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Analysis of VA Sacramento Medical Center capacity using discrete event simulation

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ANALYSIS OF VA SACRAMENTO MEDICAL CENTER CAPACITY USING DISCRETE EVENT SIMULATION

by

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ABSTRACT

The development of simulation models continues to provide effective solutions to a wide range of problems in healthcare systems. In the research presented within this thesis is the development of a representative and validated discrete event simulation model for the purpose of evaluating additional capacity. The study consists of a detailed exploratory analysis, verification and validation tests of the simulation results, and a thorough design of experiments. The exploratory analysis consisted of developing simulation models that provide similar characteristics found in the data. The design of experiments consisted of generating scenarios of various bed additions in the hospital units of care. The evaluation of the scenarios considered the characteristics of the queues in the different wards and demonstrate why DES has a substantial advantage in the ability to represent non-linear relationships.

The study used five years of real-world data containing information from 23,019 patients. The results show that certain units can benefit a reduction in waiting time by adding inpatient beds. Thus, decision makers can use the simulation to assess various changes and quantify benefits.

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ABBREVIATIONS

For Graphical purposes the following abbreviations were used (Table 1.1)

Table 1.1. Abbreviations used on graphics and statistical tests.

Nomenclature	Description	Observations
INW	Ward the patient was admitted to at time of admission.	MICU, SICU, MED, OBS, SURG, TCU-M, TCU-S.
OUTW	Ward the patient was discharged from.	MICU, SICU, MED, OBS, SURG, TCU-M, TCU-S.
YearIn	Year of the admission.	2009, 2010, 2011, 2012, 2013, 2014
MonthIn	Month stamp of the admission.	1, 2, 3, …, 12
DayIn	Day stamp of the admission.	1, 2, 3,…., 28/30/31
HourIn	Hour stamp of the admission.	1, 2, 3, …, 24
MinIn	Minute stamp of the admission.	1, 2, 3, …, 60
YearOut	Year stamp of discharge.	2009, 2010, 2011, 2012, 2013, 2014
MonthOut	Month stamp of discharge.	1, 2, 3, …, 12
DayOut	Day stamp of discharge.	1, 2, 3,…., 7
HourOut	Hour stamp of discharge.	1, 2, 3, …, 24
MinOut	Minute stamp of discharge.	1, 2, 3, …, 60
HrLOS	Length Of Stay (LOS) in hours.	
WDIn	Weekday patient was admitted.	Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday
WDOut	Weekday patient was discharged.	Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday
ExitTime	Continuous measure of time at discharge.	ExitTime = HourOut+(1/60)*MinOut
InputTime	Continuous measure of time at admission.	InputTime = HourIn+(1/60)*MinIn
ICU	Intnsive Care Unit	
MOS	Medical Observation And Surgery	
TCU	Transitional Care Unit	
MICU	Medical ICU ward	
SICU	Surgery ICU ward	
MED	Medical ward	
OBS	Observation ward	
SURG	Surgery ward	
TCU-M	TCU Medical ward	
TCU-S	TCU Surgery ward	

1. INTRODUCTION

This document describes an application of Discrete Event Simulation (DES) to the Veteran Affairs (VA) Sacramento Medical Center which is a system with constrained demand. The Medical Center's operations are comprised of the interaction of non-linear parameters, which add known and unknown variation to the outcomes. The model was developed as a research contribution to support managerial decisions to reduce waiting time, with the aim of increase the quality of the services offered and provide to veterans and their families better access to healthcare.

In the 2014 Access audit of the VA Healthcare system [1] some irregularities were found related to the appointment scheduling practices, therefore hospitals pertaining to the Veterans Affairs healthcare group were encouraged to improve the operation and in this way guarantee quality of service and access. The Veteran Affairs developed an initiative to confront the situation and defined wait time as the control factor to track the changes in access. The managers of the VA Sacramento Hospital were interested on following the initiative in efforts to present reductions in waiting time. This led to the decision of using engineering tools to assess the possible improvements.

The specific objective of this research was to study the actual state of the hospital, identifying the patterns that govern its operations, and the impact of adding four beds in different combinations to the hospital units.

A quantitative analysis was completed to identify the current characteristics of the principal variables required to model the system, then, patterns and relationships were determined to continue with the simulation model.

In this study, a DES was used to support planning and management capacity. The selection of such Operation research technique was based on its ability on modeling the variability and dependency between the system variables. These characteristics benefits for example, the analysis of changes and identification of bottlenecks. Also DES has been an important tool to demonstrate to managers and different medical staff, the importance of implementing changes.

In this investigation, the metrics used for analysis were waiting time, number of patients waiting and bed utilization rates. Different scenarios were evaluated, each one representing a different combination of four beds to be implemented in the three different units of care of the hospital. The experimental outcomes were analyzed in two parts: 1. Analysis of queues to define bottlenecks and benefits from adding beds to each unit. 2. Selection of the scenario that represented better opportunities of raising the hospital capacity based on the bed utilization rates.

The results indicated that adding a combination of 3 and 1 beds in TCU and ICU respectively, represented more benefits towards the capacity of the hospital.

1.1. MOTIVATION AND SCOPE

Through an access audit conducted by the Veterans health administration (VHA). It was found that the system was being inefficient in the achievement of the access goals. Specifically, not accomplishing the waiting time goal, weakness in the systems configuration management controls, access controls, and others.

The audit results determined that one of the reasons for the deficiencies was a complex scheduling procedures due to an insufficient allocation of resources, for instance, not enough beds, not a good scheduling of medical staff, lack in training to operate scheduling software, and manipulation of the data at patient's admission/discharge points. The first efforts for a better organization were concentered in the revision of the appointments scheduling procedures [1]. Then, as an intervention, the U.S. Department of Veterans stablished the Affairs Accelerating Access to Care Initiative, as contingency plan to focus the managerial efforts in the access capacity of the hospitals in the system.

As mentioned in the Accelerating Access to Care Initiative [2] in the key facts, the activities being reviewed to maximize our abilities include:

- Capacity and efficiency assessments.
- Ensuring Primary Care clinic panels are correctly sized and achieving the desired level of productivity.
- Extending or flexing clinic hours on nights and weekends.
- Ability for overtime for providers.

- Assessing the availability of community providers to provide the care being requested o Identification of resources required to provide timely care for Veterans. (2, p. 1).

The measure stablished for monitoring the implementation of the initiative was the waiting time. In terms of hospital access, it is a parameter closely connected with customer satisfaction and, reflects in some dimensions the patients' perception of the quality of service.

Therefore, the U.S. Department of Veterans has encouraged the hospitals in the VA Healthcare system to apply industrial engineering principles in order to enhance capital planning, productivity and improve efficiency of the provision of the services, as it is a necessity to offer better conditions of healthcare access to the U.S. Veterans.

In 2015 improvements in the national average of waiting time were reported, and hospitals of the system were more interested on increment reorganization measures by hand with engineering approaches.

For the specific case of VA Sacramento hospital, the annual report of waiting times 2014 revealed that the average wait time for specialized care was 17.8% above the national average (national average was also above of the set goals). Since then, managers have been focused on linking engineering research with the operations of the hospital. Their concerns rely on which decisions in relation with allocation of resources, scheduling, investment, and administrative process (policies) will have a better impact the hospital access capacity.

In order to address the results of this study as a reliable source to support managerial decisions there were two key research questions:

What are the characteristics of the system? Which patterns govern the operation of the system?

How the current demand is impacting the waiting time? What characteristics can be identified in the output parameters from the analysis of the observational data when beds are added to the system?

To mitigate the concerns on waiting time, offering quantifiable responses, this study proposes the development of a discrete-event simulation of the VA Sacramento hospital to provide solid decision support focused on the impact of the implementation of

4 new beds in different combination between the units of care of the hospital: ICU, MOS, TCU.

The development of such model offers a better understanding of the system, facilitating the decision making process. It can be used as a training tool, which allows an overview of the interaction between the parameters that define the delivery of the healthcare services.

The following section presents a review of the most relevant studies in the bed management field using DES, followed by a description of the hospital structure and the data that was analyzed. The following sections, fourth and fifth, provide an explanation of the study structure and methodology, and an Exploratory Data Analysis where the description of the parameters intervening in the research are presented, together with the definition of their behavior which was the base for determining the inputs of the simulation model. The sixth section, presents the simulation model development and navigates through its functioning characteristics. In section seventh the verification and validation of the model is explained, where the observational results were compared with the original data and in this way identify how the DES model captures the phenomena of the data collected from the hospital. Section eight refers to the experimentation phase, scenarios for adding different bed combinations were analyzed in conjunction with the study of incrementing the demand. To conclude, the model implementation and the results were described offering a discussion of the findings.

2. LITERATURE REVIEW

Reid, Compton, Grossman, & Fanjiang [3] researched which engineering tools where more appropriate to conduct research in the healthcare field. They found that the most used analysis tools were queueing theory and Discrete event simulation. They also specified that each approach could be used based on the goals of the projects. Queueing theory for more general studies and DES for studies that required detailed outcomes.

The technology evolution, the increase in the population and the identification of new requirements to deliver the healthcare services with more personalized approaches, turned the healthcare into more complex systems. The analysis of hospitals operations became a necessity [4]. According to Reid et al. [3] Systems Engineering tools have been successfully applied to improve “the performance of other large-scale complex systems” [3], then it was reasonable to think those tools would offer solutions for the healthcare systems issues. Hospitals process, despite of their variate and specialized platform, can be described as many other systems under the premise that resources are consider scarce and its rationalization must be optimized [5]. Nowadays, the use of Operation research approaches has made important contributions in healthcare management.

Between different Operation Research techniques DES has been of major importance in the healthcare field. Several performance comparisons between DES and other techniques for investigation and improvement of operations have been studied, demonstrating the usefulness of DES approaches. For instance, Harper & Shahani [6] showed a comparison between the use of deterministic, and simulation approaches. In their study, they demonstrated why planning and management capacity decisions should be based on simulation models, which are capable of representing complex systems with non-linear structures rather than be based on simple stochastic models. DES surpasses the limitations of stochastics methods on modeling the variability and dependency between the system variables. In the investigation, the metrics used for comparison were arrivals and Length of Stay (LOS). Four different scenarios were analyzed, some of them to recreate the stochastic approach to be able to conduct the evaluation: -Using appropriate statistical distributions for arrivals and LOS, -Using appropriate demand but only average LOS, -Using appropriate demand and LOS average for the different patient categories (elective and emergency), and using average arrivals, and average LOS. The scenarios were compared with the data collected and the results indicated that the best forecasting was the one obtained by the use of appropriate statistical distributions while the last scenario (average arrivals and LOS) totally mislead the behavior of the observed data. This study remarked the necessity of including proper distributions of LOS and demand in the estimation of hospital bed requirements. Standfield, Comans, & Scuffham, [7] prepared a literature research of the studies comparing Markov modeling and DES they expressed in the conclusions that the advantages of DES over Markov Models were "the ability to model queuing for limited resources, capture individual patient histories, accommodate complexity and uncertainty, represent time flexibly, model competing risks, and accommodate multiple events simultaneously".

The application of Discrete Event Simulation (DES) in healthcare is not new, for years it has been considered an important approach to study Healthcare systems. The evolution of the technology, availability of information (databases), computerized models and software solutions, have captured the interest of more modelers through the years. Discrete-event simulation models in past decades (1960/70) showed to be successful, what make the difference today is the large availability of electronic datasets that can be processed [8]. Simulation techniques have growth in popularity and it can be attained to the benefits its use provides, the increase on academic publications and the development of simulation software, are clear signals of its promising future as an operation research tool used in healthcare [4]. Currently there are in the market several simulation software with user friendly interfaces that simplify the adjustments and calibrations of the models [9].

In the healthcare field, as mentioned above, queueing theory is another operation research technique widely used, but is important recognize its limitations for modeling some features of the systems as for example, the non-linear relationships between the variables. In a review of DES applications, a comparison of its effectiveness to queueing theory demonstrate that DES is a more powerful resource in the description of systems with dependent events occurring synchronically. The application of queueing theory presents some limitations when representing non-linear relationships causing the addition of significant variation to forecasts, and sometimes, an inadequate recreation of the system [4].

For example, several studies have recognized a non-stationary characteristic of the patient arrivals. See for example, Wang, Hare, Vertesi, & Rutherford [10] they simulate the arrivals process including the variation of "time-of-day" and "day-of-week", G. W. Harrison, Shafer, & Macky [11] where the arrival process is considered to have too large variation to be described as a stationary Poisson process, Holm, Lurås, & Dahl [12] chose a DES because the bursts of arrivals had a different impact in each ward. Another example was Mallor & Azcárate [13], in his study the arrival rates were derived depending on the pathology and the time of the day. In a comparison of a basic system modeled with both DES and queueing theory made by Kolker [14]. In the forecasting from the queue model there was an over estimation of almost 3 times in the waiting time and almost 4 times in time in the system. Those results led to the conclusion that queuing variability was higher than the real arrival variability. Chung, Komashie, & Yorke-Smith [15], evaluated how a DES model captures the complexity of healthcare systems, through the development of a simulation using waiting time, patient in queues as measuring variables, and social network metrics for the analysis of four different complexity levels.

Other applications of queueing theory acclaim that the effectiveness of the models reside on calculations made from a steady state of the system, nevertheless the scope of the results is the description of a general pattern rather than a more detailed behavior [16]. In conclusion, as demonstrated by Kolker [9, 14, 17] DES is a powerful tool to represent a system with subsystems interdependency capable to give more accurate results in comparison with analysis of the same type of systems using queueing theory.

The use of Discrete Event Simulation (DES) in healthcare, has permitted hospital management units estimate the state nature of the system (or hospital), evaluate different scenarios of interest, and analyze relationships between different model variables. The simulation outcomes had allowed to support accurate decisions about reorganization of the systems [18]. One of the key advantage from DES models is their capability of evaluate ideas of change avoiding the costs and the efforts of physical implementations in the real-world for mere analysis [19]. Also, from past literature reviews as the ones conducted by Gunal et al. [8] and Jun et al. [18], it can be considered that the importance of applying DES concepts resides in the ability of offer the recognition and better understanding of the connection between inputs and output measures. In other words, through the use of this technique modelers can identify how variables as scheduling, patient flow, sizing and planning (resources allocation), impact in parameters such as waiting times, throughput and resources utilization or vice versa. For example, Cao, Yoon, Khasawneh, Srihari, Poranki [20] implement a model to determine the staffing levels needed to improve service and process flow. The study was analyzed measuring the waiting times and the impact of the changes in demand (patient arrivals) in throughput. Other examples are Choon, Leng, Ai & Chai [21] and Al-Araidah, Boran & wahsheh [22].

It is also important to highlight the participation of the stakeholders in the first stage of development of a Discrete event simulation, because they are the most adequate to express the concerns and problems present in the operation of the system [23, 24].

DES has been applied in healthcare with successful results in predicting impact of different situations based on bed capacity, serving as reliable support in managerial decisions [6, 25, 26]. Bed allocation is considered one of the most important hospital metrics to be optimized in order to improve quality in hospital operations [6], different models have been developed to study this variable focusing on: healthcare access, reduction of waiting time, investments and resources allocation. For example, Devapriya et al. [25] developed a model to evaluate occupancy rates and wait time. Using the DES they recreated different bed capacity configurations and analyzed their impact in access, quality of care, capital expenditure and staff satisfaction. Gangadharan & Belpanno [27] conducted a study for a tertiary care children’s hospital. Their simulation was used to identify the impact in bed requirements from changes in the supply, when it matches the demand. Clissold, Filar, Mackay, Qin, & Ward [28] created a DES model to determine the impact on the system from increasing the demand on the emergency unit in Flemings Medical Center. This study was motivated by the introduction of a copayment policy on practitioner services.

Although the objectives and structure of the models differ between authors, there is a common step in the development of DES: the analysis of the preliminary information. Exploratory data analysis is considered primordial to ensure accurate modeling. Almost all the time, an exhaustive study of the variables is conducted as a preparation of the data before feeding the simulation, to understand if the variables present patterns and significant variations in its natural state, and generate statistical support for recreating the systems as similar to the reality as it can be possible [4]. The simulation modeling of systems is strictly linked to the quality of information available.

More detailed data allows more accurate results and stronger possibility to develop advances in the investigation of healthcare operations field [13]. For example, the achievements on accuracy in the interpretation of a hospital Intensive Care Unit (ICU) in the model built by Mallor & Azcárate [13] are due to the detailed qualitative and quantitative information gathered from the system. In these exploratory analysis of the data a recognized phenomenon is very common in the hospitals' operations: the decrease in the rates of several parameters such as admission, occupancy, and discharges during the weekends. This pattern has been described in several studies (See for example [29,30]). Reid et al. [3] considered that this situation can be attributable to a "highly specialized -practitioner- driven, hospital-centered system", this means that when the hospital requires a specialized clinician, it has to adapt the allocation of resources to the clinician availability, which explains in some degree the reduction on medical staff allocation during the weekends.

One step further in the use of simulation is the validation of the data, but before a simulation is validated, modelers must have in account the time or conditions required for the system to reach steady states or at least more stable states: warm -up period [4]. When those conditions are not considered, the statistics resulted from the simulation runs will have implicit bias from the learning curves (period the system take to reach more stable state). Thus when a run starts with an empty system a warm-up period must identified, from there the statistics can be calculated with more accuracy. There is not a standardized method or specific instruction to calculate the warm-up period [31], it is mostly determined visually with the help of graphical techniques. Vasilakis & Marshal [32] defined a warm-up period of 2000 days for their simulation using the Welch graphical method with data collected from 10 runs. El-Darzi, Vasilakis, Chaussalet, & Millard [33] used a time series graph of occupancy to define the stable state of the system, which was reached after 5.5 years in a test run. Mallor et al. [13] define or their experiments 20 year-simulation with a warm up period of 3 years.

Models in the literature also showed that arrivals and LOS are the most important input parameters in the study of healthcare systems. Usually arrivals are random but non-stationary as described before in this section. LOS is a variable that shows a special behavior, its distribution is usually highly skewed to the right. Several approaches have been used to characterize the LOS. For instance, the multistage approach where the expected LOS depend on the probability of discharge based on the complication of the patient [34], and other methods employing parametric distributions that can reproduce a set of data skewed to the right like Weibull, lognormal, among other well-known distributions. In some of the cases not just one distribution was used for the entire set of data and longer stays were treated as outliers [35]. Also, the separation of the LOS in short and Long terms, has also been proposed by El-Darzi et al. [33] augmenting it on the differences in statistical parameters that short terms LOS had, in comparison with long stays. The importance of using an appropriate LOS information in the simulation models is the dependence it has with other variables, meaning LOS has a quantifiable impact in the outcomes. Hillier, Parry, Shannon, & Stack, [36] developed a model where the results showed how high occupancy, impacts negatively the throughput of a hospital, because its correlation with LOS is directly proportional.

Following, it is offered the description of several studies developed for capacity solutions in healthcare.

Devapriya et al.[25] This application of DES uses a great amount of information that allow the generalization of the model from the hospital to the healthcare system level implying few needs of customization. In this study, the wards were included in the analysis of the variables and the beds were classified according to the accommodation in private or shared rooms. These classification (of wards, and beds) are factors that have not been commonly used as part of DES applications due to the detailed information requirements the technique depend upon. Prior to the modeling, a deterministic analysis of variables was conducted to identify probabilistic distributions and seasonality effects. Variables studied an integrated in the model: admissions, patient flow (transfers), discharges, waiting times, arrival source (ward of admission), length of stay (LOS), number of beds by unit of care. Principal outputs: arrivals rate by ward, queue characteristics and occupancy rates. The model was made to be used for financial decisions based on patient volumes and LOS, bed allocation, seasonality, patient redistribution between the hospitals in the system, and to describe how discharges time impact capacity decisions. The ambiguity on the definition of level of care by the physician was described as a limitation for the development of the model. The value of this simulation is that it was developed and validated as a large scale patient flow model.

Gangadharan et al. [27] conducted a study to identify the impact from changes in supply, in bed requirements. In the first instance a set of 2 days of hourly day occupancy data was extracted from the principal database in order to validate the simulation model created as a spreadsheet as the creation of the current state. Second, the simulation was applied with a one-year information and established a demand-supply model based on arrivals, discharges and occupancy rates. From the simulation it was found that 70% of the work in the hospital was performed in 6 hours or less. Then with the supply demand model a new scenario was evaluated matching resources to demand. Scenario of interest: Distribution of 70% of the work in 12 hours of the day instead of 6 hours and displaced transfer activity to an earlier time such as before daily work rounds. The results lead to the conclusion that reorganization of discharge and transfer activity prior to management rounds, results in a dramatic difference in improving bed availability without increasing capacity. As the model was developed in a spreadsheet, patterns in demand and seasonal variation were not included which limited the ability of the model to be generalized for other hospitals.

G. Harrison, Zeitz, Adams, & Mackay [37] used simulation to study how occupancy rates impact discharges. The development of this model was motivated by the pressure that hospitals are experiencing because of the increasing demand from aging and acute patients. The input variables for the simulation were: the occupancy rates including the classification of over-occupancy when it is greater than capacity, and load levels from light to heavy. From the data collected, an occupancy profile was defined, as the current state of the hospital. In the modelling, 2 years of data were used with 60-days of warm-up period. Statistical analysis was designed to validate the model and to determine the discharges in over-occupancy-days and other days. Concluding, there was a greater chance of being discharge in patients with an elapsed stay longer than 10 days (long in over-occupancy days.

