	KS value	Result KS	AD statistic	AD value	Result AD	Parameter1	Parameter2
1	Cauchy				2.0006	1.3580	false	5.2907	2.4920	false	180	60
2	Erlang				2.6380	1.3580	false	7.9858	2.4920	false	485.62889...	343.39148...
3	Frechet				5.5071	1.3580	false	74.8518	2.4920	false	2.2844430...	236.19004...
4	Gamma				1.7886	1.3580	false	3.1269	2.4920	false	1.5394186...	242.81444...
5	Gumbel				1.9608	1.3580	false	5.0953	2.4920	false	373.79310...	531.30845...
6	Laplace				1.5348	1.3580	false	2.9210	2.4920	false	240	288.69463...
7	Logistic				2.1563	1.3580	false	5.7613	2.4920	false	373.79310...	531.30845...
8	Loglogistic				1.5083	1.3580	false	2.0109	2.4920	true	273.47224...	2.3689819...
9	Lognorm				1.3655	1.3580	false	1.8211	2.4920	true	329.78758...	254.38950...
10	Negexp				1.5237	1.3580	false	3.4342	2.4920	false	373.79310...	
11	Normal				2.1207	1.3580	false	6.0674	2.4920	false	373.79310...	522.06759...
12	Paralogistic				1.3716	1.3580	false	2.3466	2.4920	true	1.6081498...	370.09135...
13	Pareto				1.3745	1.3580	false	6.2159	2.4920	false	1.3418118...	125.03766...
14	Triangle				3.9787	1.3580	false	48.3799	2.4920	false	180	120
15	Uniform				4.3490	1.3580	false	59.8647	2.4920	false	120	2860
16	Weibull				1.6234	1.3580	false	3.3752	2.4920	false	1.0666032...	386.54691...

Fig. E.3.: Data fitting results for Intake CTs time-spans with patients, obtained from the "DataFit" tool in Tecnomatix. Data is for Model B.

	string 0	real 1	real 2	boolean 3	real 4	real 5	boolean 6	real 7	real 8	boolean 9	real 10	real 11
string	Distribution	Chi statistic	Chi value	Result Chi	KS statistic	KS value	Result KS	AD statistic	AD value	Result AD	Parameter1	Parameter2
1	Lognorm	0.9461	5.9752	true	0.5372	1.3580	true	0.3627	2.4920	true	581.67978...	382.74474...
2	Gamma	1.3474	5.9752	true	0.7834	1.3580	true	0.4415	2.4920	true	3.1054377...	185.38909...
3	Weibull	2.0000	7.8041	true	0.9172	1.3580	true	0.5823	2.4920	true	1.8545326...	651.74017...
4	Paralogistic	3.1429	7.8041	true	0.8098	1.3580	true	0.5529	2.4920	true	2.4074210...	813.30976...
5	Pareto	4.8571	7.8041	true	1.2843	1.3580	true	8.9022	2.4920	false	1.4040662...	239.77263...
6	Normal	5.4191	7.8041	true	1.2251	1.3580	true	1.2954	2.4920	true	575.71428...	331.24687...
7	Logistic	5.4286	7.8041	true	1.3108	1.3580	true	1.4400	2.4920	true	575.71428...	335.26213...
8	Erlang	5.5671	7.8041	true	0.6222	1.3580	true	0.4563	2.4920	true	556.16727...	321.10332...
9	Triangle	6.8571	5.9752	false	1.2168	1.3580	true	4.7155	2.4920	false	300	120
10	Loglogistic	9.7143	7.8041	false	1.0688	1.3580	true	1.6441	2.4920	true	508.86305...	3.6963535...
11	Laplace	14.0000	7.8041	false	0.9793	1.3580	true	1.5407	2.4920	true	480	361.63461...
12	Uniform	16.5714	7.8041	false	1.9910	1.3580	false	10.1066	2.4920	false	120	1440
13	Frechet	18.0000	7.8041	false	6.6177	1.3580	false	136.3486	2.4920	false	3.2659257...	440.15873...
14	Negexp	21.1429	9.4802	false	1.9408	1.3580	false	3.7533	2.4920	false	575.71428...	
15	Cauchy	25.2051	5.9752	false	2.4075	1.3580	false	9.6537	2.4920	false	300	210
16	Gumbel	100.0000			0.8368	1.3580	true	0.5148	2.4920	true	575.71428...	335.26213...

Fig. E.4.: Data fitting results for Intake RNs time-spans with patients, obtained from the "DataFit" tool in Tecnomatix. Data is for Model B.