Holm et al. [12] studied the improvement of hospital bed utilization through simulation and optimization. The simulation was developed as the first step of the research. The results obtained from the simulation fed an algorithm used to optimize bed allocation in the second step of the research. Input data used for the Simulation was patient flow, arrival times and length of stay The input data for the algorithm was the simulation matrix of bed utilization resulted from the simulation. Bed utilization was classified based on prevalence (number of beds overcrowded) and incidence (number of patients using overcrowded beds). The model was validated through the current state of the hospital. In their first scenario there were no restrictions in bed capacity (infinite number of beds), in this way it as possible to determine the needs in number of beds per unit of care based on the arrivals and length of stay. The simulation run with a baseline of 718 beds to generate overcrowding rates. At the end, the algorithms to optimize allocation of beds in terms of prevalence and incidence were applied. The results showed that the allocation based on bed prevalence optimization is efficient reducing the overcrowding from 6.5% to 4.2% (simulation model validated). The model can be applied to other hospitals in the geographical location where the study was conducted (Norway).

Clissold et al. [28] created a DES model with the interest of determine if the impact of increasing the demand on the emergency unit in Flemings Medical Center which would be the consequence of the introduction of a copayment policy on practitioner services. The input variables: arrivals, queues, ward allocation and weekend discharge delay were analyzed prior the construction of the model and then verified using as base line the occupancy rates. The results showed that from increasing the demand (one to four patients by hour), the length of the queue as the LOS increases in a non-linear basis. The model was purposed to be used in further investigations and, because of its animated visual representation, as a tool for a better understanding of the policy changes impact between the staff.

Mallor et al. [13] studied bed occupancy levels in an Intensive Care Unit (ICU). The factors of differentiation in this study, are, the implementation in the model of detailed qualitative information such as policies and managerial decisions through mathematical techniques to validate the results, the combination of simulation with optimization for variables estimation. First, a complete statistical analysis of the collected data was done. From there arrival rates and LOS were determined with parametric distributions. The validation was made using Occupancy as the parameter compared from the original and simulation data. The results showed not significant differences and prove the assumption of independency between LOS and workload variables. Validation of the results with the medical staff confirmed the assumption of occupancy level influence the patients LOS. One of the most important limitations in the study is the subjectivity that affect the triage decisions, which couldn't be studied because of the lack of historical data where the variation of the differences in the decisions by the physician in schedule could be evidenced. As the model was developed to evaluate capacity, it was used to determine the number of beds required when an increase in the ICU demand was present, caused by the increasing programmed surgeries. The results showed that to maintain rejection rates at 5% 2 extra beds were needed, and to keep it under 1% six more beds were required.

The application of DES models has brought important assumptions, contributions and conclusions for healthcare operations. Nevertheless, in the use of this type of simulation, some limitations have also been identified. In the literature review by Jun et al. [18], there is a discussion about how simulation modelling was limited for generalization purposes. Currently, not so many authors have developed models which can be used to support the operation of other hospitals or across healthcare systems. This situation is attributable to the information requirements to model DES. Operational data defines the system behavior, the more detailed information the better can be represented the actual characteristics of the system by simulation models. In other words, the quality of historical data, determine the accuracy of the results in the DES [38]. The models developed in several studies which present this limitation, also attributed it to the big efforts on customization needed to expand the models. Devapriya et al. [25] paper presented one of the few simulation developments that can be applied across the system. It is a response to the discussion about how simulation modelling has limitations for generalization purposes. Riney & Tolk [39] explained in their book that for healthcare simulations, the efforts to expand the models to the System of systems (SoS) levels, require the establishment of common goals. They also stated that in many cases the cost of generate simulations that represents SoS prevent institutions to model them. In other cases, the information collected impact substantially the ability of generalization of the models. Sinreich & Marmor [40] explained the modeling expertise a person should have to develop simulations depending on different levels of abstraction (generic or fixed activities to be modeled).

The results obtained from the application of DES, most of the time present important conclusions that can be implemented in the practice of healthcare systems, however just few acclaimed to be implemented, while the others do not specify its future implementation [8].

The application of DES models for the improvement in healthcare operations has been demonstrated to be a powerful tool for the identification of the systems behavior and for the evaluation of the impact of different changes to increment capacity, access, and analyze outputs for dependable variables.

3. HOSPITAL CHARACTERISTICS

The VA Sacramento hospital belongs to the VA Northern California healthcare system as an inpatient facility that offers healthcare services including medical, surgical, primary, and mental and behavioral care

The VA Sacramento medical center is comprised of 60 beds distributed in three medical care units such as ICU with 10 beds, MOS with 24 beds, transitional care unit TCU with 16 beds and 10 beds in BHICU [41].

The medical units include different wards or medical departments where the patients are allocated according to their acuteness level. ICU offers services for MICU and SICU wards, MOS for MED, OBS and SURG wards, and TCU for TCU-M and TCU-S. BHICU offers services of mental/behavioral care. Table 3.1 presents the wards distribution in the units of care. (Refer to Table 1.1 for a clarification of the nomenclature used in this section).

Table 3.1. VA Sacramento Units of care and their wards.

Unit of care	Wards in the Unit
ICU	MICU SICU
MOS	MED OBS SURG
TCU	TCU-M TCU-S

4. METHODOLOGY

A data set of 23,019 admissions starting at January 1st, 2009 ending in December 31st, 2014 from hospital was collected for analysis. The information was extracted from the Bed Management System (BMS) which is used by the hospital to register the records of patients. The data offers detailed patient information such as ward, date and time of admission and ward, date and time of discharge. Length of Stay (LOS), and daily occupancy were defined from the given information.

An Exploratory Data Analysis (EDA) was performed to determine the statistical characteristics of the main variables that support the study. For example, patterns and distributions were determined directly from the data. The EDA was done to acquire a detailed understanding of the parameters behavior required for the DES modeling in its initial phase and to support its validation. Minitab17 statistical package was used for accomplishing the EDA and some calculations were supported by the use of Excel.

The DES model was developed using a commercially available discrete event simulation package (Arena™, version 15). Arena™ uses SIMAN as core language. and provides a platform to build the model with the drag and drop flow chart methodology [31]. In the modeling, Arena™ allows the creation of a system logic based on parameters defined by the user, which can be attributed from the creation of the entity until its disposal, passing through different required processes defined by the modeler. The recording features of the program are event-based, and although the software has some predetermined statistical reports, the user can establish other elements within the model to be documented. In this manner the DES model uses Patients as entities with different attributes assigned through the flow of the simulation in order to recreate the behavior of the hospital. The attributes of the patients allowed the introduction of the patterns defined in the EDA. The logic of the simulation permitted also the collection of different variables as outcomes with the statistical features of the software, for instance it was possible to obtain the daily average of the patients in the hospital by ward, the queue characteristics by ward, and throughput, important parameters used in the experimentation phase to identify the impact caused in the system by changes in the resources allocation.

In the experimentation phase, the Process Analyzer software (included in the Arena Package) was used to evaluate the impact of changing the number of beds in the different units of care. Four beds were allocated in the different possible combinations and the parameters of the queues were studied in order to determine the implications of it.

5. EXPLORATORY DATA ANALYSIS

5.1. ANALYSIS OF THE LENGTH OF STAY (LOS)

LOS is one of the dependable variables considered across this study, it was defined as the difference between discharge date (month/day/year and time) and Admissions date (month/day/year and time).

From the data set it was possible to observe that patients were initially admitted in all wards except in BHICU that only showed discharge registers which meant that patients were most likely being transferred rather than being admitted in that ward. Thus the first step of the analysis was a LOS calculation characterized by the discharge ward in order to involve information from all of the units of care. As a result, it was found a considerably difference between the LOS in BHICU and its variability compared to the other wards (refer to Figure 5.1). Therefore, it was decided to exclude BHICU from the analysis as its behavior differed from the other medical wards, for example, approximately 90 patients from all admitted were discharged from BHICU, however those few patients had the longest LOS in the data. In a way the presence of BHICU ward would impact the veracity of modeling techniques to be employed.

After the information corresponding to BHICU ward was discarded to eliminate bias in the study, the data set was comprised of 22,926 patients. The data by ward of admission is presented in Figure 5.2.

Subsequently, it was conducted an analysis of LOS by the year the patient was admitted in the hospital (YearIn). A yearly growth was evidenced in the graphical comparison (refer to Figure 5.3) where the year 2009 had the lower LOS.

A one-way ANOVA test was performed to confirm the situation observed in the plot. The results led to the conclusion that there was no statistically significant difference between the six years of LOS data. Also a Tukey pairwise comparison was done. The results of the tests are presented in Table 5.1.

In the hypothesis tests used, the null hypothesis was defined as N_0: All means were equal, and as alternative hypothesis Ha: At least one mean was different with a significance level of $\alpha=0.05$.

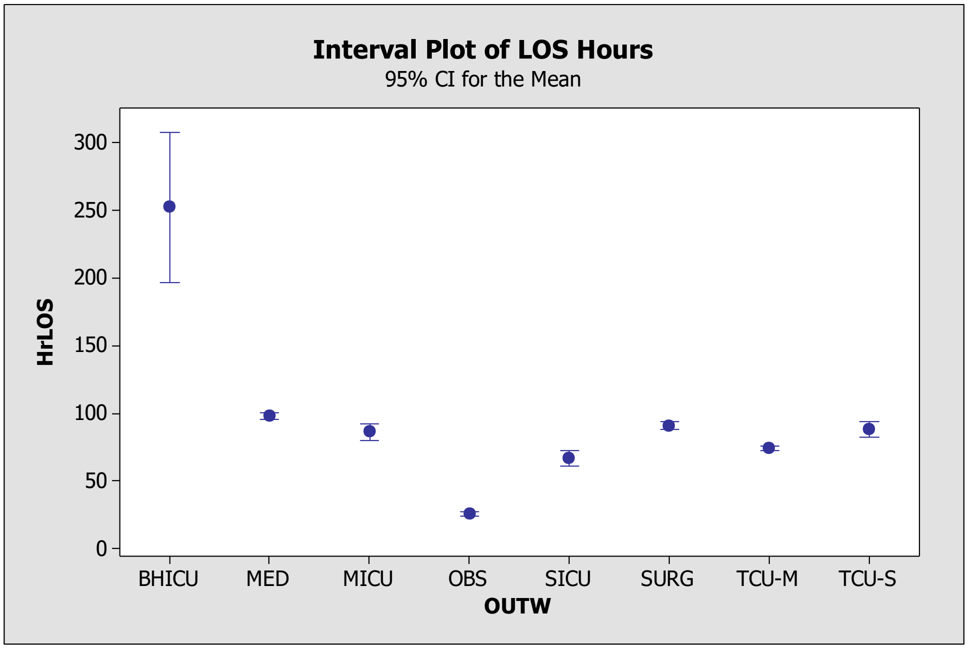


Figure 5.1. LOS by ward of discharge.

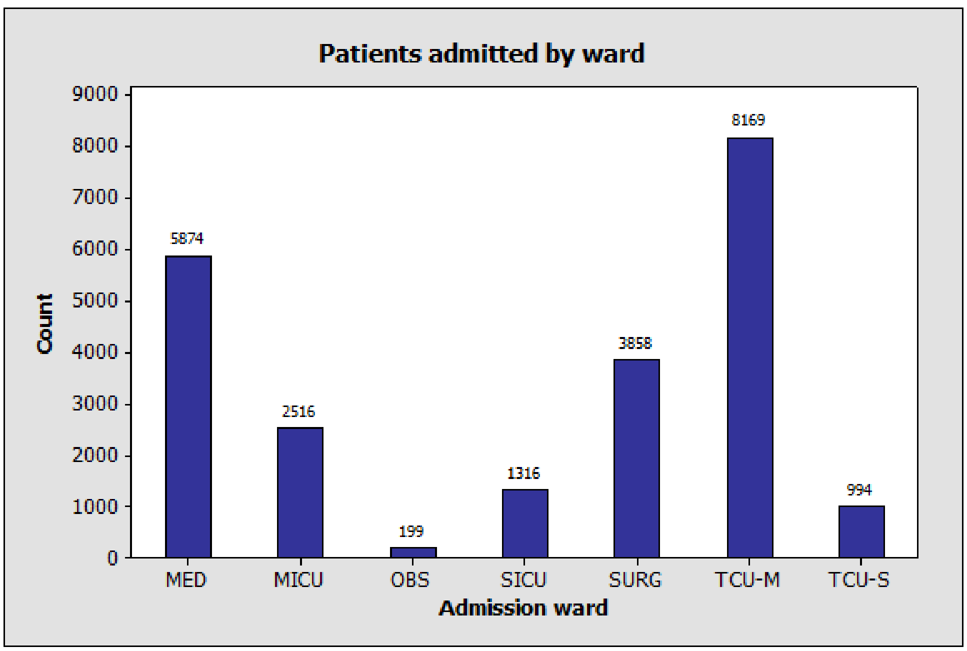


Figure 5.2. Number of data points (patients) by ward of admission.

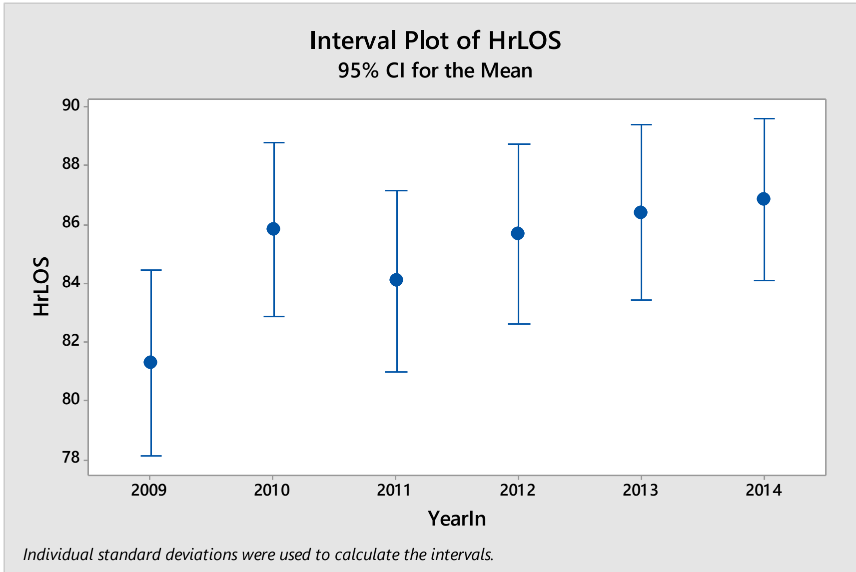


Figure 5.3. LOS Interval plot by year.

Table 5.1. ANOVA test and Tukey Pairwise comparison of LOS by YearIn.

HrLOS versus YearIn		
Test	**Results**	**Conslusion**
One way ANOVA	P-Value = 0.112	Means not significantly different.
Tukey Pairwise Comparisons	Means from 2009; 2010; 2011; 2012; 2013; 2014 were grouped in the same group.	Means not significantly different.

Statistical differences were not found across the years. Hence, it was natural to explore the influence when the ward of admission is considered. The LOS in the data was analyzed, graphically and through the ANOVA test and Tukey pairwise comparison for each ward. The results are presented in Figure 5.4 and Table 5.2.

The interval plot (Figure 5.4), showed a considerable difference in the LOS distribution and its variability, this situation was confirmed by the statistical test employed. The results implied that admission ward influenced the LOS of the patients. This deduction could be a reflection of the dependence the patient level of acuteness could have with the admission ward, meaning that if every ward offered specific treatments, that specification could also influence the time a person was in a medical care division.

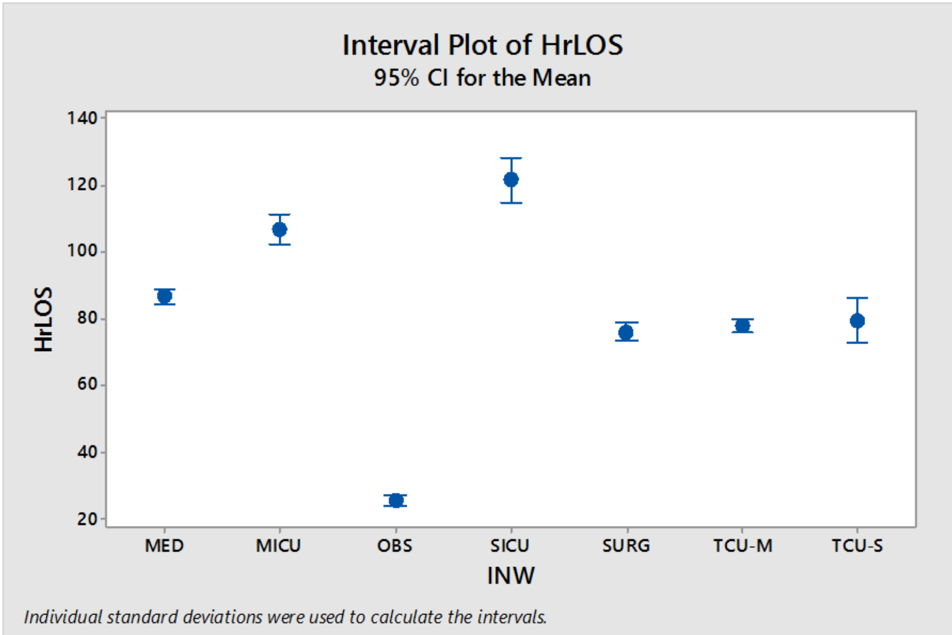


Figure 5.4. Analysis of LOS by ward of admission.

Table 5.2. ANOVA test and Tukey pairwise comparison of LOS by ward of admission.

HrLOS versus INW		
Test	**Results**	**Conslusion**
One way ANOVA	P-Value = 0.000	Means significantly different.
Tukey Pairwise Comparisons	INW Grouping SICU A MICU B MED C TCU-S C D TCU-M D SURG D OBS E	Means significantly different.

Hospital managers communicated that the OBS ward's primary operational characteristic was to hold patients for no longer than 24hrs. That is for situations where a patient needed to be admitted and would be either transferred to another unit within the hospital or was discharged. These decisions are often made by the hospitalist.

Another observation was found for the LOS behavior: a considerable amount of observations were outliers, as it can be seen in Figure 5.5 boxplot of LOS by ward of admission. This implied that the distribution of the LOS was skewed to the right. To confirm such assumption a p-p plot was drawn (Figure 5.6) and the same situation could be evidenced for each ward of admission with the concave shape of the data around the normal line. The conclusion was that LOS has a heavy tailed distribution for each ward of admission except for OBS. The distribution of LOS for OBS is less skewed, but still do not seem to be normal.

Heavy tailed distributions are characterized by the high probability of find data points in the tail. Thus, it is not appropriate to handle the data points located in the tail as outliers. For this particular situation he fit of classical distribution models could generate bias from the original data.

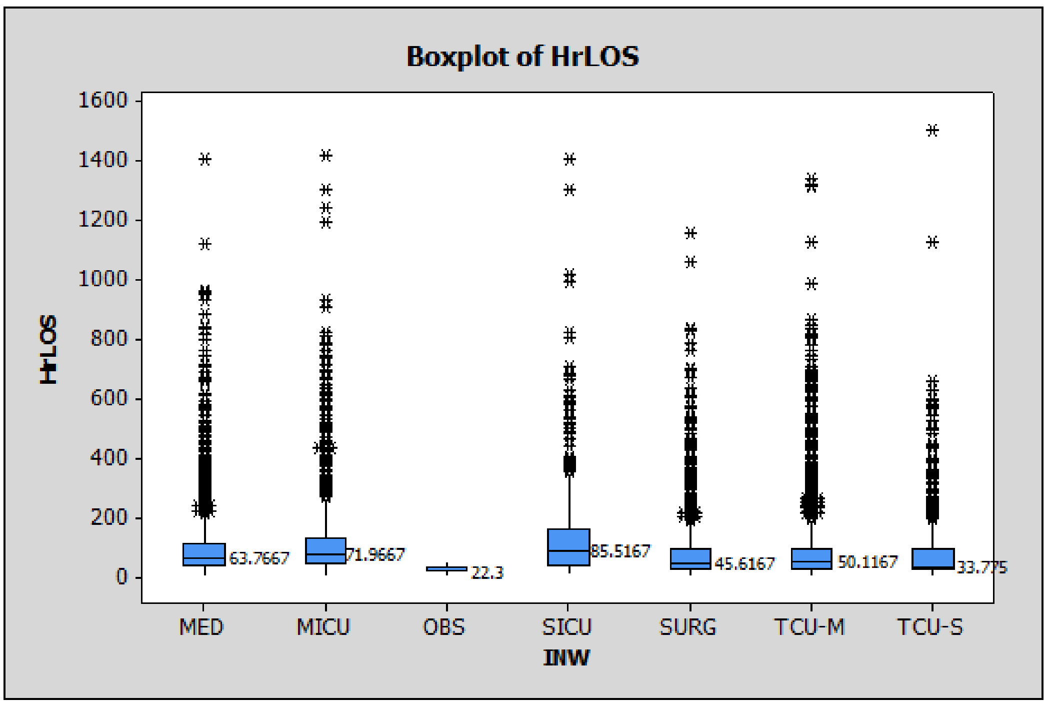


Figure 5.5. Boxplot of LOS hours by ward of admission.

As the LOS was defined from the differences between discharge and admission dates, it was considerably important to identify the patterns of arrivals and discharges, which would outline the details that must be considered in the modeling of the LOS. For example, if the arrival process has a daily pattern, this tendency must be model for LOS also. Then an analysis of those variables was performed as it follows.