	string 0	real 1	real 2	boolean 3	real 4	real 5	boolean 6	real 7	real 8	boolean 9	real 10	real 11
string	Distribution	Chi statistic	Chi value	Result Chi	KS statistic	KS value	Result KS	AD statistic	AD value	Result AD	Parameter1	Parameter2
1	Cauchy				1.3072	1.3580	true	1.5580	2.4920	true	900	240
2	Erlang				0.7593	1.3580	true	0.7008	2.4920	true	618.60395...	309.30197...
3	Frechet				2.6144	1.3580	false	47.2971	2.4920	false	3.7367716...	512.17451...
4	Gamma				0.7070	1.3580	true	0.6606	2.4920	true	4.1383505...	154.65098...
5	Gumbel				0.7513	1.3580	true	0.8046	2.4920	true	640	300.39973...
6	Laplace				0.6997	1.3580	true	0.6660	2.4920	true	750	339.41125...
7	Logistic				0.7056	1.3580	true	0.5838	2.4920	true	640	300.39973...
8	Loglogistic				0.8559	1.3580	true	1.2915	2.4920	true	585.70874...	4.3463355...
9	Lognorm				0.7338	1.3580	true	0.6924	2.4920	true	652.97324...	379.83353...
10	Negexp				0.8175	1.3580	true	0.9805	2.4920	true	640	
11	Normal				0.6983	1.3580	true	0.5964	2.4920	true	640	274.22618...
12	Paralogistic				0.7413	1.3580	true	0.7197	2.4920	true	2.8297808...	944.62642...
13	Pareto				0.8905	1.3580	true	2.0477	2.4920	true	1.1336305...	245.57960...
14	Triangle				0.8715	1.3580	true	0.5798	2.4920	true	900	240
15	Uniform				1.0695	1.3580	true	1.7139	2.4920	true	240	900
16	Weibull				0.7170	1.3580	true	0.6869	2.4920	true	2.6400568...	722.53453...

Fig. E.5.: Data fitting results for Intake physicians time-spans with patients, obtained from the "DataFit" tool in Tecnomatix. Data is for Model B.

	string 0	real 1	real 2	boolean 3	real 4	real 5	boolean 6	real 7	real 8	boolean 9	real 10	real 11
string	Distribution	Chi statistic	Chi value	Result Chi	KS statistic	KS value	Result KS	AD statistic	AD value	Result AD	Parameter1	Parameter2
1	Cauchy				1.3072	1.3580	true	1.5580	2.4920	true	900	240
2	Erlang				0.7593	1.3580	true	0.7008	2.4920	true	618.60395...	309.30197...
3	Frechet				2.6144	1.3580	false	47.2971	2.4920	false	3.7367716...	512.17451...
4	Gamma				0.7070	1.3580	true	0.6606	2.4920	true	4.1383505...	154.65098...
5	Gumbel				0.7513	1.3580	true	0.8046	2.4920	true	640	300.39973...
6	Laplace				0.6997	1.3580	true	0.6660	2.4920	true	750	339.41125...
7	Logistic				0.7056	1.3580	true	0.5838	2.4920	true	640	300.39973...
8	Loglogistic				0.8559	1.3580	true	1.2915	2.4920	true	585.70874...	4.3463355...
9	Lognorm				0.7338	1.3580	true	0.6924	2.4920	true	652.97324...	379.83353...
10	Negexp				0.8175	1.3580	true	0.9805	2.4920	true	640	
11	Normal				0.6983	1.3580	true	0.5964	2.4920	true	640	274.22618...
12	Paralogistic				0.7413	1.3580	true	0.7197	2.4920	true	2.8297808...	944.62642...
13	Pareto				0.8905	1.3580	true	2.0477	2.4920	true	1.1336305...	245.57960...
14	Triangle				0.8715	1.3580	true	0.5798	2.4920	true	900	240
15	Uniform				1.0695	1.3580	true	1.7139	2.4920	true	240	900
16	Weibull				0.7170	1.3580	true	0.6869	2.4920	true	2.6400568...	722.53453...

Fig. E.6.: Data fitting results for Intake physicians time-spans with patients, obtained from the "DataFit" tool in Tecnomatix. Data is for Model B.

	string 0	real 1	real 2	boolean 3	real 4	real 5	boolean 6	real 7	real 8	boolean 9	real 10	real 11
string	Distribution	Chi statistic	Chi value	Result Chi	KS statistic	KS value	Result KS	AD statistic	AD value	Result AD	Parameter1	Parameter2
1	Cauchy				0.8769	1.3580	true	1.0557	2.4920	true	1680	420
2	Erlang				0.8287	1.3580	true	0.4124	2.4920	true	1376.6247...	562.00471...
3	Frechet				3.1567	1.3580	false	46.5297	2.4920	false	4.1108590...	1139.8367...
4	Gamma				0.8094	1.3580	true	0.4068	2.4920	true	6.0437674...	229.43746...
5	Gumbel				0.8641	1.3580	true	0.5048	2.4920	true	1386.6666...	566.39209...
6	Laplace				0.9150	1.3580	true	0.9731	2.4920	true	1620	650.53823...
7	Logistic				0.7391	1.3580	true	0.4246	2.4920	true	1386.6666...	566.39209...
8	Loglogistic				0.9651	1.3580	true	0.8128	2.4920	true	1292.3096...	4.8656943...
9	Lognorm				0.8476	1.3580	true	0.4367	2.4920	true	1395.8168...	625.80513...
10	Negexp				1.1087	1.3580	true	1.5691	2.4920	true	1386.6666...	
11	Normal				0.7086	1.3580	true	0.3776	2.4920	true	1386.6666...	533.99958...
12	Paralogistic				0.7950	1.3580	true	0.3993	2.4920	true	3.1748056...	2075.2726...
13	Pareto				0.9541	1.3580	true	2.1135	2.4920	true	1.7093124...	725.49206...
14	Triangle				1.0021	1.3580	true	2.9641	2.4920	false	1680	600
15	Uniform				0.5136	1.3580	true	1.5469	2.4920	true	600	2280
16	Weibull				0.7172	1.3580	true	0.3726	2.4920	true	2.9069223...	1561.1216...