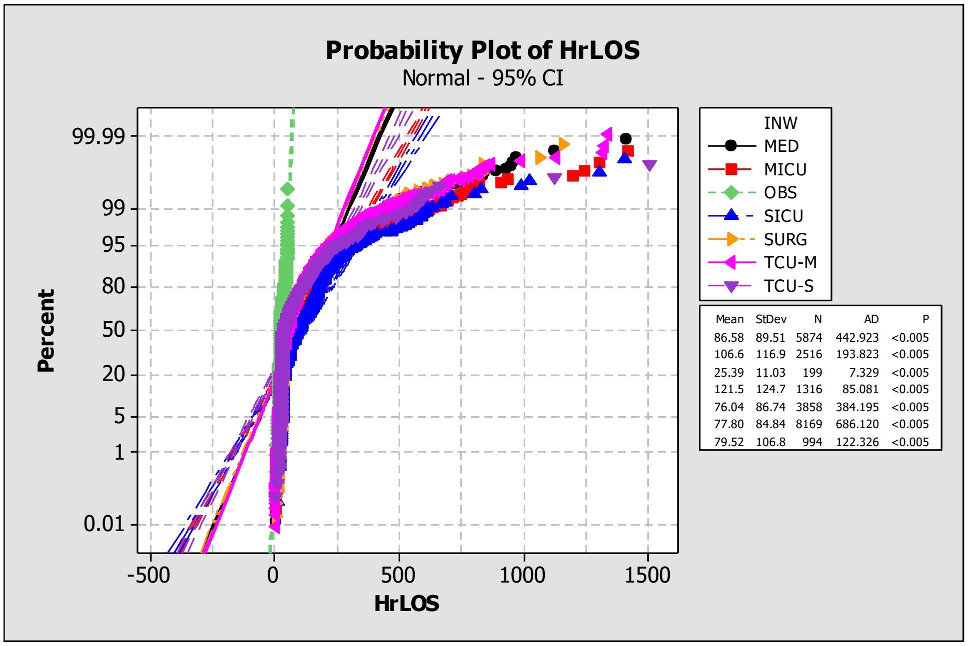


Figure 5.6. P-P plot of LOS hours by ward of admission.

5.2. ANALYSIS OF DISCHARGES

5.2.1. Analysis of Discharge Time. The exploratory analysis of the discharges was structured beginning with the search of yearly seasonality and finalizing with the day of the week evaluation by ward.

Analyzing the discharges by the time of the day across the data, it was observed a peak between 3:00-4:00 pm (refer to top of Figure 5.7), indicating that most of the patients were discharged in the late afternoon. The pattern evidenced was also found in A yearly basis (refer to bottom of Figure 5.7), meaning that there were no substantial differences in the discharge time of day throughout the years. From this situation can be concluded that the discharge policies of the hospital through the period of data collection had little changes.

NOTE: the commas seen in the figure are the equivalent of a period, e.g. 9,75 in Figure 5.7 is actually 9.75)

Continuing with the analysis, a categorization of the discharge time patterns by ward of admission preceded. The comparison of the discharge time distribution in the different wards was made through a One-way ANOVA test, and to obtain more information a Tukey Pairwise comparison was card out (Table 5.3). The results indicated a significant statistical difference in discharge time between wards. For a better understanding a boxplot was produced which allowed a visualization of the variation of the discharge time for each ward (Figure 5.8). The plot shows similarities in discharge peaks for all the wards, however the variance was substantially different. This information allows the inference that every ward has unique practices respect to discharges. This could be an important conclusion for modeling purposes.

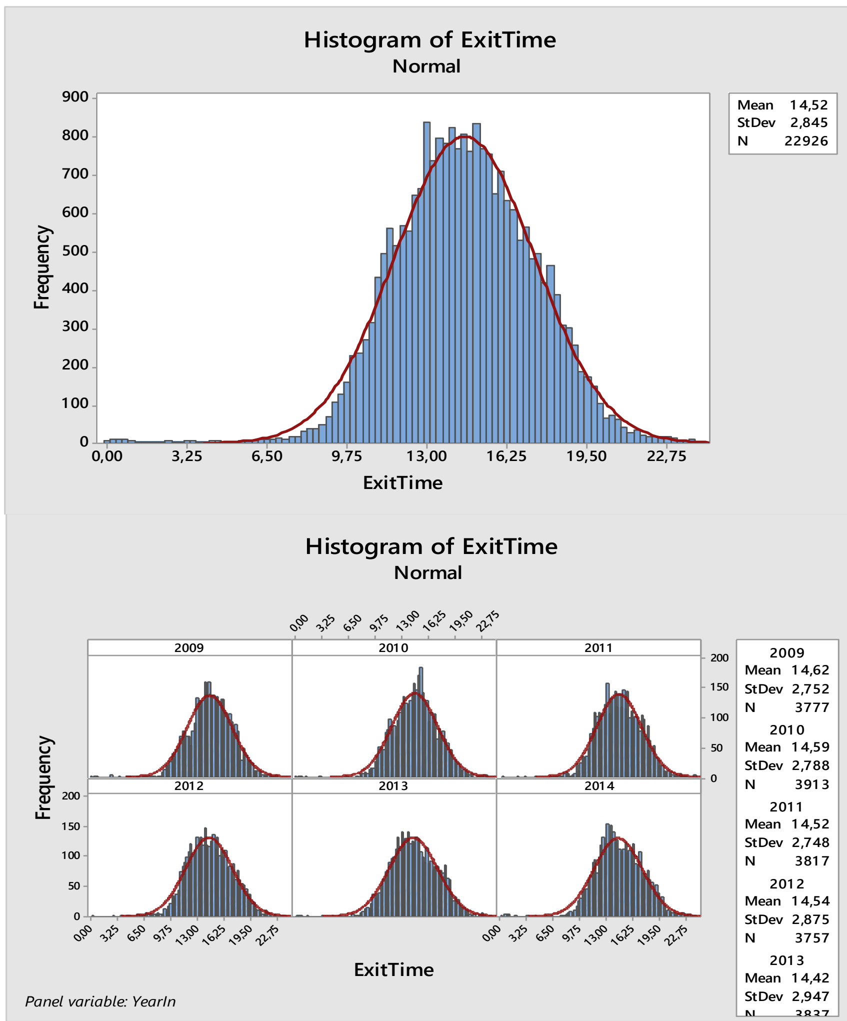


Figure 5.7. Exit Time distribution for the data set (top) and Exit time distribution by year (bottom).

Then, as for LOS, an influence of ward of admission in discharges was found, which was congruent with the suggested idea that the ward of admission was a surrogate of the patient level of acuteness. However, more detailed information was necessary to give a significant conclusion.

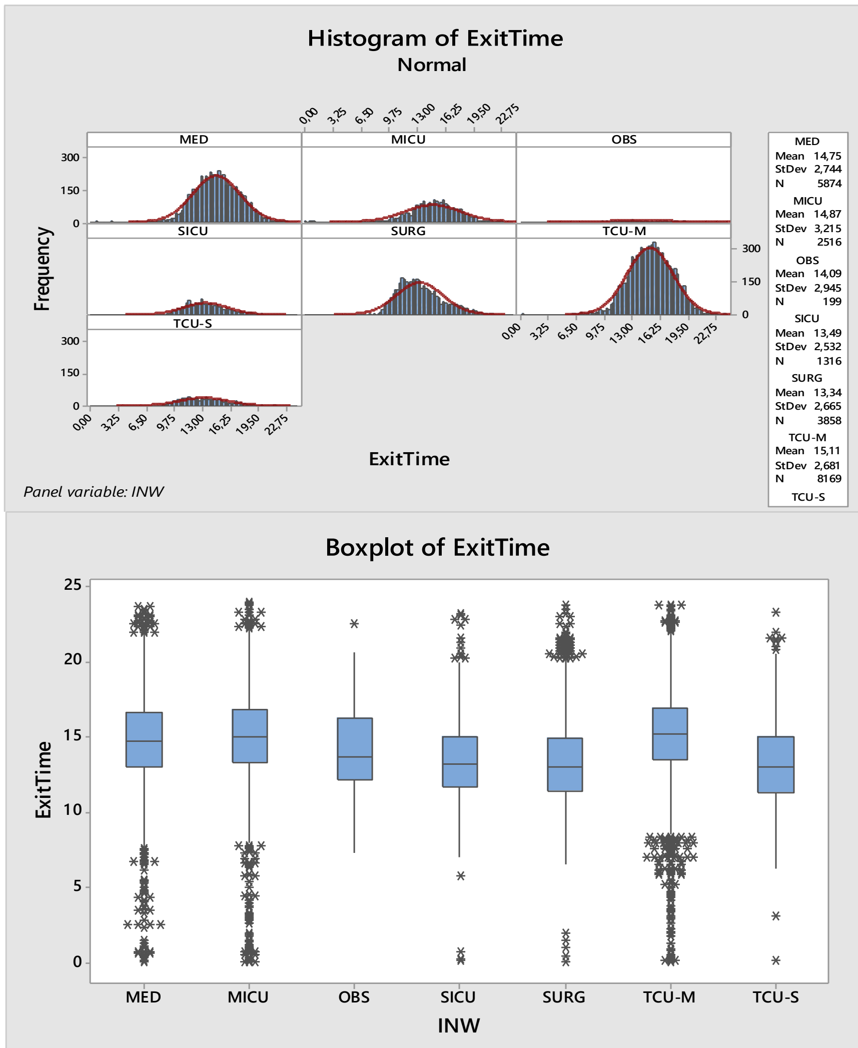


Figure 5.8. Time of discharge vs Ward of admission.

5.2.1. Analysis of the Discharge Month. In this segment of the analysis the objective was to identify if the discharge parameter present seasonality in monthly basis. Figure 5.9 (top) displays a plot of quantity of patients discharged by month, from the graphic was possible to assume that for the entire set of data, every month presented the same quantity of discharges. Subsequently the data was divided by month and year of admission (Figure 5.9 bottom) and no statistical significant differences were found for discharges between the months each year (see Table 5.4).

Table 5.3. ANOVA test and Tukey pairwise comparison to identify differences in discharge time by ward of admission.

ExitTime versus INW		
Test	**Results**	**Conslusion**
One way ANOVA	P-Value = 0.000	Means significantly different.
Tukey Pairwise Comparisons	INW Grouping TCU-M A MICU B MED B OBS C SICU C D SURG D TCU-S D	Means significantly different.

When evaluating the ward of admission, a x^2 test showed significant differences in the discharges by ward of admission by month; however, it was also found that OBS presented a small groups of discharges which could be generating a bias that forced the rejection of the x^2 test, therefore, the data was analyzed once more excluding OBS and the results of the new test indicated that there was no significant difference in discharges by ward of admission on a monthly basis. (Table 5.5)

5.2.2. Analysis of the Discharges by Day of the Week. A similar analysis was conducted for discharges by day of the week starting with the search for yearly patterns, and after, looking for the behavior of the discharges for the day of the week by ward of admission.

As it is displayed in Figure 5.10, substantial differences between the discharges by day of the week were present, indicating that Friday had the highest level of patients leaving the hospital and that a decreasing quantity of discharges can be seen on the weekends. To confirm the pattern repetition through the years, the data was divided in the seven days of the week and compared yearly (see Figure 5.10 top). Year by year the same seasonality was observed. However, a statistical test was required to confirm if every day has the same behavior for each of the years (refer to Table 5.6). The results of the test indicated a significant difference between the discharges each week day compared by year, this phenomenon could be present because the data was still not categorized by ward.

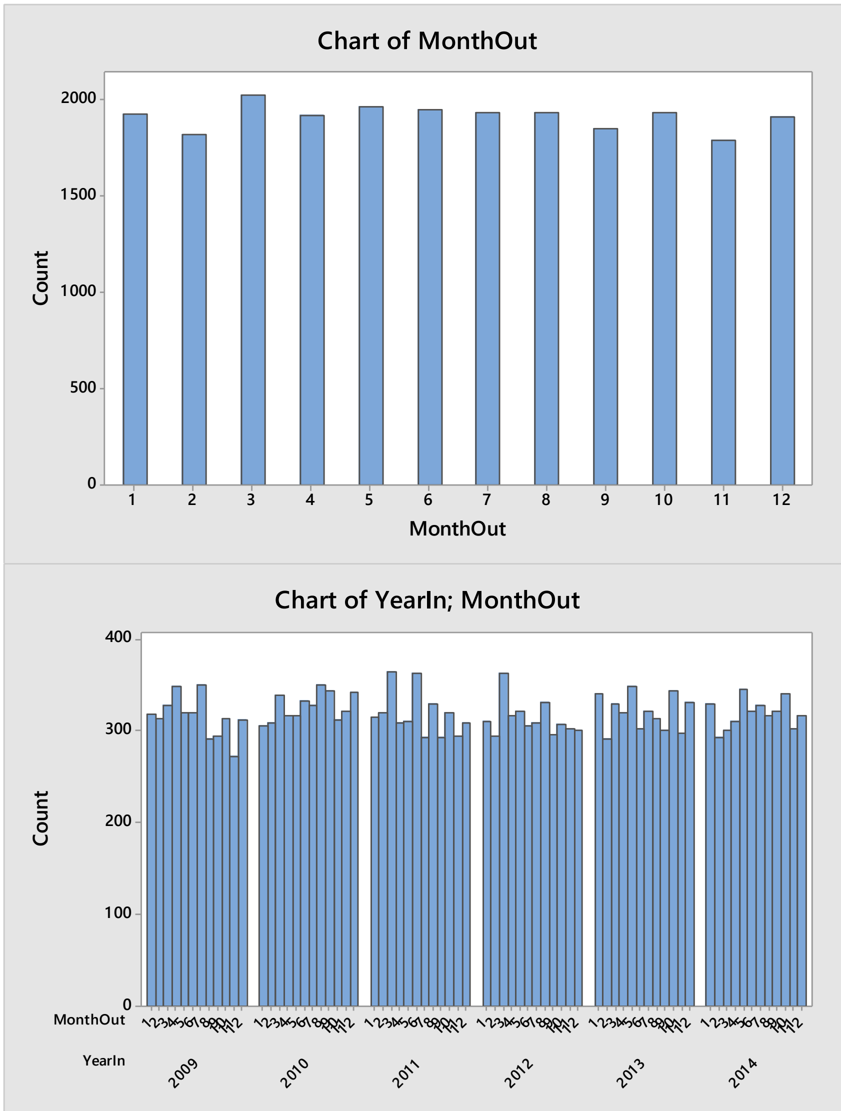


Figure 5.9. Number patients discharged by month (top) and by month by year (bottom).

As it had been seen the ward of admission influenced significantly the discharges, hence, to confirm its role in the discharges by day, a further analysis was made where the discharges by day of the week were compared yearly for each ward of admission, Table 5.7 shows the results.

Table 5.4. Statistical test for differences in discharges by month by year.

MonthOut; YearIn		
Test	**Results**	**Conslusion**
Pearson Chi-Square	P-Value = 0.508	Distributions of the samples were not significantly different.

Table 5.5.Statistical test for differences in discharges by month by ward of admission (top) and without include OBS ward (bottom).

MonthOut; INW (OBS included)		
Test	**Results**	**Conslusion**
Pearson Chi-Square	P-Value = 0.003	Distributions of the samples were significantly different.

MonthOut; INW (OBS included)		
Test	**Results**	**Conslusion**
Pearson Chi-Square	P-Value = 0.629	Distributions of the samples were not significantly different.

The results of the tests confirmed the premise that the differences between the years of the discharges by day of the week was related to the admission process, showing that categorizing the number of patient going out by the ward of admission and comparing them with the days of the week by year did not have significant fluctuations.

Another implication should be confirmed: did all the wards present the same daily pattern?, Had the day of the week the same level of discharges for each ward? In order to answer, a x^2 squared test was applied to measure if there were significant differences between the wards respect the number of patient discharges every day of the week. Table 5.8 presented the outcomes of the test which identified that between the days of the week discharge levels were significantly different by wards of admission. (See also Figure 5.11)

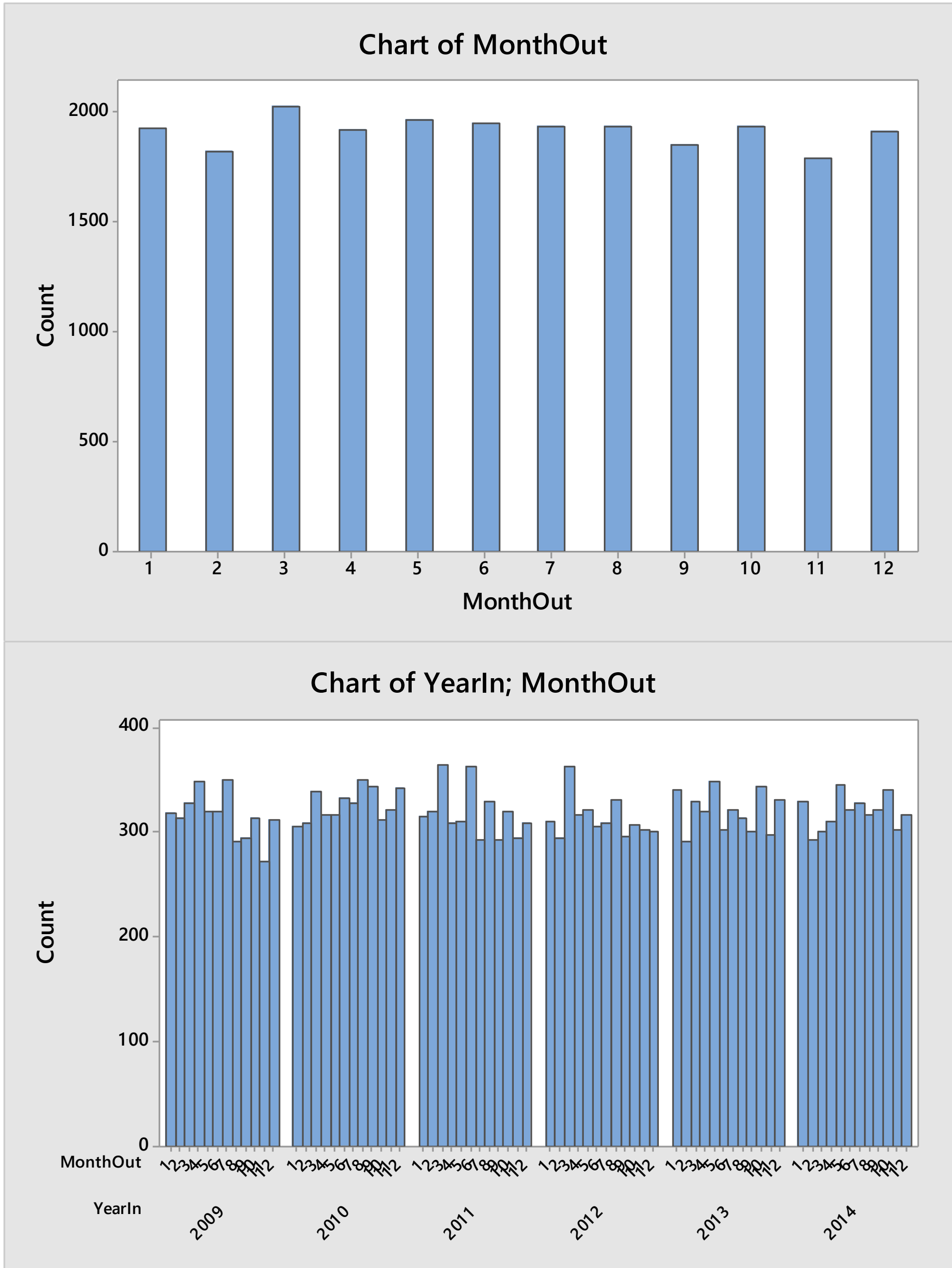


Figure 5.10. Number of patient discharged by day of the week (top) and by the of the week compared by year (bottom)

Table 5.6. Number of patient discharged by day of the week by year.

WDOut; YearIn		
Test	**Results**	**Conslusion**
Pearson Chi-Square	P-Value = 0.001	Distributions of the samples were significantly different.

Table 5.7. Statistical test for year by year differences in discharges by day of the week by ward of admission.

WDOut; YearIn; INW			
INW	**Test**	**Results**	**Conslusion**
MED	Pearson Chi-Square	P-Value = 0.051	Distributions of the samples were not significantly different.
MICU	Pearson Chi-Square	P-Value = 0.216	Distributions of the samples were not significantly different.
OBS	Pearson Chi-Square	Chi squared approximation ptobably invalid.	Inconclusive.
SICU	Pearson Chi-Square	P-Value = 0.166	Distributions of the samples were not significantly different.
SURG	Pearson Chi-Square	P-Value = 0.565	Distributions of the samples were not significantly different.
TCU-M	Pearson Chi-Square	P-Value = 0.262	Distributions of the samples were not significantly different.
TCU-S	Pearson Chi-Square	P-Value = 0.792	Distributions of the samples were not significantly different.

Table 5.8. Statistical test for differences in discharges by day of the week by ward of admission.

WDOut; INW		
Test	**Results**	**Conslusion**
Pearson Chi-Square	P-Value = 0.000	Distributions of the samples were significantly different.

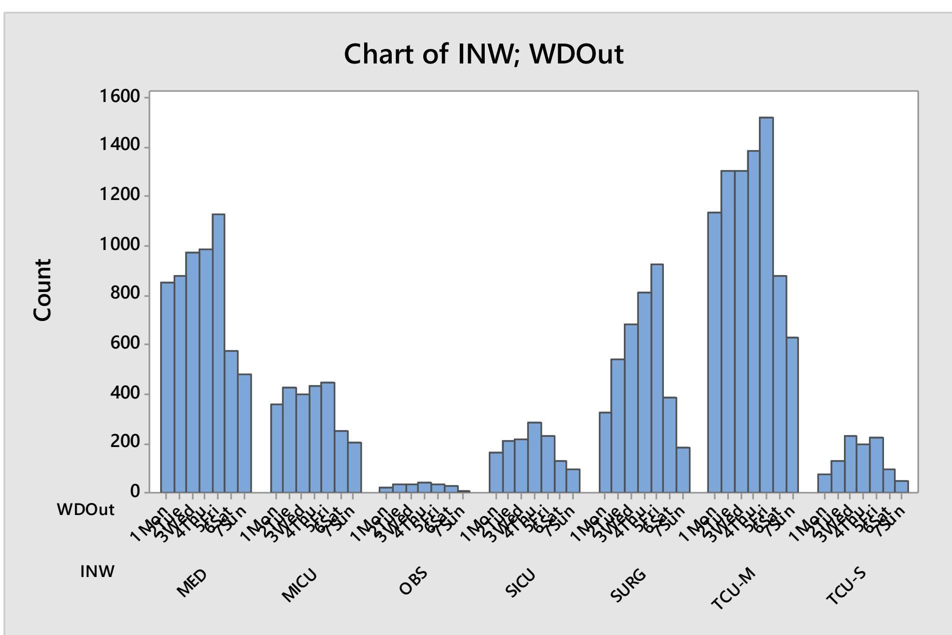


Figure 5.11. Discharges by day of the week by ward of admission.

5.3. ANALYSIS OF ARRIVALS

The exploratory analysis of the arrivals was structured in the same form as the discharges, beginning with the search of yearly seasonality and finalizing with the day of the week evaluation by ward.

5.3.1. Analysis of Admission Time. The resulting pattern displayed on top of Figure 5.12 shows a peak between 6:00 and 7:00 pm, which was interesting knowing that the discharge time peak was right before the admissions peak. This situation suggests that the admission time was related to the discharge time. The repetition of this pattern across the years and wards would suggest a direct relationship between the peaks of admissions and discharges based on the notion that in order to open up capacity, discharges must had taken place. To confirm the repetition of the pattern the admission time was studied in yearly bases (refer to top of Figure 5.12) and there were no significantly differences.

Categorizing the data by ward of admission, significant differences in the input time were found (refer to Figure 5.13) This results confirmed that the ward of admission was highly informative. As every ward showed different patterns during the day hours, each one must be a model separately

5.3.2. Analysis of the Month of Arrival. To continue with the analysis, the distribution of number of patients admitted at the hospital was evaluated by month. As was evident in Figure 5.14 (top) there were slightly fluctuations in the overall data for admissions by month, but those did not represent statistically significant differences.

From Figure 5.14 (bottom) some seasonality was suggested, thus the possible differences between admission month by year were verified using a chi- square test (Table 5.9). The test results confirmed that the patterns observed in the graph were not statistically significant.

The same was done by wards, and for discharges, a bias in the results was introduced by OBS ward. Once OBS was not included in the test, there were statistically significant differences in the number of patients admitted in each ward by month. For a better illustration, see Table 5.10 and Figure 5.15.

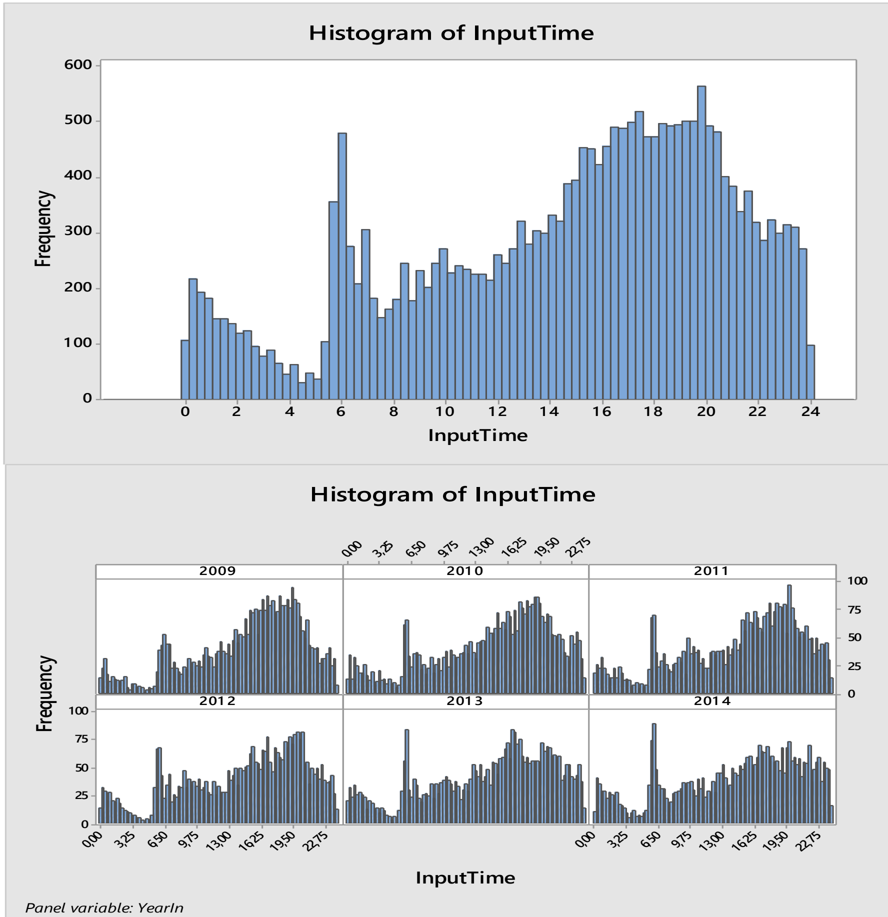


Figure 5.12. Input time distribution for the data set (top) and Input time distribution by year (bottom).

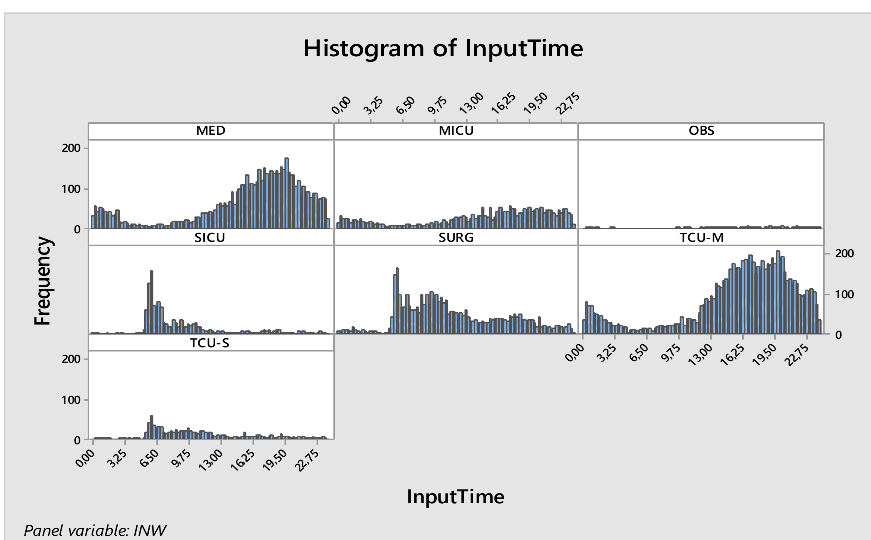


Figure 5.13. Input time distribution by ward of admission.

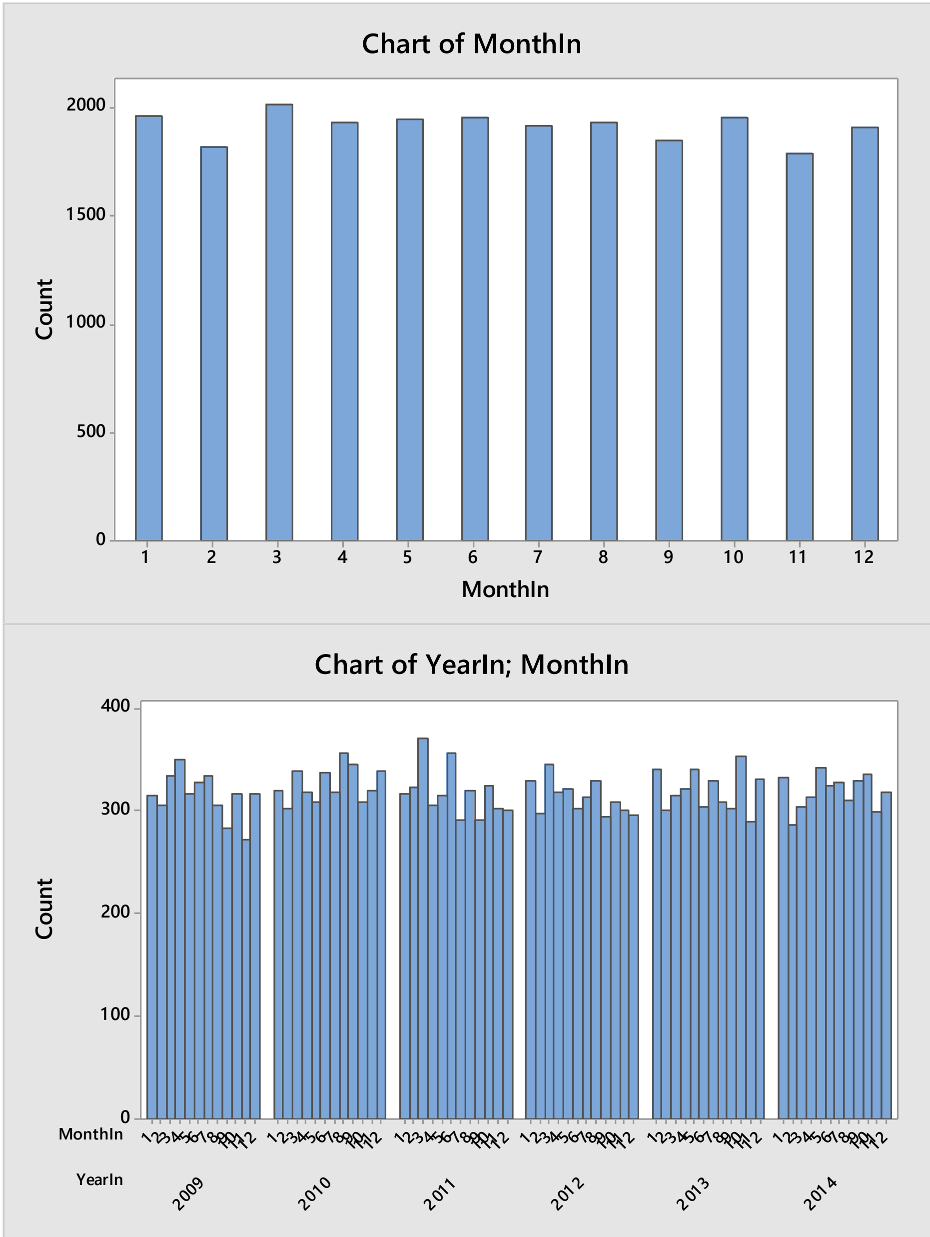


Figure 5.14. Patient admissions monthly (top) and patient admissions monthly by year (bottom).

Table 5.9. Chi square test for admissions by month by year.

MontIn;YearIn		
Test	**Results**	**Conslusion**
Pearson Chi-Square	P-Value = 0.508	Distributions of the samples were not significantly different.

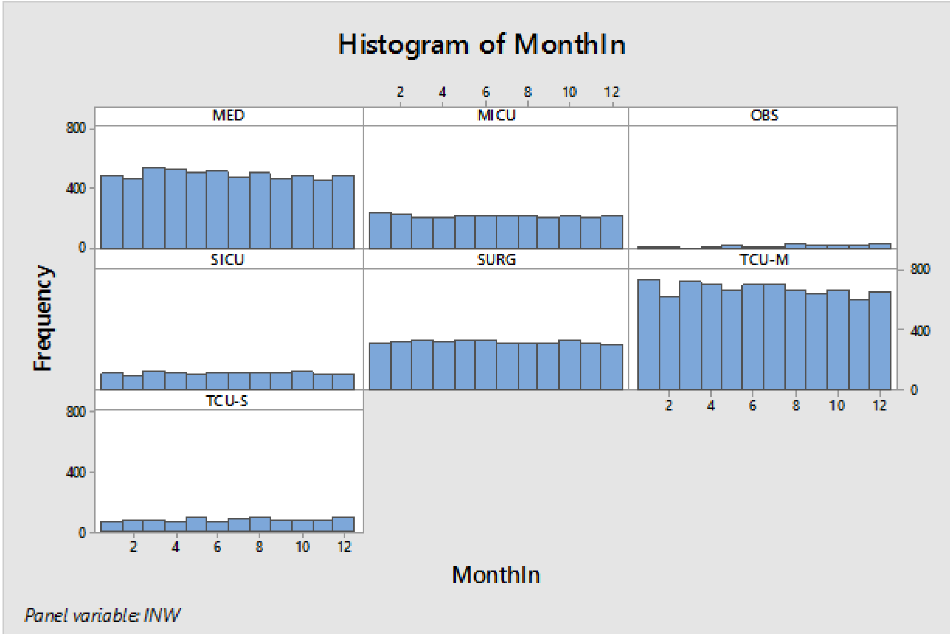


Figure 5.15. Patient admissions monthly by ward.

Table 5.10. Chi square test for admissions by month by ward.

MonthOut; INW (OBS included)		
Test	**Results**	**Conslusion**
Pearson Chi-Square	P-Value = 0.002	Distributions of the samples were significantly different.

MonthOut; INW (OBS included)		
Test	**Results**	**Conslusion**
Pearson Chi-Square	P-Value = 0.553	Distributions of the samples were not significantly different.

5.3.3. Analysis of the Admission by Day of the Week. Similar to the monthly analysis of the arrivals, an analysis was carried out to determine the existence of seasonality caused by the day of the week.

Across the data a pattern was displayed (Figure 5.16 top), where a lower number of admission was located during the weekends. This pattern was in line with the idea that during the weekends less of medical staff was allocated. However, information about the distribution of the arrivals by ward for the days of the week was necessary to confirm this operational behavior was still influencing the outcome.

Thus, a statistical test was applied to identify the similarity or difference in the weekly distribution between the wards Figure 5.17 demonstrated that the pattern was repeated, for every ward the lowest admissions were presented during the weekends.

It was also important to describe if every admission ward receive the same proportion of patients by day of the week. Table 5.11 presents the results of the x^2 square test from where is recognizable that there were differences by in the admission by day of the week for each ward (p-value is cero). In conclusion, the ward of admission was highly important to the number of admission on any given day of the week.

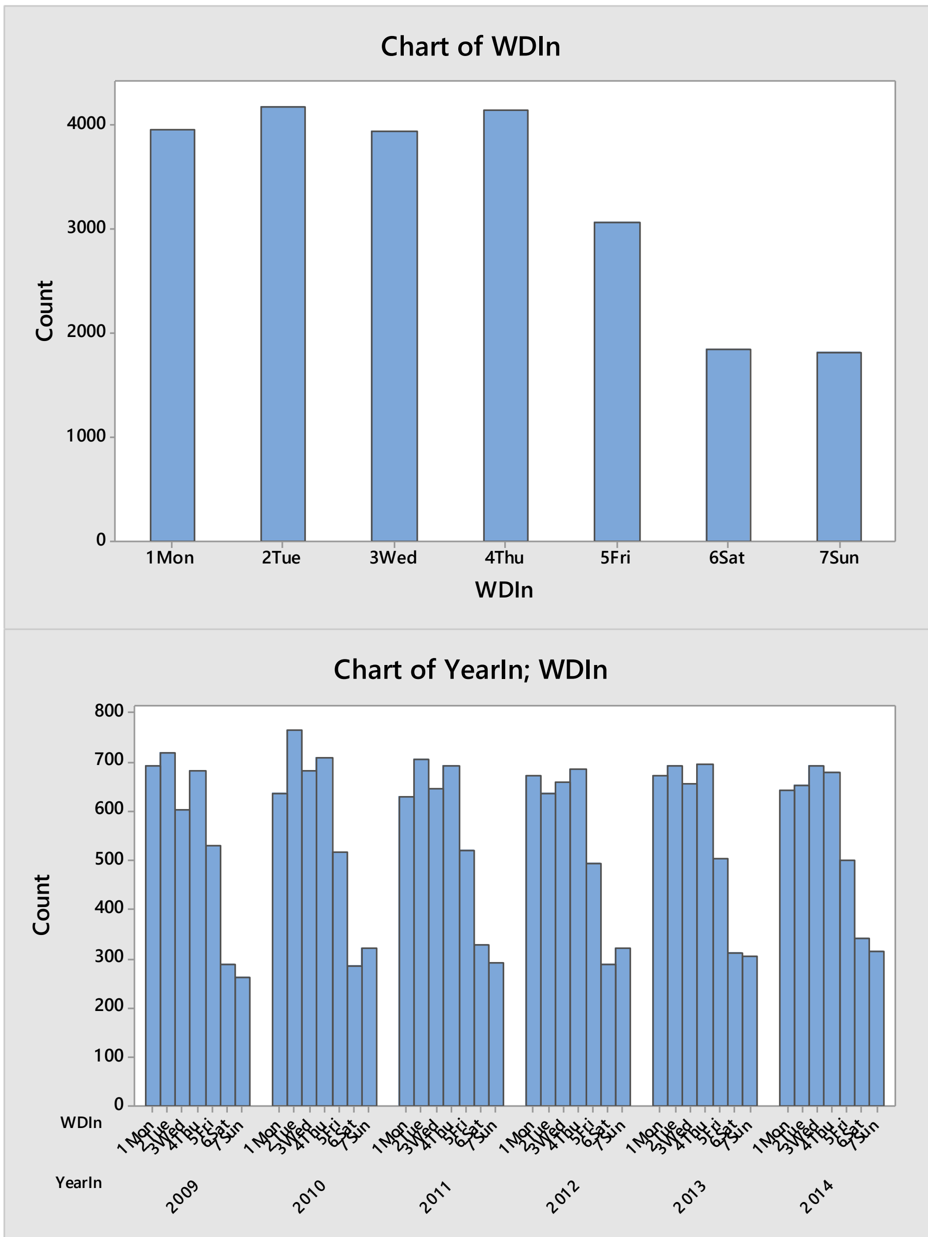


Figure 5.16. Patient admissions monthly (top) and patient admissions monthly by year (bottom).

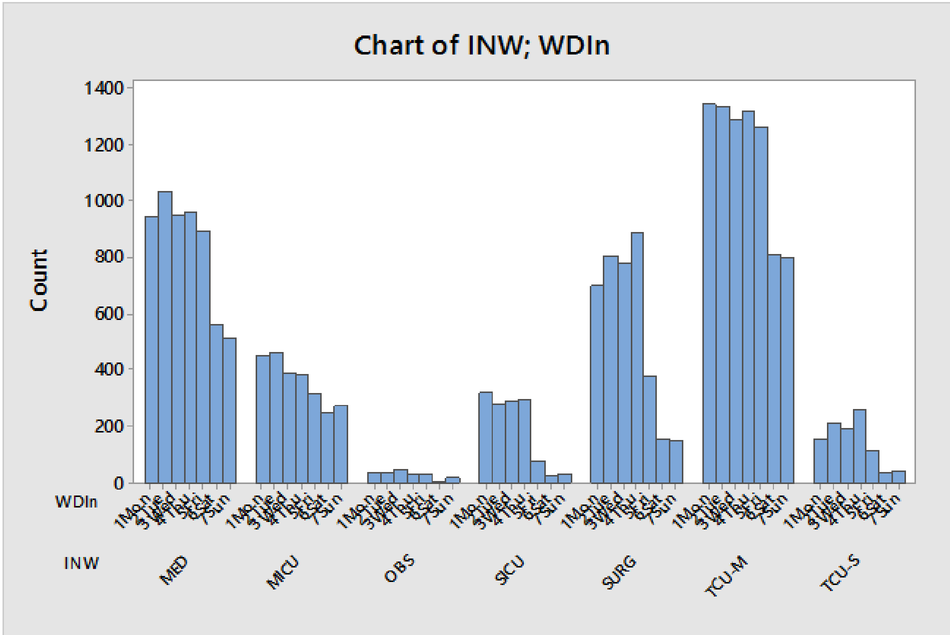


Figure 5.17. Patient admissions daily

Table 5.11. Chi square test for admissions by day of the week by ward of admission.

WDIn; INW		
Test	**Results**	**Conslusion**
Pearson Chi-Square	P-Value = 0.000	Distributions of the samples were significantly different.

5.4. EDA SUMMARY

The EDA proportionated the following statements that must be taking in consideration in the estimation of accurate statistical models for each of the principal parameters that will be used in the structure of the simulation:

- Because of the differences in the behavior of BHICU (which was not considered a medical ward) compared with the other wards, and the quantity of data points that represented it, this ward was not considered in the analysis. The inclusion of BHICU would generate bias in the exploration of the patterns of the variables studied.
- Neither yearly nor monthly seasonality was determined to be statistically significant for the modeling of the LOS.