Fig. E.7.: Data fitting results for HA CT time-spans with patients, obtained from the "DataFit" tool in Tecnomatix. Data is for Model B.

	string 0	real 1	real 2	boolean 3	real 4	real 5	boolean 6	real 7	real 8	boolean 9	real 10	real 11
string	Distribution	Chi statistic	Chi value	Result Chi	KS statistic	KS value	Result KS	AD statistic	AD value	Result AD	Parameter1	Parameter2
1	Cauchy				1.5783	1.3580	false	3.3516	2.4920	false	300	300
2	Erlang				0.7573	1.3580	true	0.5840	2.4920	true	927.27873...	535.36462...
3	Frechet				3.1557	1.3580	false	42.7152	2.4920	false	2.9598729...	606.83854...
4	Gamma				0.5395	1.3580	true	0.2757	2.4920	true	2.6744924...	309.09291...
5	Gumbel				0.5148	1.3580	true	0.2692	2.4920	true	826.66666...	576.10762...
6	Laplace				0.5713	1.3580	true	0.3638	2.4920	true	720	584.54160...
7	Logistic				0.6095	1.3580	true	0.4450	2.4920	true	826.66666...	576.10762...
8	Loglogistic				0.7072	1.3580	true	0.5430	2.4920	true	705.74286...	3.2771408...
9	Lognorm				0.4849	1.3580	true	0.2510	2.4920	true	824.87365...	571.94016...
10	Negexp				0.9607	1.3580	true	0.7218	2.4920	true	826.66666...	
11	Normal				0.5770	1.3580	true	0.4998	2.4920	true	826.66666...	543.15948...
12	Paralogistic				0.5096	1.3580	true	0.2438	2.4920	true	2.1431724...	1103.5656...
13	Pareto				0.7015	1.3580	true	2.1416	2.4920	true	1.3030001...	323.97053...
14	Triangle				0.8032	1.3580	true	2.4438	2.4920	true	300	300
15	Uniform				1.2276	1.3580	true	5.4270	2.4920	false	300	2100
16	Weibull				0.5042	1.3580	true	0.2874	2.4920	true	1.6476527...	932.04834...

Fig. E.8.: Data fitting results for HA RNS time-spans with patients, obtained from the "DataFit" tool in Tecnomatix. Data is for Model B.

	string 0	real 1	real 2	boolean 3	real 4	real 5	boolean 6	real 7	real 8	boolean 9	real 10	real 11
string	Distribution	Chi statistic	Chi value	Result Chi	KS statistic	KS value	Result KS	AD statistic	AD value	Result AD	Parameter1	Parameter2
1	Cauchy				0.5438	1.3580	true	0.3934	2.4920	true	360	60
2	Erlang				0.4041	1.3580	true	0.2184	2.4920	true	336.55860...	68.699736...
3	Frechet				2.1194	1.3580	false	9.9503	2.4920	false	6.3348848...	294.62798...
4	Gamma				0.4138	1.3580	true	0.2046	2.4920	true	23.532306...	14.023275...
5	Gumbel				0.4580	1.3580	true	0.2103	2.4920	true	330	77.459666...
6	Laplace				0.4279	1.3580	true	0.2037	2.4920	true	330	84.852813...
7	Logistic				0.3670	1.3580	true	0.1757	2.4920	true	330	77.459666...
8	Loglogistic				0.4595	1.3580	true	0.2067	2.4920	true	321.53911...	7.9788397...
9	Lognorm				0.4311	1.3580	true	0.2100	2.4920	true	330.13262...	69.691043...
10	Negexp				1.1240	1.3580	true	1.1840	2.4920	true	330	
11	Normal				0.3755	1.3580	true	0.2007	2.4920	true	330	67.082039...
12	Paralogistic				0.3393	1.3580	true	0.1602	2.4920	true	5.3070835...	479.85949...
13	Pareto				0.5438	1.3580	true	1.0835	2.4920	true	3.3137480...	245.00669...
14	Triangle				0.7250	1.3580	true	0.8700	2.4920	true	360	240
15	Uniform				0.5438	1.3580	true	0.5488	2.4920	true	240	420
16	Weibull				0.4144	1.3580	true	0.2015	2.4920	true	5.6588518...	357.57091...