- The ward of admission influenced significantly the LOS of the patients. This could be a reflection of the dependence the patient level of acuteness has with the admission ward, meaning that if every ward offered specific treatments, that specification could also influence the time a person was in a specific medical care division. This situation was confirmed by the dependence of the ward of admission in the discharge time. Abundant evidence of the necessity for including the ward categorization for the LOS simulation model.
- The boxplot for LOS by ward of admission (Figure 5.5) showed a significant amount of data points were outliers an indication of right skewness. A p-p plot confirmed his situation, in other words, LOS distribution was intensively skewed to the right. Thus the heavy- tailed phenomenon were recognizing in the distribution of the LOS, which indicates that an important proportion of the data could be located in the tail. The deletion of the data points in the tail (treating them as outliers) would reduce validity in the simulation development, because they won't be accurate representations of the real data, but classical distributions would not be able to reproduce the situation. Then in the modeling purposes the description for the LOS should take in account the concentration of the data patients for short periods and also include the people who could require longer stays.
- Yearly or monthly seasonality was no present in discharges across the dataset
- Examining the discharges by time of the day it was found a peak between 3:00 and 4:00 pm. This pattern was repeated throughout the years.
- Analyzing the exit time by ward of admission, significantly differences were found in the discharges. Meaning that the ward of admission had a considerable influence on the exit time.
- The OBS ward covered a small group of discharges which could be generating bias in the analysis. As it was mentioned, OBS presented a

different behavior due to small dataset. However, because it is medical ward of admission it should be considered in the modeling.

- A substantial difference in the number of patients discharged by ward of admission was determined. This was due to the noticeable influence the ward of admission had on admissions and discharges. The data reflected the operation of the hospital, where the medical staff released patients on Fridays knowing that human resources allocation for the weekend was lower than it was for the week days.
- In the analysis of admission time it was found a peak between 6:00 and 7:00 pm which was repeated in a yearly basis leading to the conclusion that the patients must be discharged in order to free capacity for admissions.
- When categorizing the data by ward of admission, the arrivals pattern visualized on a yearly basis changed. This allowed the inference that every ward had their own distribution of admission times, which validated the premise that the ward of admission was highly informative, hence, it must be incorporated in the simulation.
- No seasonality by month was present. In the data tendencies were not presented on a yearly basis.
- Analyzing the admissions across the data by day of the week contained significant differences between the number of people coming in every day of the week. The weekends showed lower rates of arrival while Tuesday and Thursdays were the days that received the most patients. This pattern was present during the years and across all wards.
- Although for arrivals every ward displayed the same weekly pattern, the number of patient each ward received changed significantly from day to day. For example, MED and TCU-S were the most populated wards. From this observation was possible to deduct the necessary inclusion of distributions for each ward in the simulation.

In the analysis of discharges and arrivals it was concluded that pattern in the weekly basis was found and as LOS is a parameter directly related to those variables the modeling of its distribution should be implemented in such a way, it represents the assignation of the LOS to the patients by day of the week in each ward.

5.5. THE PREDICTION MODELS

The conclusions obtained throughout the EDA regarding LOS, arrivals and discharges patterns, highlight the most important characteristics of the system to include in the simulation.

5.5.1. Arrivals. Statistical analysis is presented for arrivals in the following subsections.

5.5.1.1 Daily arrival rates by ward. As it was stated from the EDA, the modeling of the arrivals was separated by ward, and also by day of the week.

The arrivals were analyzed to determine whether they followed a Poisson process or not. Hence, for each day of the week the arrival data for each ward was fitted to a Poisson distribution to determine the parameters that would allow the prediction of the number of new patients being admitted daily to the hospital in each ward.

The statistical results of each day (Monday through Friday) for arrivals in each confirmed that the data followed a Poisson distribution with an exception on Saturday for OBS. The result of that particular test was inconclusive due to the low number of data points.

Figure 5.18 displayed the graphical results for the comparison between the observed (real-data) and the Poisson function (expected) for MICU ward, an example of the fitting tests. Graphical information for the other wards is presented in the Appendix. Table 5.12 presents the summary of the rates resulted from the distribution fitting (Poisson means) by ward for each day of the week.

Note: in Figure 5.18. MICU Observed Vs Expected arrivals by day of the week. the x axis corresponds to the number of patients arriving, and the y axis to the frequency.

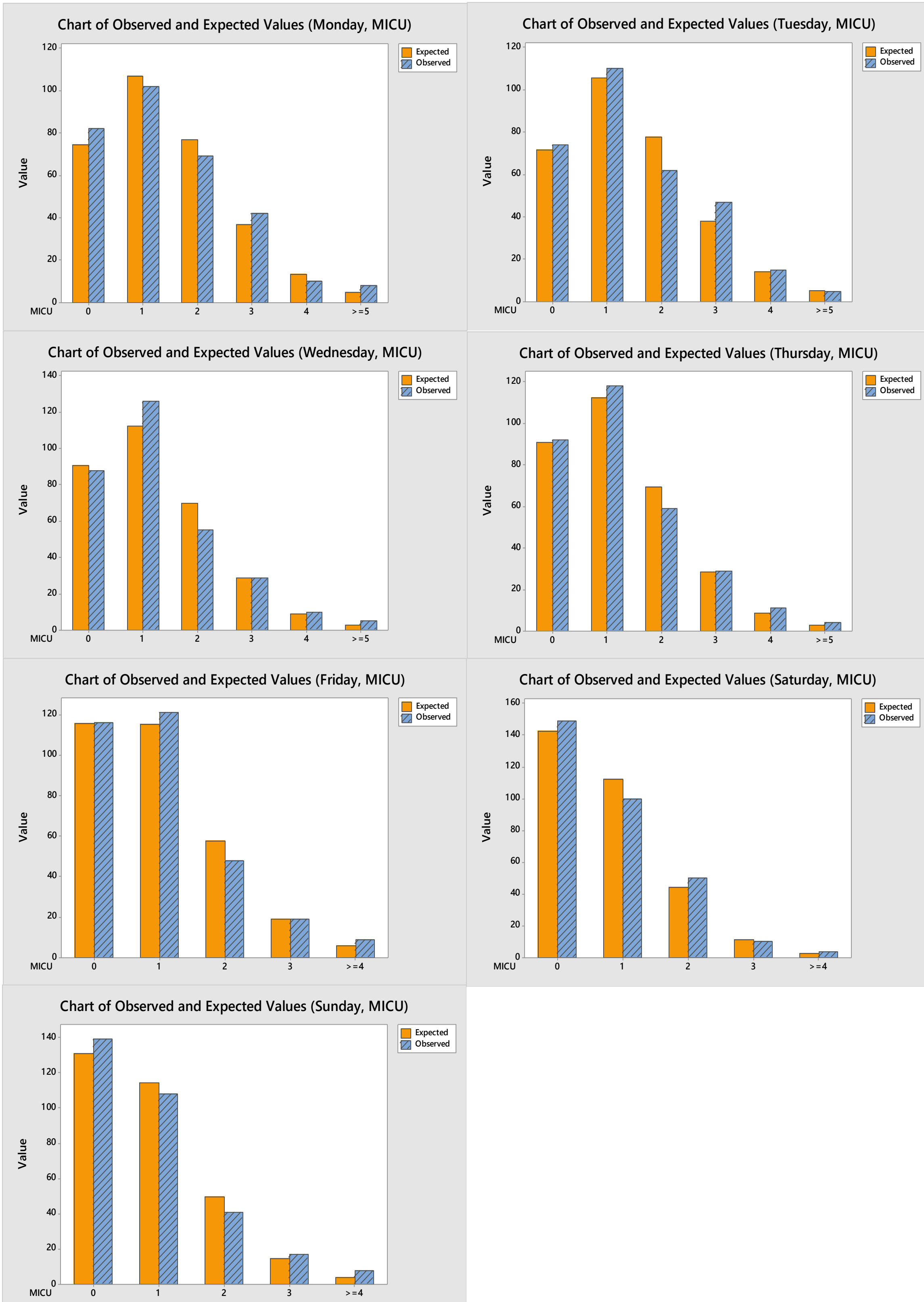


Figure 5.18. MICU Observed Vs Expected arrivals by day of the week.

Table 5.12. Summary of fitted arrival distributions Poisson means.

Day of the week Poisson Mean Arrivals							
Ward	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**
MICU	1.4345	1.47284	1.23962	1.23642	0.996805	0.785942	0.872204
SICU	1.01278	0.891374	0.929712	0.948882	0.252396	0.0766773	0.0926518
MED	3.02875	3.3099	3.05112	3.07348	2.85642	1.80511	1.63898
OBS	0.115016	0.115016	0.14377	0.0958466	0.086262	N/A	0.057508
SURG	2.23323	2.57827	2.49201	2.84665	1.20447	0.498403	0.472843
TCU-M	4.30032	4.28435	4.12141	4.21406	4.03834	2.59105	2.54952
TCU-S	0.485623	0.0674121	0.603834	0.827476	0.351438	0.108626	0.124601

In summary, it seems for all days and in all wards the Poisson arrival assumption was justified. Hence, this statistical distribution could be used to both simulate the arrivals per day and ward.

5.5.1.2 Arrivals by hour of the day. Since, the data exploration analysis states that day of admission and ward of admission were highly relevant and influence the LOS. A unique arrival distribution must be derived each day for each ward. The best fitting distribution was statistically determined as explained before in subsection 5.3.3. Then for time of the day, the percentage of patients arriving per hour in each ward for each day was calculated. Figure 5.19.and Table 5.13 listed the resulted values for the MED ward as an example of the procedure, the graphical information for the other wards is presented in the Appendix.

With the definition of the proportion of patients arriving per hour, and the mean arrival rate by day by ward, it was possible to determine an hourly rate, then the model would be able to reproduce the patterns each ward showed during each day of the week.

5.5.2. LOS. The EDA brought important conclusions for the modeling of the LOS, evidencing that there was intraday variability in the both the arrival and discharge process. Therefore, the type of patient (i.e. defined by the type of ward at which the patient was allocated after admission) has a strong influence on the LOS and also in the distribution of arrival day and discharge day. In this way the distribution of the LOS parameter was developed including the ward of admission.

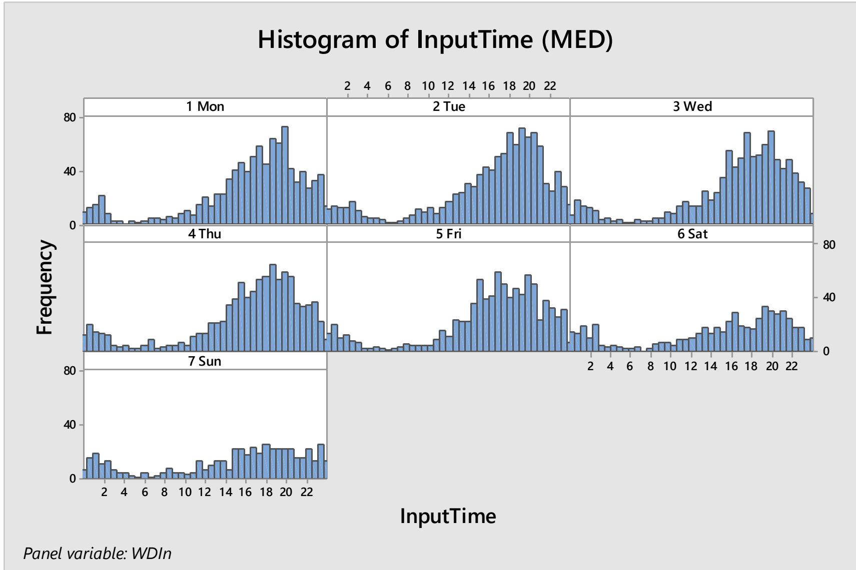


Figure 5.19. MED Arrival distribution by day.

The search for distributions that fitted LOS was done carefully, making sure the longer stays were included. At first, a distribution was tailored for all the patients and no fit was recommendable. Hence, recognizing that 90% of all patients in the data set had a LOS of 168 hours or less and only 10% exceeded 168 hours (up to 66 days), the patients were separated in the ones short LOS (less or equal to 168 hours or 7 days) and long LOS (greater than 168 hours up to 66 days).

The short-term patient, defined as a patient spending 168 hours or less (7 full days) in the hospital, showed a very unique and complex behavior which could be driven by the up and downs of arrivals and discharges. Figure 5.20 presented an example of the situation for the MED ward (one of the most populated wards) there where up and downs in the LOS of patients with 168 hours or less. The peaks showed in the data, were induced by the daily discharge distribution (as mentioned in section 5.4 EDA Summary). Thus, it was difficult to determine the probability of LOS distribution for any patient using parametric distributions. To confirm this, fitting tests were applied, and effectively the parametric distributions did not fit well, while empirical distributions offered better results.

Table 5.13. MED Arrival distribution for the entire week by hour of the day.

Day \ Time		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Mon	Total Patients	24	29	13	3	2	1	6	7	7	11	15	23	33	34	65	72	65	93	95	117	69	55	55	54
	Proportion	0.025	0.031	0.014	0.003	0.002	0.001	0.006	0.007	0.007	0.012	0.016	0.024	0.035	0.036	0.069	0.076	0.069	0.0981	0.1002	0.1234	0.0728	0.058	0.058	0.057
Tue	Total Patients	26	21	25	10	9	5	1	4	13	19	16	21	36	46	46	70	74	103	105	110	112	62	58	44
	Proportion	0.025	0.02	0.024	0.01	0.009	0.005	1E-03	0.004	0.013	0.018	0.015	0.02	0.035	0.044	0.044	0.068	0.071	0.0994	0.1014	0.1062	0.1081	0.06	0.056	0.042
Wed	Total Patients	0.25	0.23	0.14	0.05	0.05	0.01	0.05	0.02	0.05	0.14	0.16	0.27	0.24	0.39	0.35	0.89	0.79	1.01	0.84	1.14	0.72	0.77	0.58	0.41
	Proportion	0.026	0.024	0.015	0.005	0.005	0.001	0.005	0.002	0.005	0.015	0.017	0.028	0.025	0.041	0.037	0.093	0.083	0.1058	0.088	0.1194	0.0754	0.081	0.061	0.043
Thu	Total Patients	35	24	15	5	7	3	14	4	8	11	13	20	35	32	55	86	64	94	101	102	76	59	63	36
	Proportion	0.036	0.025	0.016	0.005	0.007	0.003	0.015	0.004	0.008	0.011	0.014	0.021	0.036	0.033	0.057	0.089	0.067	0.0977	0.105	0.106	0.079	0.061	0.065	0.037
Fri	Total Patients	36	15	16	6	3	4	2	7	10	7	13	20	32	42	60	81	86	77	75	83	78	50	51	41
	Proportion	0.04	0.017	0.018	0.007	0.003	0.004	0.002	0.008	0.011	0.008	0.015	0.022	0.036	0.047	0.067	0.091	0.096	0.086	0.0838	0.0927	0.0872	0.056	0.057	0.046
Sat	Total Patients	0.33	0.23	0.26	0.05	0.06	0.04	0.03	0.02	0.1	0.1	0.14	0.12	0.3	0.2	0.28	0.33	0.41	0.29	0.39	0.58	0.47	0.41	0.3	0.21
	Proportion	0.058	0.041	0.046	0.009	0.011	0.007	0.005	0.004	0.018	0.018	0.025	0.021	0.053	0.035	0.05	0.058	0.073	0.0513	0.069	0.1027	0.0832	0.073	0.053	0.037
Sun	Total Patients	29	23	17	8	6	5	4	5	10	7	7	17	13	24	19	37	35	34	43	38	37	23	29	43
	Proportion	0.057	0.045	0.033	0.016	0.012	0.01	0.008	0.01	0.019	0.014	0.014	0.033	0.025	0.047	0.037	0.072	0.068	0.0663	0.0838	0.0741	0.0721	0.045	0.057	0.084
All	Total Patients	208	158	126	42	38	23	35	31	63	79	94	140	203	237	308	468	444	531	542	622	491	367	344	280
	Proportion	0.035	0.027	0.021	0.007	0.006	0.004	0.006	0.005	0.011	0.013	0.016	0.024	0.035	0.04	0.052	0.08	0.076	0.0904	0.0923	0.1059	0.0836	0.062	0.059	0.048

The ups and downs observed in the short LOS were also present in the long LOS This situation led to the conclusion that in order to achieve accuracy in the predictions, LOS also should be modeled with the empirical distribution, then the second part of the hybrid model was composed by the empirical distribution that represented long LOS. In the Appendix graphical information for the other wards is presented.

With the prediction models stablished, it can be said the fundamental parameters were ready to start the simulation modeling. The variables were ready to start the study of the impact in capacity from the addition of beds in the units.

The following section offer a detailed description of the development of the DES model, since the conceptual model until its verification.

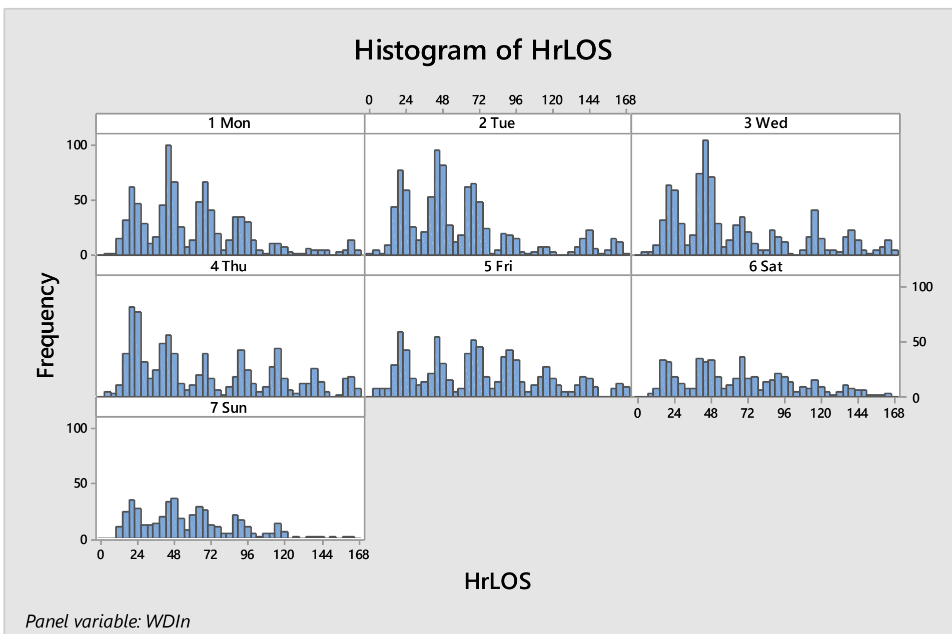


Figure 5.20. MED LOS by day of the week.

6. DES MODEL DEVELOPMENT

6.1. CONCEPTUAL MODEL

For simulation purposes the original layout of the hospital was simplified to capture the appropriate performance variables. As it was indicated by Kolker (2010) it is not necessary to simulate the most complete model but keeping it simple while capturing the essential to accomplish the objectives.

As it was stated at the beginning of section 5 (EDA), the VA Sacramento hospital offers inpatient services for seven different levels of acuteness known as wards MICU, SICU, MED, OBS, SURG, TCU-M and TCU-S (The model doesn't include BHICU for the reasons exposed in the EDA). The wards were categorized in three different units of care where they share a set of beds as was shown in Table 6.1, 50 beds were allocated between the units, ICU with 10 beds, MOS with 24 and TCU with 16.

Table 6.1. Allocation of beds in the VA Sacramento hospital.

Unit of care	No. of Beds	Wards in the Unit
ICU	10	MICU
		SICU
MOS	24	MED
		OBS
		SURG
TCU	16	TCU-M
		TCU-S

As the operation of the hospital, the simulation model was proposed as a set of three units of care which comprised the wards sharing beds.

To follow the objective of the simulation which was to conduct experiments on different combinations of beds in the medical units, the essential control variables to initialize the model were:

- Arrival rates by each arrival source, day of the week, and hour of the day. In section 5 the preliminary analysis of the data displays a detailed description of the arrival rates performance as an explanation of why arrivals must be model by day of the week and hour of the day.

- Distributions of Length of stay for short and long term for each of the wards, and arrival day (day of the week). As for arrivals, the actual performance of LOS variable was described in the preliminary analysis section of this document.
- Number of beds in each medical care unit.

The design of the model allows the adjusting to the input data to perform the different scenarios of interest. The following output parameters were selected to evaluate the impact from operational changes in the inputs (e.g. Changing the number of beds in one of the units of care)

- Patient waiting time for a bed after being admitted in the hospital.
- Average of number of patients waiting for a bed after being admitted in a specific
- Occupancy: number of beds occupied at the end of the day, bay ward by day

Having defined the inputs and required outputs of the system, a conceptual model was developed for each unit of care (ICU, MOS and TCU), as an example; Figure 6.1 presents the model for ICU. MOS and TCU units of care followed the same logic.

6.2. LOGIC OF THE SIMULATION MODEL

The first step in the simulation logic was the creation of the entities (patients). To ensure an accurate number of patients in the system, through a decision unit, the patient arrival was accepted or declined according to the different arrival rates specified by the simulation current day of the week (day one to seven) and hour of the day (hour one to 24). The arrival rates were modeled as a nonstationary Poisson process. Each would have specific rates, within the wards the rates were introduced in the model by day of the week and by time of the day. Leaving a set of 168 rates per ward.

When the patient was accepted in the hospital ward, the initial attributes were assigned, for instance, day of arrival, hour of arrival, and ward of admission became characteristics of the patients through the system and facilitated their tracing and the recording of the statistics in the simulation.