Fig. E.9.: Data fitting results for HA physicians time-spans with patients, obtained from the "DataFit" tool in Tecnomatix. Data is for Model B.

	string 0	real 1	real 2	boolean 3	real 4	real 5	boolean 6	real 7	real 8	boolean 9	real 10	real 11
string	Distribution	Chi statistic	Chi value	Result Chi	KS statistic	KS value	Result KS	AD statistic	AD value	Result AD	Parameter1	Parameter2
1	Cauchy				0.9040	1.3580	true	0.9835	2.4920	true	480	180
2	Erlang				0.5720	1.3580	true	0.5238	2.4920	true	628.20541...	362.69456...
3	Frechet				3.6159	1.3580	false	9.8254	2.4920	false	3.4814113...	465.46334...
4	Gamma				0.7096	1.3580	true	0.5506	2.4920	true	2.8414272...	209.40180...
5	Gumbel				0.5644	1.3580	true	0.5170	2.4920	true	595	311.72540...
6	Laplace				0.4655	1.3580	true	0.2186	2.4920	true	570	332.34018...
7	Logistic				0.3882	1.3580	true	0.1975	2.4920	true	595	311.72540...
8	Loglogistic				0.5935	1.3580	true	1.1959	2.4920	true	535.49225...	3.9931986...
9	Lognorm				0.8719	1.3580	true	0.8633	2.4920	true	628.96386...	495.85175...
10	Negexp				1.2282	1.3580	true	1.3477	2.4920	true	595	
11	Normal				0.4055	1.3580	true	0.2236	2.4920	true	595	298.45435...
12	Paralogistic				0.5485	1.3580	true	0.5677	2.4920	true	2.5987296...	861.77809...
13	Pareto				1.4105	1.3580	false	4.4812	2.4920	false	0.9732339...	182.04776...
14	Triangle				0.6026	1.3580	true	2.1635	2.4920	true	480	120
15	Uniform				0.7031	1.3580	true	2.8589	2.4920	false	120	1200
16	Weibull				0.5521	1.3580	true	0.3854	2.4920	true	2.0528844...	668.84793...

Fig. E.10.: Data fitting results for LA RNs time-spans with patients, obtained from the "DataFit" tool in Tecnomatix. Data is for Model B.

	string 0	real 1	real 2	boolean 3	real 4	real 5	boolean 6	real 7	real 8	boolean 9	real 10	real 11
string	Distribution	Chi statistic	Chi value	Result Chi	KS statistic	KS value	Result KS	AD statistic	AD value	Result AD	Parameter1	Parameter2
1	Cauchy				1.7075	1.3580	false	5.6195	2.4920	false	120	225
2	Erlang				1.0408	1.3580	true	1.2852	2.4920	true	527.60551...	527.60551...
3	Frechet				3.3171	1.3580	false	12.1534	2.4920	false	2.6284321...	522.81965...
4	Gamma				0.7085	1.3580	true	0.4317	2.4920	true	1.4328887...	527.60551...
5	Gumbel				0.8345	1.3580	true	0.5733	2.4920	true	756	683.63733...
6	Laplace				0.7855	1.3580	true	0.7770	2.4920	true	660	627.91082...
7	Logistic				1.0743	1.3580	true	0.9578	2.4920	true	756	683.63733...
8	Loglogistic				0.7168	1.3580	true	1.3748	2.4920	true	609.78995...	2.8276475...
9	Lognorm				0.6873	1.3580	true	0.4319	2.4920	true	788.02157...	919.03427...
10	Negexp				0.6164	1.3580	true	0.4436	2.4920	true	756	
11	Normal				1.0685	1.3580	true	0.9980	2.4920	true	756	648.55531...
12	Paralogistic				0.6397	1.3580	true	0.6376	2.4920	true	1.8703461...	908.01438...
13	Pareto				0.9653	1.3580	true	2.7593	2.4920	false	0.8278603...	159.74681...
14	Triangle				0.9044	1.3580	true	2.0530	2.4920	true	120	120
15	Uniform				1.6171	1.3580	false	4.5999	2.4920	false	120	2040
16	Weibull				0.7267	1.3580	true	0.4584	2.4920	true	1.2078899...	808.24314...

Fig. E.11.: Data fitting results for LA physicians time-spans with patients, obtained from the "DataFit" tool in Tecnomatix. Data is for Model B.

	string 0	real 1	real 2	boolean 3	real 4	real 5	boolean 6	real 7	real 8	boolean 9	real 10	real 11
string	Distribution	Chi statistic	Chi value	Result Chi	KS statistic	KS value	Result KS	AD statistic	AD value	Result AD	Parameter1	Parameter2
1	Cauchy				1.0291	1.3580	true	2.4074	2.4920	true	1380	555
2	Erlang				0.6952	1.3580	true	0.5858	2.4920	true	4003.9850...	2831.2449...
3	Frechet				2.6144	1.3580	false	39.8044	2.4920	false	2.7342379...	2585.5844...
4	Gamma				0.6000	1.3580	true	0.4646	2.4920	true	1.8281786...	2001.9925...
5	Gumbel				0.5955	1.3580	true	0.4719	2.4920	true	3660	3013.1710...
6	Laplace				0.7349	1.3580	true	0.8166	2.4920	true	2310	3167.8383...
7	Logistic				0.7814	1.3580	true	0.6731	2.4920	true	3660	3013.1710...
8	Loglogistic				0.8043	1.3580	true	1.0559	2.4920	true	3014.8667...	2.9705048...
9	Lognorm				0.5983	1.3580	true	0.3804	2.4920	true	3670.7321...	3333.4084...
10	Negexp				0.6359	1.3580	true	0.4187	2.4920	true	3660	
11	Normal				0.7710	1.3580	true	0.6832	2.4920	true	3660	2750.6362...
12	Paralogistic				0.6362	1.3580	true	0.5503	2.4920	true	1.9556296...	4576.7682...
13	Pareto				0.4739	1.3580	true	1.3811	2.4920	true	0.9646557...	1021.9755...
14	Triangle				0.8536	1.3580	true	3.5717	2.4920	false	1380	1020
15	Uniform				1.0660	1.3580	true	2.9764	2.4920	false	1020	7740
16	Weibull				0.5901	1.3580	true	0.4654	2.4920	true	1.3852335...	4036.8040...

Fig. E.12.: Data fitting results for Shock RN time-spans with patients, obtained from the "DataFit" tool in Tecnomatix. Data is for Model B.

	string 0	real 1	real 2	boolean 3	real 4	real 5	boolean 6	real 7	real 8	boolean 9	real 10	real 11
string	Distribution	Chi statistic	Chi value	Result Chi	KS statistic	KS value	Result KS	AD statistic	AD value	Result AD	Parameter1	Parameter2
1	Cauchy				1.2347	1.3580	true	2.5846	2.4920	false	300	210
2	Erlang				0.6098	1.3580	true	0.3993	2.4920	true	1185.9846...	1185.9846...
3	Frechet				2.6144	1.3580	false	29.9284	2.4920	false	2.5036000...	846.84583...
4	Gamma				0.6861	1.3580	true	0.3719	2.4920	true	1.0624083...	1185.9846...
5	Gumbel				0.7677	1.3580	true	0.5251	2.4920	true	1260	1297.9984...
6	Laplace				0.7588	1.3580	true	0.9411	2.4920	true	645	1286.9343...
7	Logistic				0.9304	1.3580	true	0.7339	2.4920	true	1260	1297.9984...
8	Loglogistic				1.0148	1.3580	true	1.9355	2.4920	true	986.84948...	2.6600515...
9	Lognorm				0.5716	1.3580	true	0.3141	2.4920	true	1333.8559...	2021.5317...
10	Negexp				0.6405	1.3580	true	0.3836	2.4920	true	1260	
11	Normal				0.9188	1.3580	true	0.7394	2.4920	true	1260	1184.9050...
12	Paralogistic				0.8274	1.3580	true	0.9171	2.4920	true	1.7723027...	1428.5045...
13	Pareto				0.5762	1.3580	true	1.4734	2.4920	true	0.6747496...	181.48969...
14	Triangle				0.9644	1.3580	true	3.2483	2.4920	false	300	150
15	Uniform				1.2627	1.3580	true	3.0596	2.4920	false	150	3090
16	Weibull				0.6555	1.3580	true	0.3978	2.4920	true	1.0174631...	1269.5098...

Fig. E.13.: Data fitting results for Shock physicians time-spans with patients, obtained from the "DataFit" tool in Tecnomatix. Data is for Model B.

F. OTHER OUTPUT DATA

Product Statistics - Cumulated Statistics of the Classes

Product-Oriented Statistics of all Existing and Deleted MUs (by Classes)

Class	Count	Deleted	Mean Life Time
Patient	65	275999	3:41:27.7470

Mean Time Portions of an MU Class of the Mean Life Span

Class	Production						Transport						Storage					
	Working	Set-up	Waiting	Stopped	Failed	Paused	Working	Set-up	Waiting	Stopped	Failed	Paused	Working	Set-up	Waiting	Stopped	Failed	Paused
Patient	43.64%	0.00%	36.41%	0.00%	0.00%	0.00%	0.03%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	19.69%	0.00%	0.00%	0.23%

Fig. F.1.: Patients' general statistics.

Drain Statistics

Name	Mean Life Time	Throughput	Throughput per Hour	Production	Transport	Storage	Value added	Portion
Patient	3:53:54.8907	4905	0.19	83.44%	0.03%	16.53%	39.64%	

.Models.Frame.CDU_Admission

Name	Mean Life Time	Throughput	Throughput per Hour	Production	Transport	Storage	Value added	Portion
Patient	3:14:13.4449	232023	8.82	74.31%	0.03%	25.66%	38.43%	

.Models.Frame.Discharge

Name	Mean Life Time	Throughput	Throughput per Hour	Production	Transport	Storage	Value added	Portion
Patient	6:07:41.9418	44614	1.70	95.21%	0.02%	4.77%	57.53%	

.Models.Frame.AdmittionH

Indianapolis, 7.10.2017

Mohamed Elshal

Fig. F.2.: Throughput Report for Model B.

Table of the p-values of the T-test of the output value *Patients Average LOS*

	Exp 2	Exp 3	Exp 4	Exp 5	Exp 6
Exp 1	0	0	0	0	0
Exp 2		0	0	0	0
Exp 3			0	0	0
Exp 4				0	0
Exp 5					0.004

Fig. F.3.: Resulting P-values for the optimum resource allocation case-study. All values are reported to be lower than 0.05.

Table of the p-values of the T-test of the output value *Average Patient LOS*

	Exp 2	Exp 3	Exp 4	Exp 5	Exp 6
Exp 1	0	0	0	0	0
Exp 2		0	0	0	0
Exp 3			0	0	0
Exp 4				0	0
Exp 5					0.1

Fig. F.4.: Resulting P-values for the case study that involves adding resource to Intake/LA. All values are reported to be lower than 0.05.