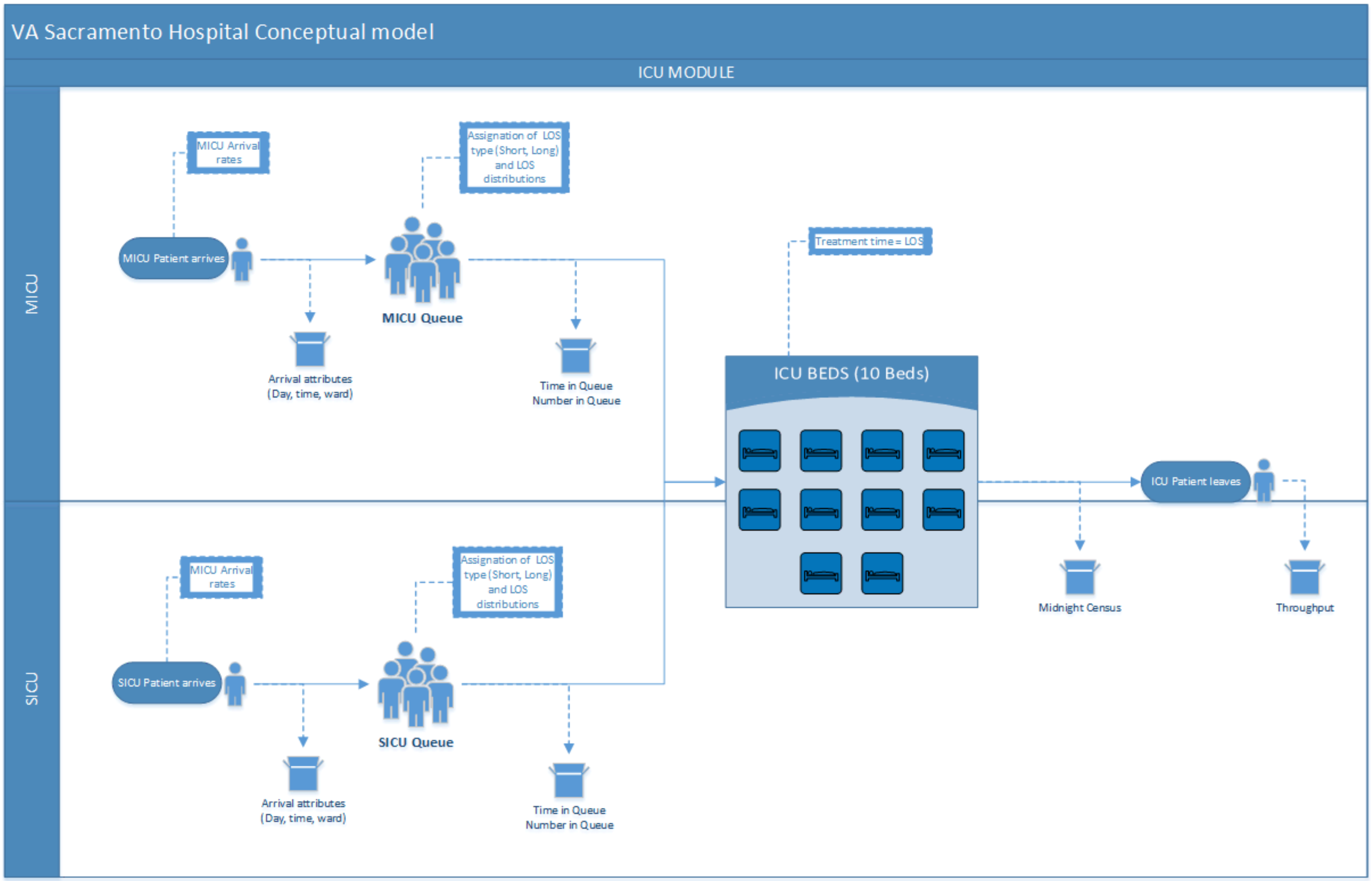


Figure 6.1. Conceptual model ICU

Once this assignation was complete, a decision element was placed to give the patients the LOS type, short or long, based on the proportions of short and long stays extracted from the hospital data for each ward. After the LOS characterization, the simulation logic gave the LOS time according to the empirical distributions of LOS for each ward subtracted from the hospital data. As for the behavior of the original data, the model was design to designate a Length of stay according to the patient's ward and day of arrival from the empirical distribution determined from the EDA.

When the beds were allocated to the patients, LOS time was used as the treatment time. The beds were given in a cyclical manner, meaning that an available bed was the next to be assign. If there were not available beds, the patient waited in queue until a bed was available, and the first patient in queue got the first available bed (FIFO). The patient was discharged after the completion of the treatment time. The simulation model used to record commands between the different assignations and activities to report the relevant statistics: queue characteristics, daily occupancy and throughput. Figure 6.2 presents a fragments of the simulation model, it represents ICU, the other two Units of care (MOS and TCU) were modeled in the same fashion to complete the operation of the simulated system.

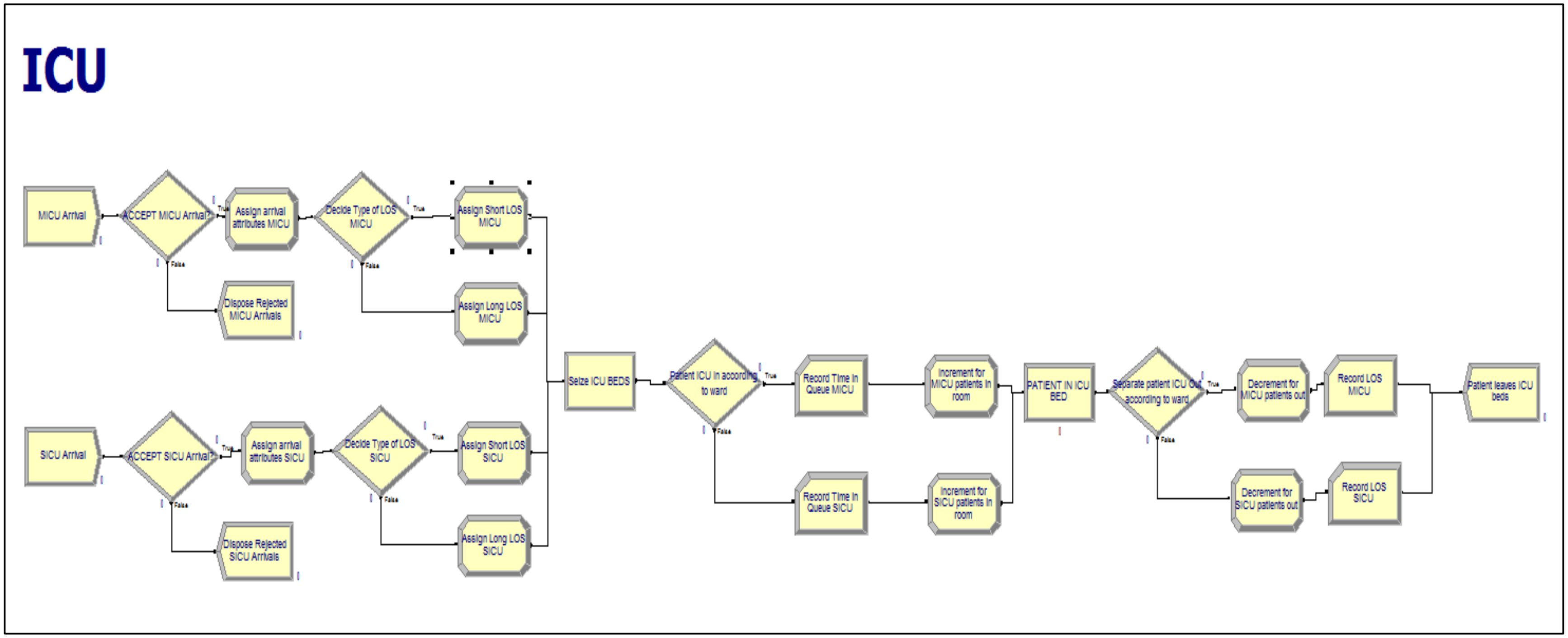


Figure 6.2. DES model (ICU fragment)

7. VALIDATION AND VERIFICATION

To validate the model, a comparison was conducted between the values of the variables generated by the simulation and the operational data collected from January of 2009 to December of 2014, a total of 313 consecutive weeks.

The simulation outputs were compared graphically and the similarities/differences were confirmed statistically by the application of different hypothesis test like Wilcoxon, crustal Wallis, among others. Choosing the statistical test depend on the nature of the data collected. Due to the use of empirical probability distributions to describe the LOS behavior, and the time-dependent characteristics of the arrival rates, the non-parametric Wilcoxon and Kruskal Wallis statistic tests, were used to verify significant difference between the sets of data for arrivals and length of stay and Occupancy. The simulation run is defined as a sequence of samples of the same size, thus one run may contain several samples or replications with the same initial conditions but different numerical seed generated randomly by Arena™. This allows each sample to be independent.

When running the simulation, each replication initiates with an empty system, thus a warm-up period (WP) was included in order to guarantee the system had reached a stable state before the collection of the information for the run can be done. Control variables as arrivals and length of stay were not sensitive to an empty initial system, however output parameters as occupancy, waiting time and length of the queue were affected by the initial conditions. Welch's graphical procedure was applied to stablish the WP, it consisted in a calculation of the cumulative average which was superimposed to a Welch plot to determined when the data was stable, to offer a better visualization, the calculation of the growth of the cumulative average was plotted instead. This technique was applied to the WP sensitive variables (occupancy and length of the queue) and the longest WP identify was chosen to be implemented in the model. For this purpose, a trial run of 5 replications (length 313 weeks each) was used. The results observed from the run are displayed in Table 7.1, a WP of 200 days (4800 hours) was stablished as it was the longest time a variable took to stabilize. The visual representation of the approach is presented in Figure 7.1 and Figure 7.2.

Table 7.1. WP identification

Unit of care	Variable	WP (days)	WP(Hours)
ICU	Occupancy	63	1512
	Time in Queue	62	1488
MOS	Occupancy	60	1440
	Time in Queue	200	4800
TCU	Occupancy	46	1104
	Time in Queue	185	4440

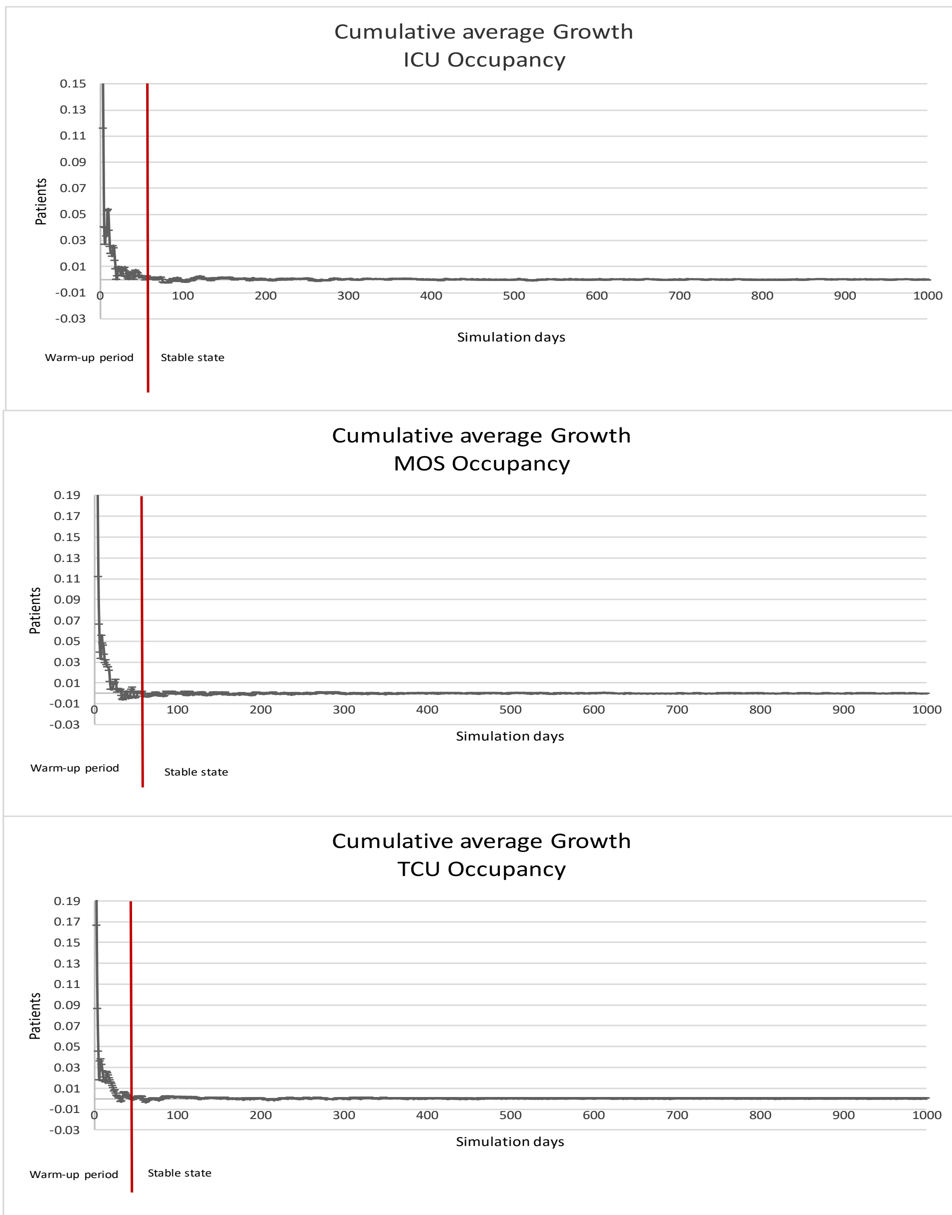


Figure 7.1. Visual identification of the warm-up period for occupancy.

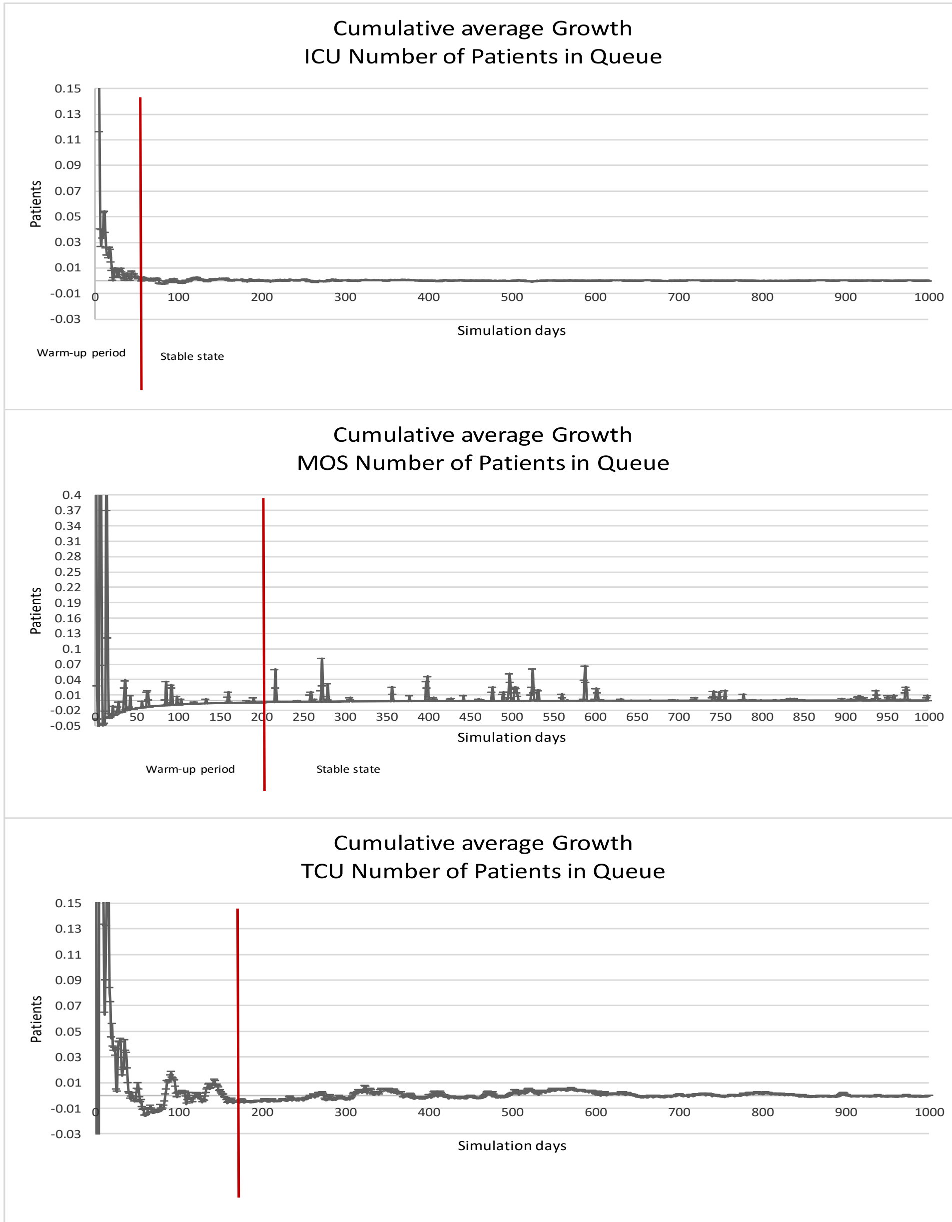


Figure 7.2. Visual identification of the warm-up period for waiting time.

With the interest of simplify the graphical comparisons for the model verification, the length of the replications was kept equal to the original set of data 313 weeks (52584 hours) including the warm-up period. The number of replications was defined using the half width ratio method as Arena™ automatically compute 95% confidence half width for the measured variables.

Calculation of the number of replications:

- Pilot run of 5 replications, 313 weeks long each.
- The parameter chosen to calculate the sample size (number of replications) was the occupancy and its bound, *E*, (marginal error) was expected to be less than 5% of the average occupancy for each unit of care taken from the original set of data. Table 7.2 specified the expected *E* for each unit of care.

Table 7.2. Expected error for occupancy.

Unit of care	Average Occupancy (Patients)	Expected Error (5% Of the average Occupancy)
ICU	7.622	0.3811
MOS	18.2928	0.91464
TCU	12.1952	0.60976

As stated in Table 7.3, 6.37 was the optimal size of the sample required to obtain the desired error level, then, the appropriate number of replications to validate the model was seven.

Table 7.3. Sample size to obtain the desired margin error

Unit of care	ICU	MOS	TCU
Pilot run number of replications (n0)	5		
Initial Half with (h0)	0.43	0.28	0.2
Desired Half width (h)	0.3811	0.91464	0.60976
Requiered sample size	$\boxed{6.3654}$	0.4686	0.5379

All simulation replications started on Monday at midnight (12 Am). The data collected at the end of each run was graphically compared with the original data set and statistically tested under the following hypothesis:

H_0: There was no difference between the two groups of data

H_A: There was a statistically significant difference between the groups.

Excel and Minitab 17 were used to perform the statistical tests and the graphical comparisons.

7.1. ARRIVALS

The graphical verification was based on the average number of arrivals each hour by day of the week. Original averages were plotted together with the simulation results for a visual revision of the similitudes/differences. Figure 7.3, Figure 7.4, and Figure 7.5 display the arrival rates behavior by ward. The rates were plot by hour and every 24 hours represent a day of the week; therefore, the peaks are the time of the day were more patients arrive to the hospital.

In conclusion, the data obtained by the simulation behaves accordingly to the data collected from the hospital, having that there was not statistically significant difference between the behavior of the two groups. (Table 7.4. Arrivals hypothesis tests results.).