Table of the p-values of the T-test of the output value *Patients Average LOS*

	Exp 2	Exp 3	Exp 4	Exp 5	Exp 6
Exp 1	0	0	0	0	0
Exp 2		0	0	0.001	0
Exp 3			0	0	0.032
Exp 4				0	0
Exp 5					0

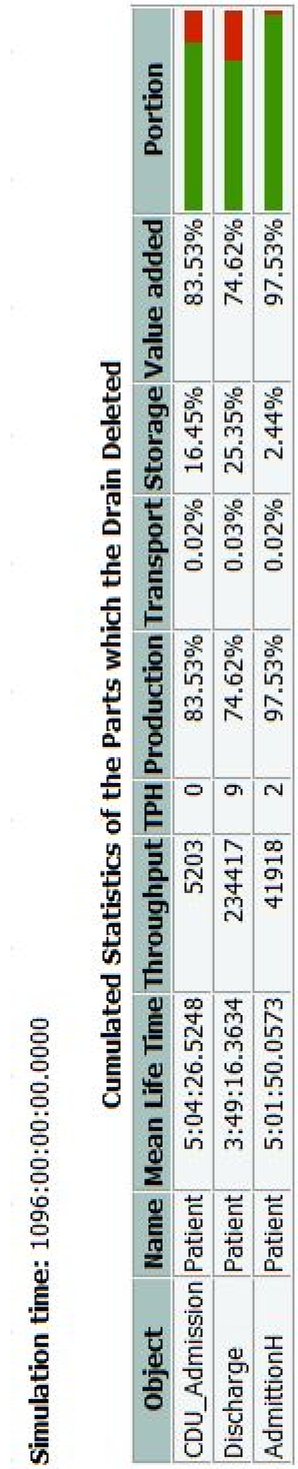
Fig. F.5.: Resulting P-values for the case study that involves adding resource to HA/Shock. All values are reported to be lower than 0.05.

Simulation time: 1096:00:00:00.0000

Cumulated Statistics of the Parts which the Drain Deleted

Object	Name	Mean Life Time	Throughput	TPH	Production	Transport	Storage	Value added	Portion
CDU_Admission	Patient	3:28:22.5045	1191	0	99.92%	0.03%	0.05%	49.62%	
Discharge	Patient	1:58:36.2366	53658	2	99.87%	0.06%	0.08%	71.55%	
AdmittionH	Patient	4:08:45.1218	9595	0	99.97%	0.03%	0.01%	91.78%	

Fig. F.6.: Tecnomatix throughput report after using an arrival distribution for patients instead of timestamps, showing a larger deviation in the output.



Simulation time: 1096:00:00:00.0000

Cumulated Statistics of the Parts which the Drain Deleted

Object	Name	Mean Life Time	Throughput	TPH	Production	Transport	Storage	Value added	Portion
CDU_Admission	Patient	5:04:26.5248	5203	0	83.53%	0.02%	16.45%	83.53%	
Discharge	Patient	3:49:16.3634	234417	9	74.62%	0.03%	25.35%	74.62%	
AdmittionH	Patient	5:01:50.0573	41918	2	97.53%	0.02%	2.44%	97.53%	

Fig. F.7.: Tecnomatix throughput report after using average distributions for all processing times, showing a larger deviation in the output.