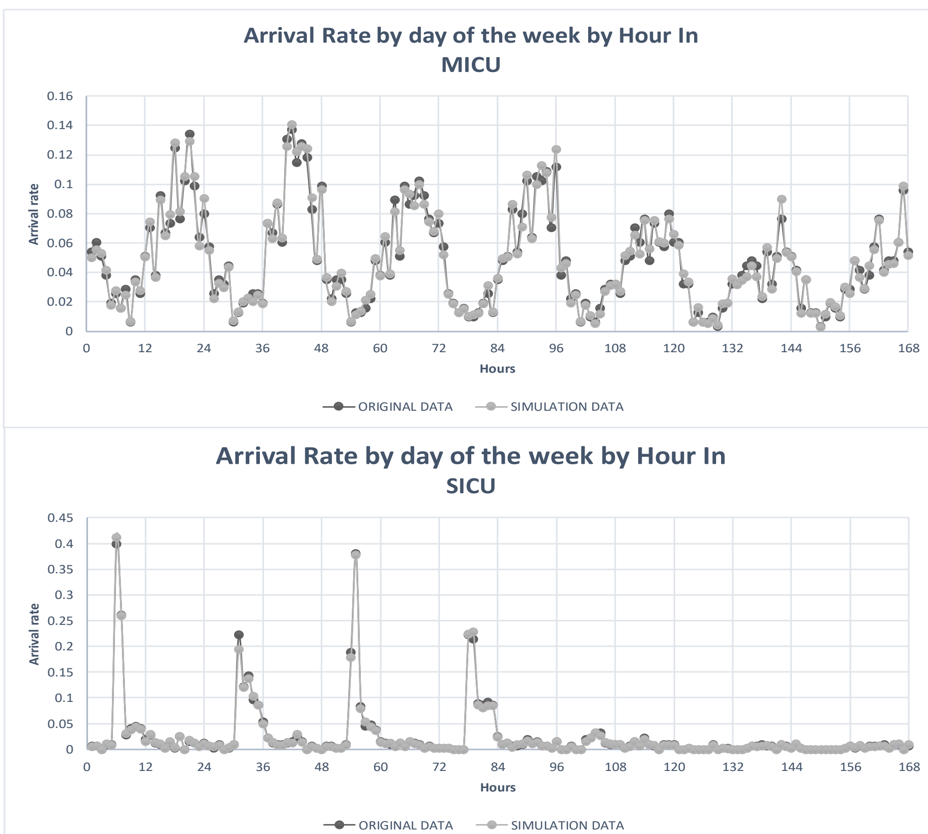
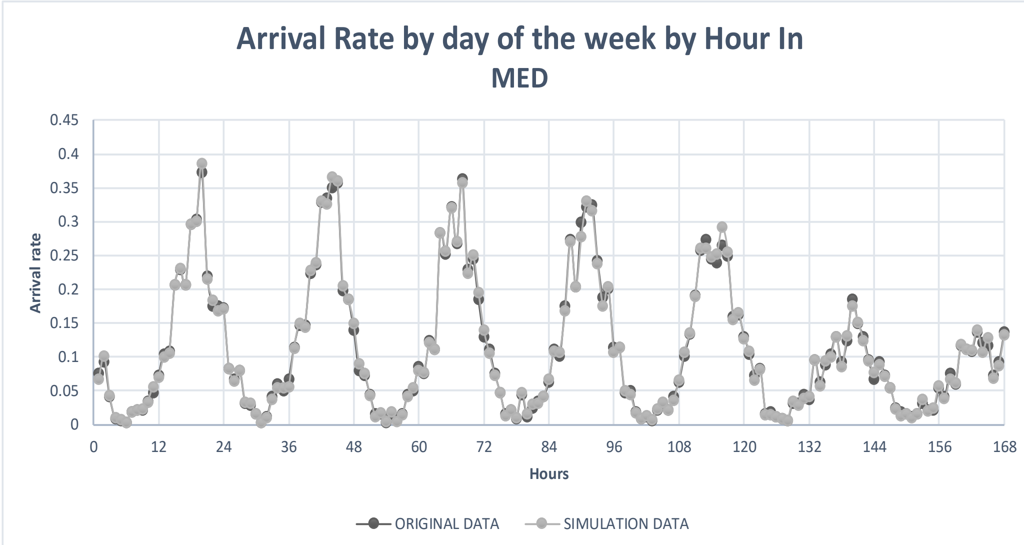
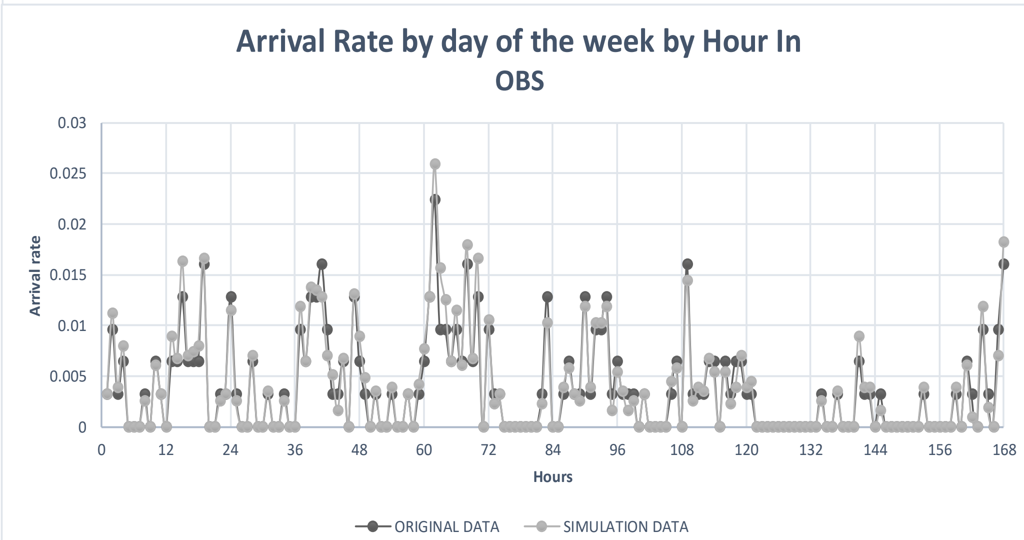


Figure 7.3. Graphic verification of arrivals by ward. MICU, SICU.





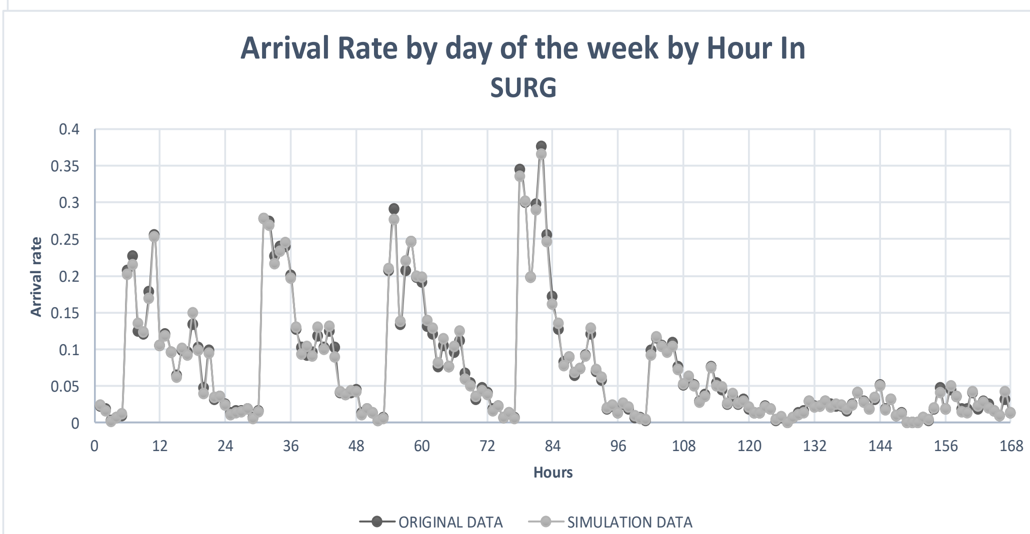
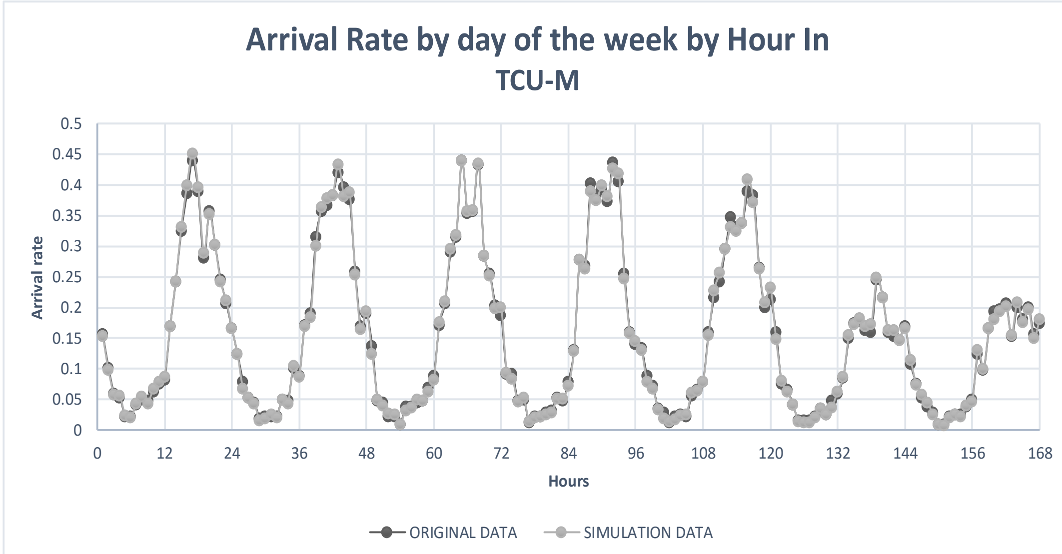


Figure 7.4. Graphic verification of arrivals by ward. MED, OBS.SURG.



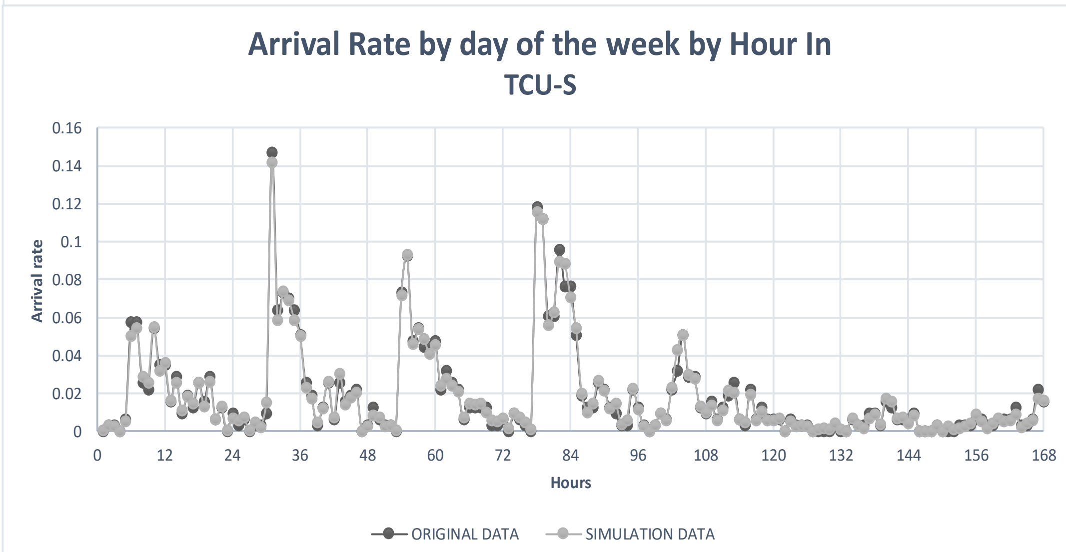


Figure 7.5. Graphic verification of arrivals by ward. TCU-M, TCU-S.

7.2. LOS

The graphical verification of LOS was done using the CDF of both original dataset and dataset obtained from each replication from the simulation run (seven replications). The comparison was presented by ward according to the characteristics of LOS (short, long).Figure 7.6, Figure 7.7 and Figure 7.8.

Table 7.5 displays the results from the statistical tests of each ward. Concluding, the data distribution from the simulation and the data distribution from the hospital do not present statistical difference, neither for short LOS nor long LOS.

Table 7.4. Arrivals hypothesis tests results.

INW	Test	Results	Conslusion
MICU	Wilcoxon	P-Value = 0.9996	Distribution of the samples is not significantly different.
SICU	Wilcoxon	P-Value = 0.7595	Distribution of the samples is not significantly different.
MED	Wilcoxon	P-Value = 0.9861	Distribution of the samples is not significantly different.
OBS	Wilcoxon	P-Value = 0.8314	Distribution of the samples is not significantly different.
SURG	Wilcoxon	P-Value = 0.9575	Distribution of the samples is not significantly different.
TCU-M	Wilcoxon	P-Value = 0.9749	Distribution of the samples is not significantly different.
TCU-S	Wilcoxon	P-Value = 0.769	Distribution of the samples is not significantly different.

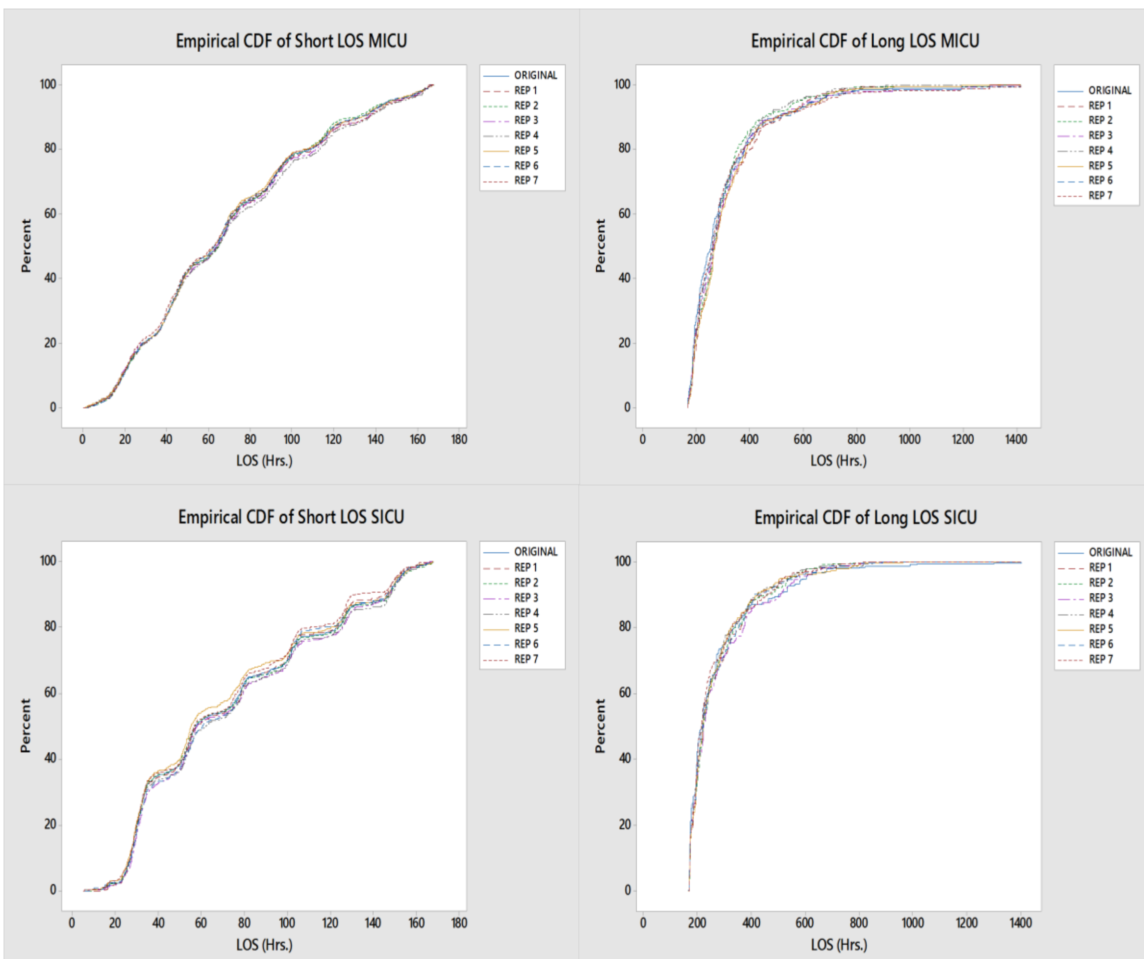


Figure 7.6. Graphical verification of LOS short and long for MICU, SICU.

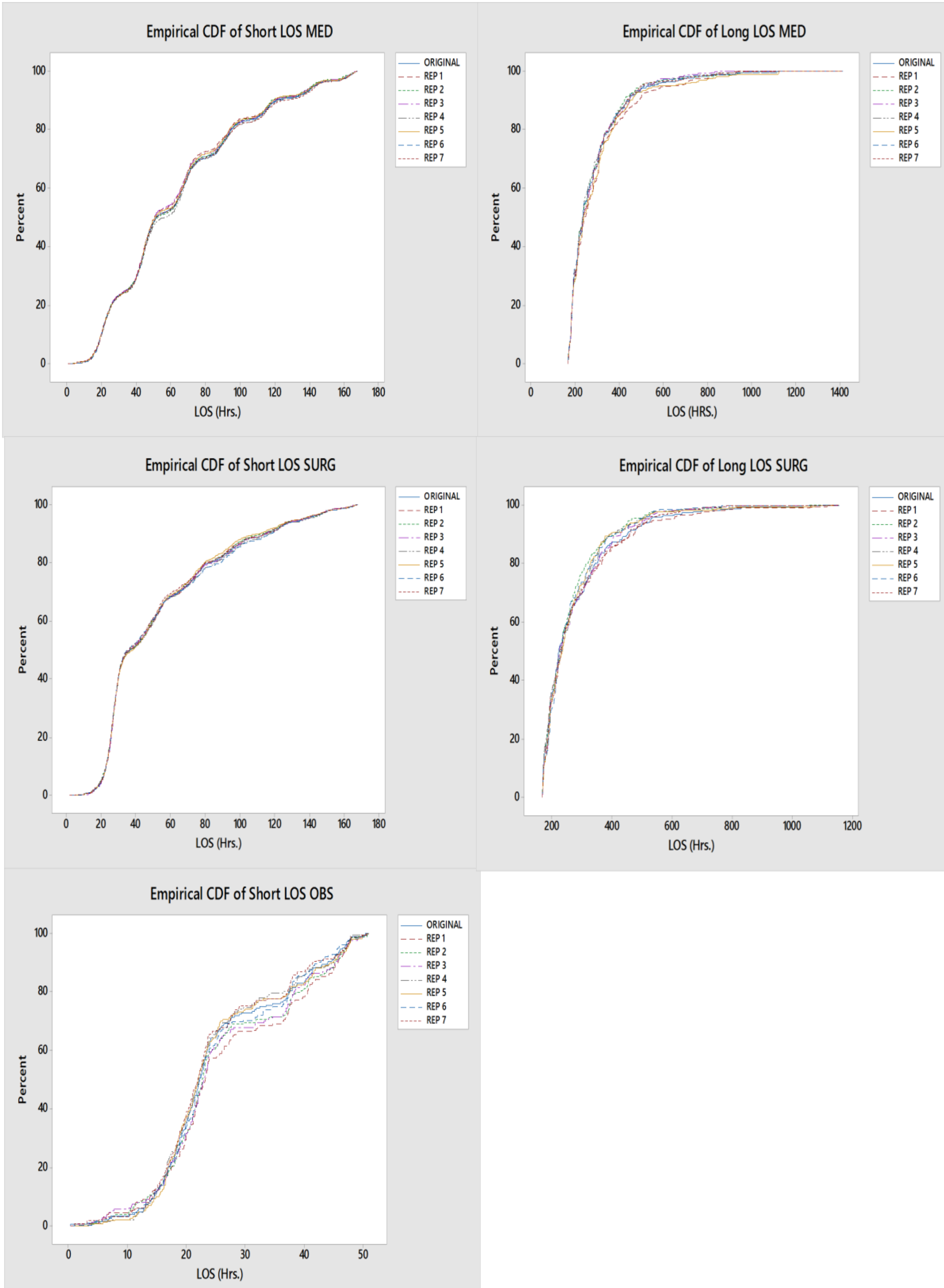


Figure 7.7. Graphical verification of LOS short and long for MED, SURG, OBS.

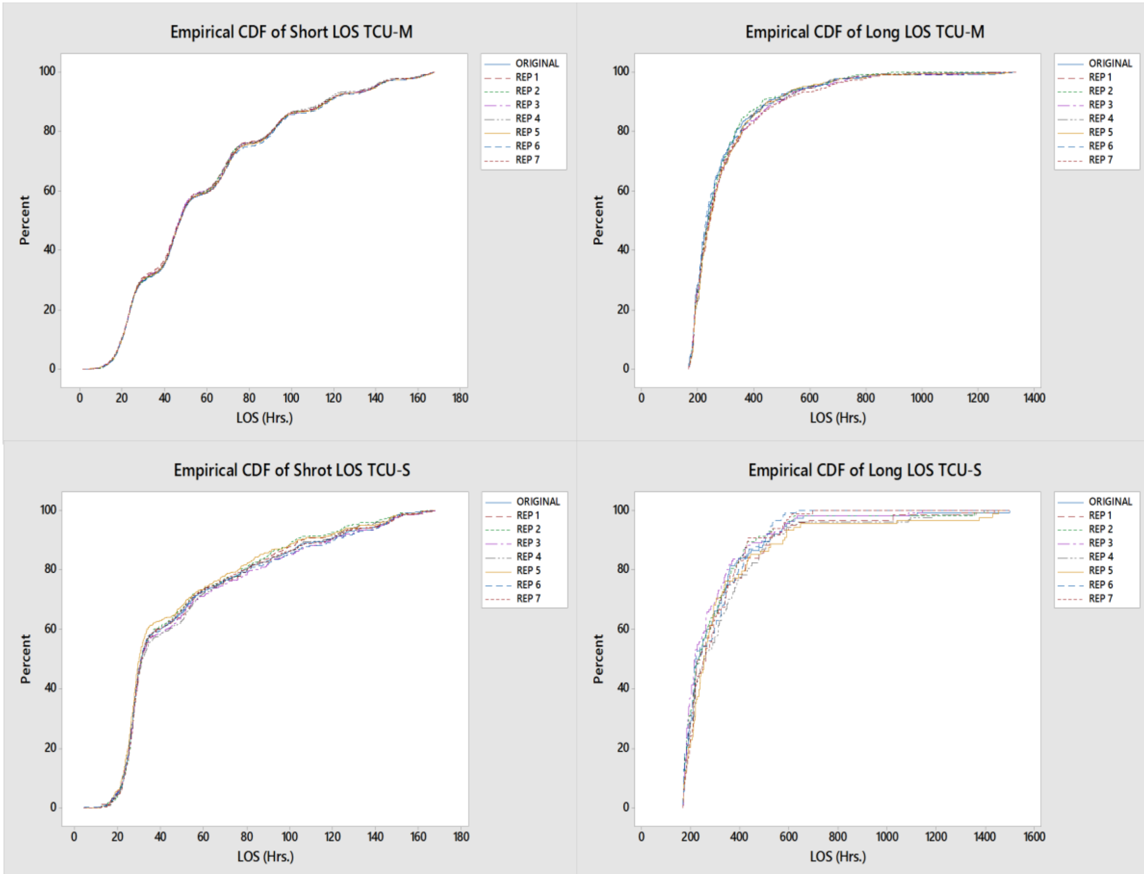


Figure 7.8. Graphical verification of LOS short and long for TCU-M, TCU-S.