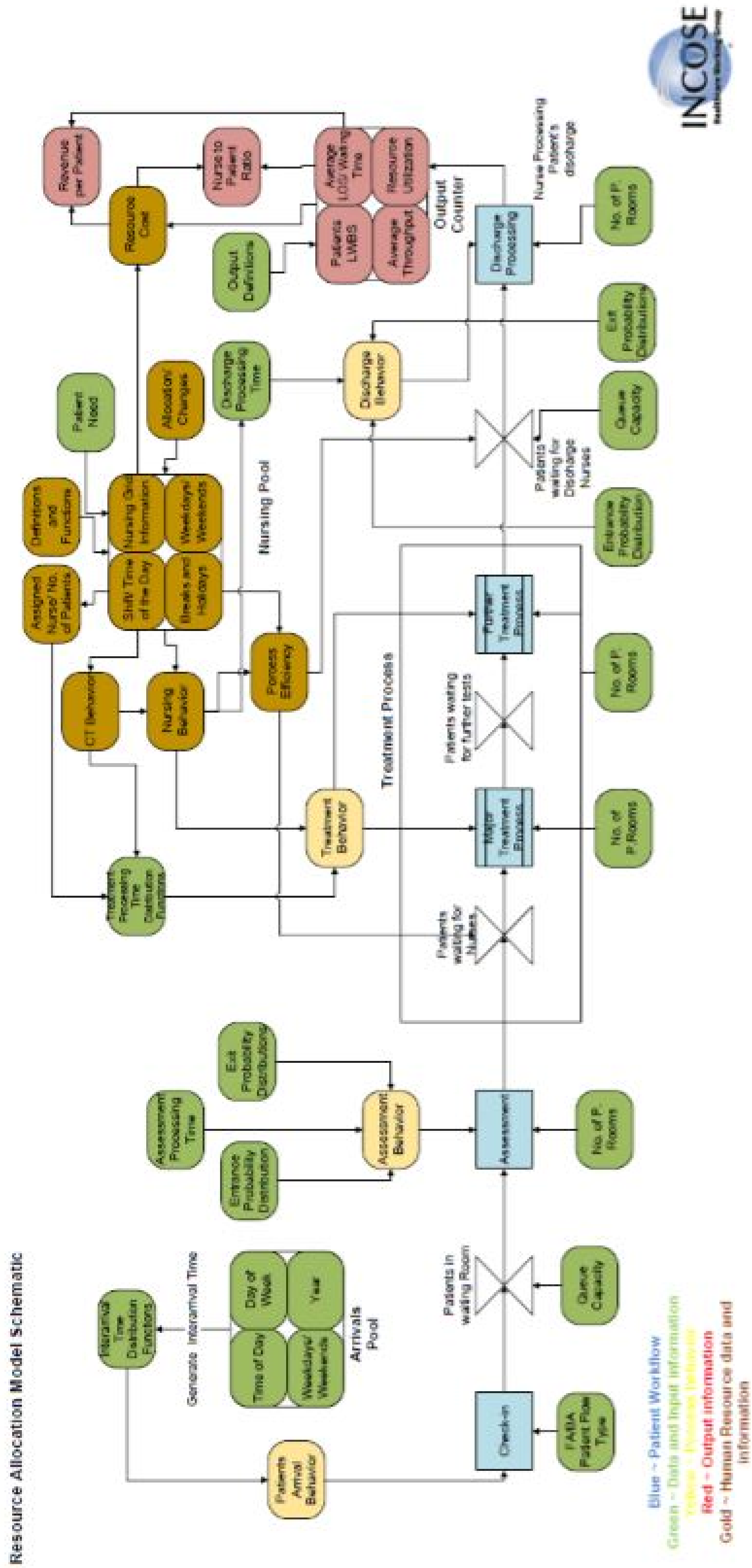


Fig. F.8.: Tecnomatix Model Behavior, described in a block digram implemented using Visio [1].

	A	B	C	D
1	**General model key decisions**	**Requirement**	**do we have these probabilites**	**Probability % out of total patients**
2	walkin	arrival data shall be used to create patient walk in	kalpak & Rapeepan code, 2014-16 Daven from Star or Picasso	
3	checkin	all patients shall be listed as walkin	Data collected from observation at Reg. (Mohamed sheet)	
4	decision No Serious injury	Probability distribution of acuity shall be used to route to Intake	Extracted from Daven's file "Arrivals by first room"	71.76%
5	decision Yes Serious injury	Probability distribution shall be used to route to intense bedside care either LA south+HA or to shoc	Extracted from Daven's file "Arrivals by first room"	28.24%
6	decision No Intense bedside care	Probability distribution shall be used to route to LA South and HA	Extracted from Daven's file "Arrivals by first room"	19.35%
7	decision Yes intesne bedsie care	Probability distribution shall be used to route to shock room	Extracted from Daven's file "Arrivals by first room"	5.72%
8	decision Yes is LA patient	Probability distribution shall be used to route to LA south room	Extracted from Daven's file "Arrivals by first room"	8.86%
9	decision No not LA patient	Probability distribution shall be used to route to HA room	Extracted from Daven's file "Arrivals by first room"	10.49%
10	decision Yes serious pateint stabilized	Probability distribution shall be routed to LA south and HA	Extracted from Savannah observation sheets	2.86%
11	decision Yes serious pateint stabilized	Probability distribution pateitn continues to stay in shock room to be transferred to ICU or inpatinet	Extracted from Savannah observation sheets	2.86%
12	decision yes still needs intake treatment	Probability distribution patient is transferred to LA and HA or continue in intake	Extracted from Savannah observation sheets	23.92%
13	decision no still needs intake	Probability distribution pateitn transfer to pending/discharge	Extracted from Savannah observation sheets	47.84%
14	decision yes transfer to LA+HA from intake	Probability distribution transfer to room available in LA or HA	Extracted from Savannah observation sheets	0.00%
15	decision No transfer to LA+HA from intake	Probability distribution transfer to room available in LA or HA	Extracted from Savannah observation sheets	47.84%
16	decsion transfer to LA or HA (this one is room and not acuity)	shall use decision for "decision Yes is LA patient"	Extracted from Savannah observation sheets	23.92%
17	decsion Yes transfer to inpatient or to CDU	Probability of inpatient room open for patient	Daven's file "number of patients currently going to sp	17.48%
18	decsion No transfer to inpatient or to CDU	Probaiblity of inpatient room not available for patient	Daven's file "number of patients currently going to sp	34.68%
19	decision Yes transfer to inpatient from	Probability distribution of inpatient room opening in time x after being in CDU	Daven's file "number of patients currently going to sp	13.74%
20	decsion No discharge patient from CDU	Probaiblity distirbution for a patient stay in CDU before discharge.	Daven's file "number of patients currently going to sp	3.74%

Fig. F.9.: Excel template used for verifying model input requirements, and ensure it conforms to process requirements.

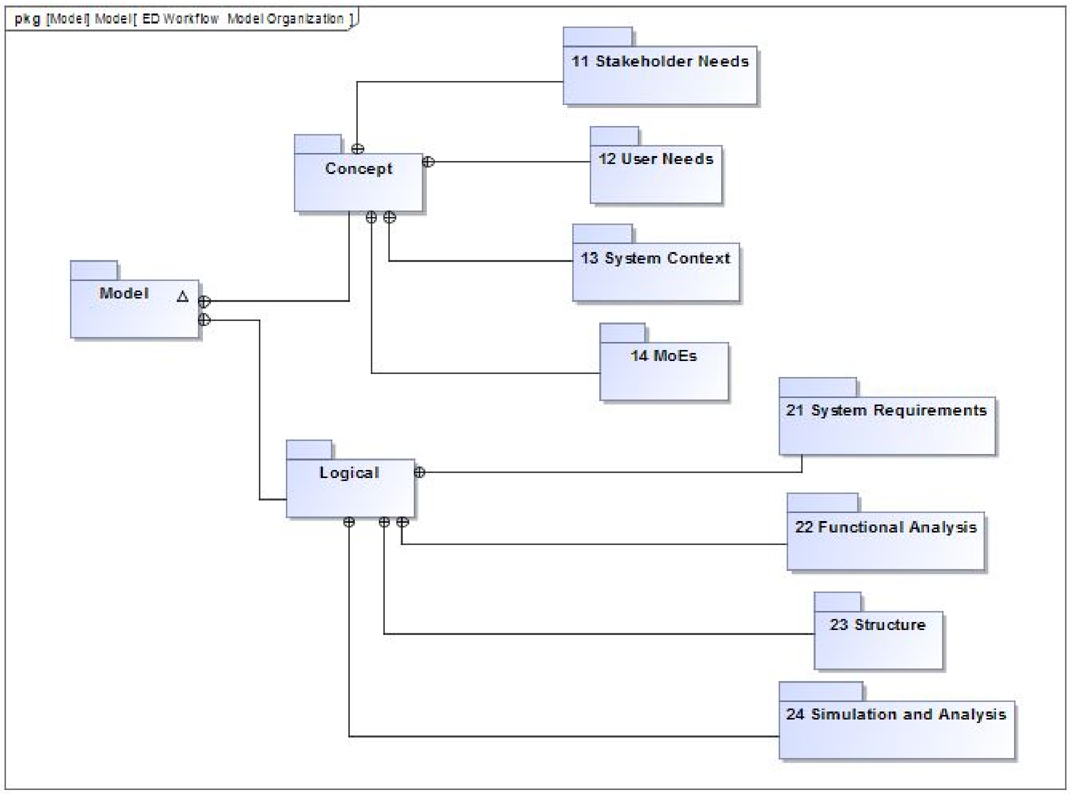


Fig. F.10.: SysML package diagram describing model organization in the form of a group of folders.

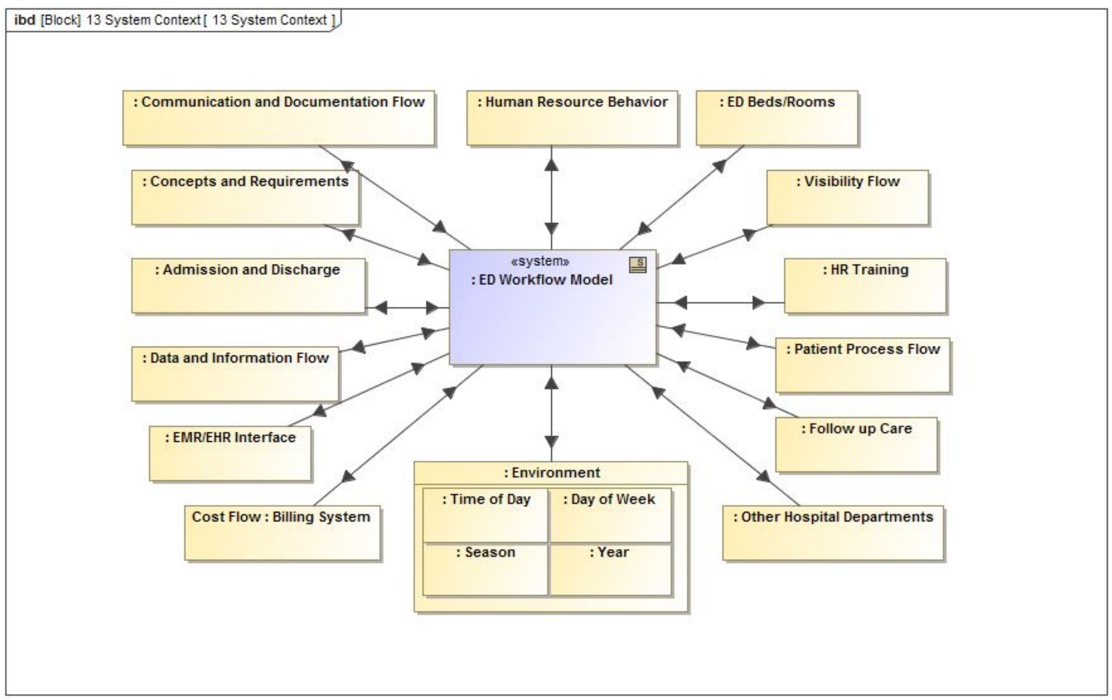


Fig. F.11.: SysML IBD describing the system's context.