Table 7.5. LOS verification Hypothesis test results

INW	LOS Type	Test	Results	Conslusion
MICU	Short	Kruskal Willis	P-Value = 0.821	Distribution of the samples is not significantly different.
	Long	Kruskal Willis	P-Value = 0.206	Distribution of the samples is not significantly different.
SICU	Short	Kruskal Willis	P-Value = 0.268	Distribution of the samples is not significantly different.
	Long	Kruskal Willis	P-Value = 0.829	Distribution of the samples is not significantly different.
MED	Short	Kruskal Willis	P-Value = 0.318	Distribution of the samples is not significantly different.
	Long	Kruskal Willis	P-Value = 0.780	Distribution of the samples is not significantly different.
OBS	Short	Kruskal Willis	P-Value = 0.507	Distribution of the samples is not significantly different.
SURG	Short	Kruskal Willis	P-Value = 0.984	Distribution of the samples is not significantly different.
	Long	Kruskal Willis	P-Value = 0.873	Distribution of the samples is not significantly different.
TCU-M	Short	Kruskal Willis	P-Value = 0.749	Distribution of the samples is not significantly different.
	Long	Kruskal Willis	P-Value = 0.274	Distribution of the samples is not significantly different.
TCU-S	Short	Kruskal Willis	P-Value = 0.453	Distribution of the samples is not significantly different.
	Long	Kruskal Willis	P-Value = 0.344	Distribution of the samples is not significantly different.

8. MODEL IMPLEMENTATION AND RESULTS

After the model was verified, it was used to simulate the implementation of four beds within the three units of care (ICU, MOS and TCU) to determine in which, the addition of beds could be of more benefit.

The quantity of beds used in this analysis was specified based on the information obtained from Hospital managers. They expressed their interest on studies that could determine the impact in capacity from of adding beds, which could be an important tool to support the decisions about investment in new resources. However, the managers explained that, to increase the number of beds in the hospital, it was possible to assign various rooms which can house two patients instead of one, but, this distribution of the space will allow the implementation of maximum four beds.

The performance was measured from the outcome variables: Waiting time, number of patients waiting, bed utilization rates and throughput.

The experimental outcomes were analyzed in two parts:

1. Analysis of queues to define bottlenecks and benefits from adding beds to each unit.
2. Selection of the scenario that represented better opportunities of raising the hospital capacity based on the bed utilization rates

8.1. ANALYSIS OF THE QUEUES

The evaluation of the what if scenarios was done using the process analyzer tool from the Arena™ package. The is tool allowing to stablish control and response parameters to run the simulation and obtain the results as the design of the experiment requires, for example, if from the experimentation it is necessary changing the number of beds between the trials, number of beds could be stablished as a control parameter, and if the waiting time was the needed outcome for the analysis, it can be defined as a response variable.

The first part of the analysis, an experiment was designed in order to collect the necessary outcomes which could help in determining: 1. Queue characteristics and 2. The benefits of adding beds based on those queue features.

In this way, a total of 15 scenarios were proposed, each one representing a possible combination for adding four beds in the three units of care. (refer to Table 8.1.)

Table 8.1. Different combinations for adding four beds in the three units of VA Sacramento Hospital.

Scenario Name	No. Beds to Add in the scenario			Total beds to run the scenario		
	ICU	MOS	TCU	ICU	MOS	TCU
Current state	0	0	0	10	24	16
Scenario 1	4	0	0	14	24	16
Scenario 2	3	1	0	13	25	16
Scenario 3	3	0	1	13	24	17
Scenario 4	2	2	0	12	26	16
Scenario 5	2	0	2	12	24	18
Scenario 6	2	1	1	12	25	17
Scenario 7	1	3	0	11	27	16
Scenario 8	1	0	3	11	24	19
Scenario 9	1	1	2	11	25	18
Scenario 10	1	2	1	11	26	17
Scenario 11	0	4	0	10	28	16
Scenario 12	0	0	4	10	24	20
Scenario 13	0	3	1	10	27	17
Scenario 14	0	1	3	10	25	19
Scenario 15	0	2	2	10	26	18

The simulation was run with 10 replications for each scenario and the length of each replication was 313 weeks total (Warm-up period of 200 days included). Table 8.2 and show the results of the experiments.

However, to calculate the benefits from adding beds in each ward, the data must be organized presenting the outcomes for each unit by number of beds added (Refer to Table 8.3 and Figure 8.1). The % of benefit from adding between 1 up to 4 beds in each unit, are presented in Table 8.4 and Figure 8.2.

It could be observed from the results in the figures, that the output measures (waiting time and patients waiting) were significantly lower for MOS in comparison with the other two units (ICU, TCU) which is confirmed by the benefits curve (Figure 8.2). This means that there are more benefits in adding beds to ICU and TCU.

The reason why more stabilized queues are observed for MOS, is the number of beds it has allocated (24 beds) which represent the largest assignation between the units (2.4 and 1.5 times the number of beds in ICU and TCU respectively). This distribution can be attributed to several reasons, like internal policies and managerial decisions in the day to day operation. For example, the ward of admission is determined according to the level of the acuteness of the illness (mentioned in section 3 of this document), from there it is recognizable that different wards have different requirements of resources.Also, as mentioned by the hospital managers, in some circumstances of high occupancy, wards from different units can proportionate beds to other wards. This situation can represent implications in the quality of the service, mostly for the Intensive care unit, because of the specialized needs for resources. This study aims to contribute in the recognition of different implications of bed distributions to support the managers in the identification of opportunities for improvement.

Table 8.2. Output parameters for each scenario. (Time in Hours).

	Name	Reps.	Total beds in the scenario			Avg. Patients in Queue			Avg. Time in Queue		
			ICU	MOS	TCU	ICU	MOS	TCU	ICU	MOS	TCU
1	**Current state**	10	10	24	16	2.043	0.085	3.422	13.958	0.433	19.355
2	Scenario 1	10	14	24	16	0.078	0.085	3.422	0.543	0.433	19.355
3	Scenario 2	10	13	25	16	0.167	0.048	3.422	1.141	0.268	19.355
4	Scenario 3	10	13	24	17	0.167	0.085	1.567	1.141	0.433	8.833
5	Scenario 4	10	12	26	16	0.36	0.027	3.422	2.436	0.144	19.355
6	Scenario 5	10	12	24	18	0.36	0.085	0.788	2.436	0.433	4.442
7	Scenario 6	10	12	25	17	0.36	0.048	1.567	2.436	0.268	8.833
8	Scenario 7	10	11	27	16	0.799	0.015	3.422	5.468	0.074	19.355
9	Scenario 8	10	11	24	19	0.799	0.085	0.423	5.468	0.433	2.392
10	Scenario 9	10	11	25	18	0.799	0.048	0.788	5.468	0.268	4.442
11	Scenario 10	10	11	26	17	0.799	0.027	1.567	5.468	0.144	8.833
12	Scenario 11	10	10	28	16	2.043	0.008	3.422	13.958	0.036	19.355
13	Scenario 12	10	10	24	20	2.043	0.085	0.228	13.958	0.433	1.295
14	Scenario 13	10	10	27	17	2.043	0.015	1.567	13.958	0.074	8.833
15	Scenario 14	10	10	25	19	2.043	0.048	0.423	13.958	0.268	2.392
16	Scenario 15	10	10	26	18	2.043	0.027	0.788	13.958	0.144	4.442

Table 8.3. Waiting time and Number of Patients waiting by unit.

No. Beds added	Avg. Patients in Queue			Avg. Time in Queue		
	ICU	MOS	TCU	ICU	MOS	TCU
0	2.043	0.085	3.422	13.958	0.433	19.355
1	0.799	0.048	1.567	5.468	0.268	8.833
2	0.36	0.027	0.788	2.436	0.144	4.442
3	0.167	0.015	0.423	1.141	0.074	2.392
4	0.078	0.008	0.228	0.543	0.036	1.295

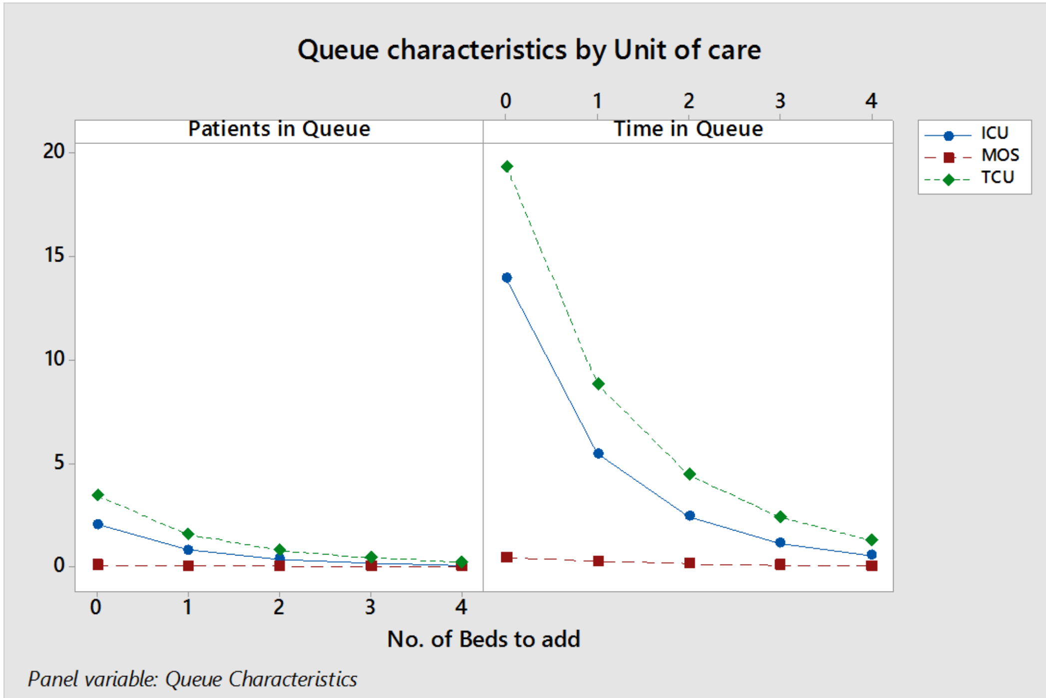


Figure 8.1. Changes in queue characteristics by adding beds to the hospital units.

Table 8.4. % Benefit from adding 1 up to 4 beds by unit.

% of Benefit						
No. Beds added	Avg. Patients in Queue			Avg. Time in Queue		
	ICU	MOS	TCU	ICU	MOS	TCU
0	0	0	0	0	0	0
1	63.31%	48.05%	58.08%	63.29%	41.56%	58.26%
2	85.65%	75.32%	82.47%	85.89%	72.80%	82.57%
3	95.47%	90.91%	93.89%	95.54%	90.43%	93.93%
4	100%	100%	100%	100%	100%	100%

When observing the results in waiting times for MOS and the lower benefits this unit presented when adding beds, a question raised: Is the current number of beds assigned proportionally to the patients that each unit of care attended?

To answer, it was important to evaluate waiting time and number of patients waiting, together with average arrival rates, LOS and % of utilization (Table 8.5). This analysis was conducted using the values of the current state (shown before in Table 8.2).

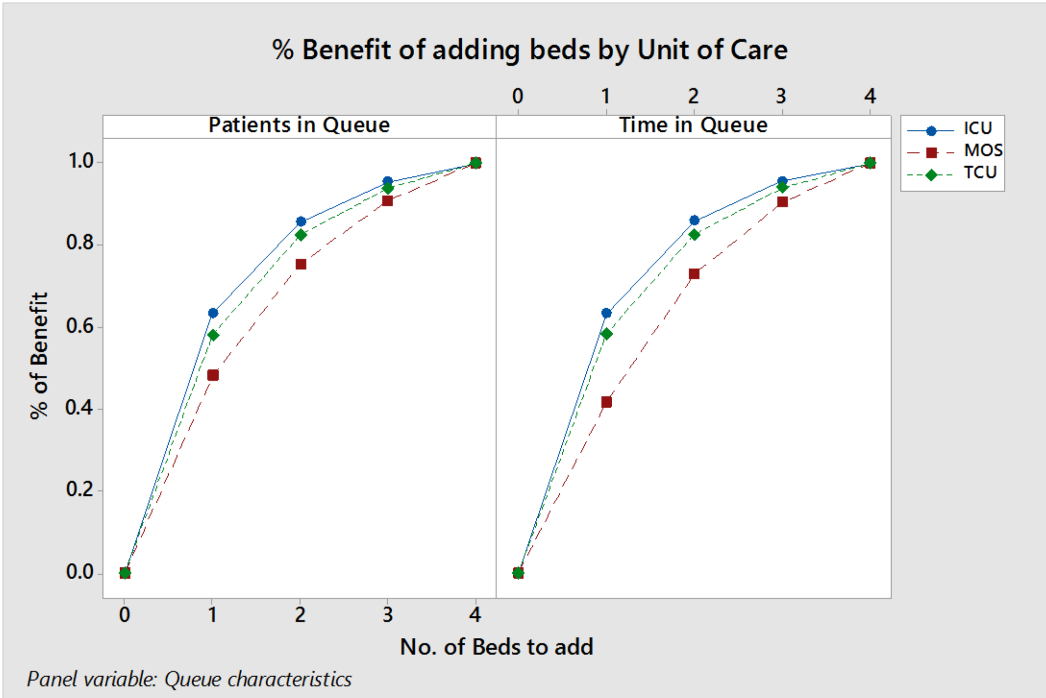


Figure 8.2. % of Benefit from adding beds to the Hospital units.

Table 8.5. Output parameters vs Arrivals, LOS and Bed utilization rate.

Unit of care	Avg Time in Queue	Avg. Num. Patients in Queue	Avg. Daily Arrival rate	Avg. LOS (Hrs.)	% Bed Utilization
ICU	13.958	2.043	12.24	111.23	81.33%
MOS	0.433	0.085	31.70	81.89	64.68%
TCU	19.355	3.422	28.67	78.58	86.09%

The data obtained showed that the current distribution of beds between the units could be considered inadequate, the observations that lead to this assumption are:

- Although the queues are more stable for the MOS unit, its bed utilization rate is almost 20% below the rates of the other units.
- The number of beds allocated for MOS is 1.5 times the ones in TCU, but the arrival rates are almost the same, also LOS is almost equal, which does not justify the difference in quantity of beds.
- Although the arrival rates for ICU are less than half of the other units, its LOS influence the utilization rate until the point it is almost equal as TCU. This indicated that ICU still need beds to reduce the waiting times.

- The benefit of adding beds in MOS is relatively low in comparison with the benefits for ICU and TCU.

It is important to highlight that this assumption was based on the quantitative analysis of the results, managerial decisions and hospital policies, unrevealed for this study, may add a significant impact in the definition of the best bed allocation, in this regard the optimization of beds distribution within the hospital, will be proposed as future work with the aim of include in the evaluation the policies and qualitative details.

Knowing there is some inadequacy in the beds distribution between the units, because there is a large assignation of beds in MOS, the analysis of the results (from adding beds) was focused on determine in which unit, the addition of beds had a better impact, therefore, offer solid arguments to support managerial decisions.

As it was presented in Figure 8.2, the unit that received more benefits from adding 1 up to 4 beds was ICU. The reason for this result came from the influence of the LOS had on bed utilization. Despite the arrival rates for ICU were lower than the other units, its LOS was larger, which influenced directly the % of bed utilization (as shown in Table 8.5) leading to the conclusion that ICU has a deeper need of implementing beds in order to increase the access capacity of the hospital. To confirm this premise, Figure 8.3 presents the benefits from adding beds in each unit in terms of bed utilization. It was observed again that ICU had more benefit when adding beds.

Figure 8.4 presents the observations of the queue characteristics for each ward. Table 8.6 and Figure 8.5 show the benefit each ward has by adding beds. The behavior of the wards within the units is very similar to the unit they belong to (e.g. MICU and SICU belong to ICU and their queues had similar performance when adding beds). This situation is caused by the condition of sharing beds within the wards in the unit. As the wards are grouped by specific level of acuteness, the beds are assigned as they become available, which is the reason why the queue characteristics are very close one ward to another within the unit.

The data categorized by ward followed the same pattern than before, wards pertaining to ICU will have the largest benefit if beds are added. It is observed that MICU could be as benefitted as SICU.

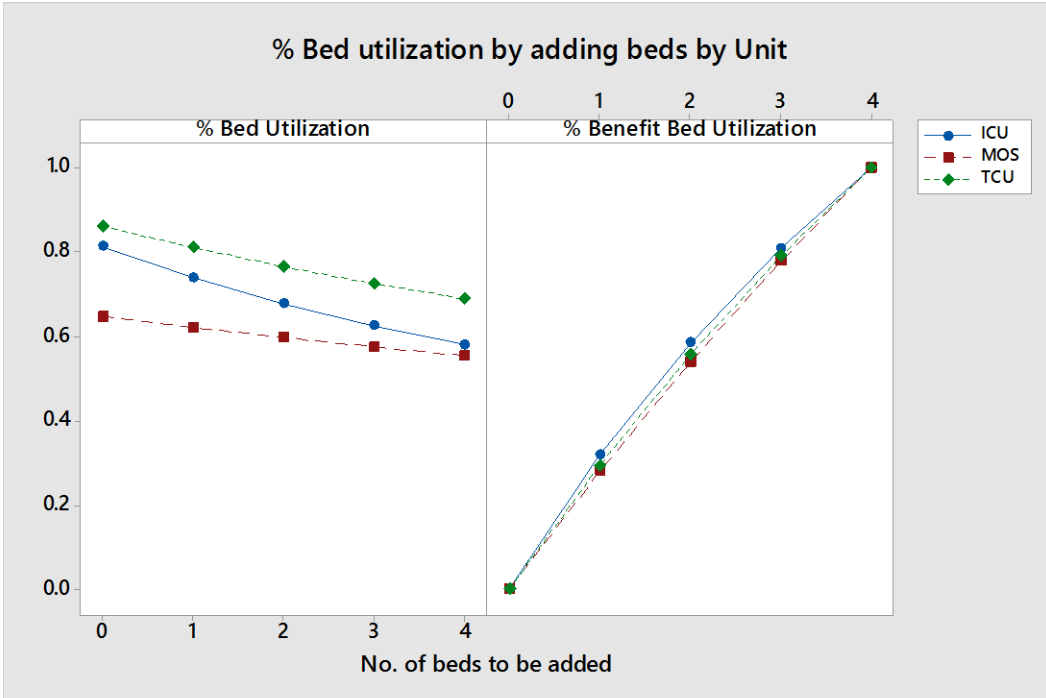


Figure 8.3. % Utilization by adding beds by Unit.

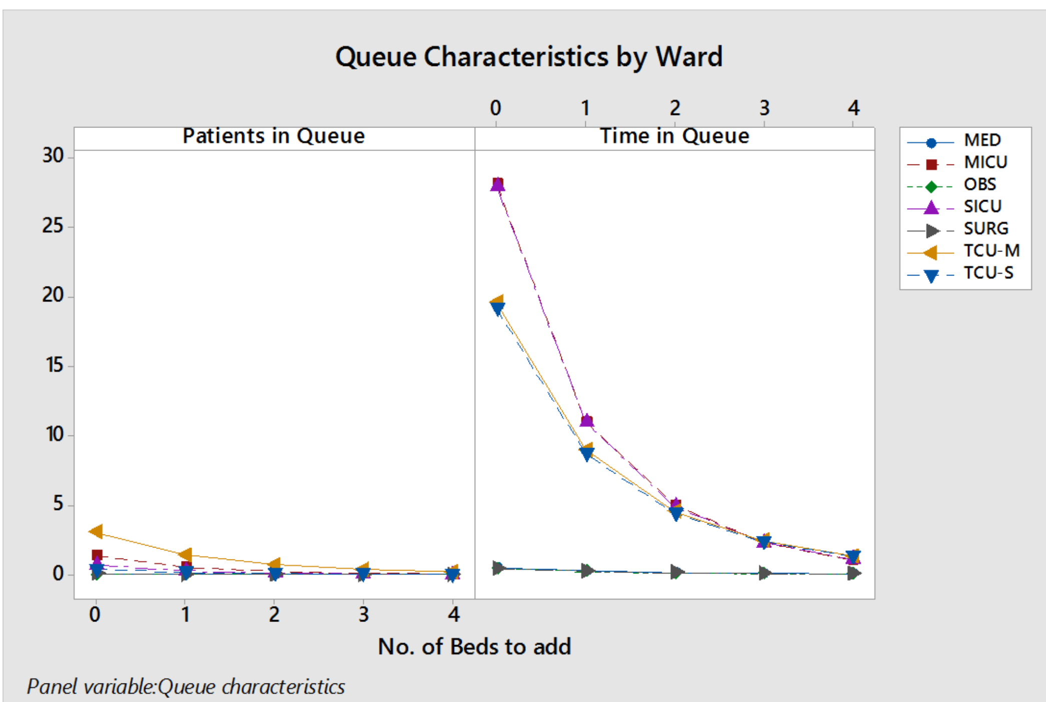


Figure 8.4. Changes in queue characteristics by adding beds to each ward.

Table 8.6. Benefit rate from adding 1 up to 4 beds by ward.

% of Benefit														
No. Beds added	Avg. Patients in Queue							Avg. Time in Queue						
	MICU	SICU	MED	OBS	SURG	TCU-M	TCU-S	MICU	SICU	MED	OBS	SURG	TCU-M	TCU-S
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	63.35%	63.17%	48.98%	50.00%	48.15%	58.04%	58.36%	63.24%	63.28%	48.49%	55.33%	48.12%	58.02%	58.51%
2	85.57%	85.93%	75.51%	100%	77.78%	82.44%	82.70%	85.52%	85.89%	75.41%	81.64%	75.81%	82.43%	82.71%
3	95.45%	95.51%	89.80%	100%	92.59%	93.87%	93.84%	95.40%	95.54%	90.72%	94.79%	91.94%	93.87%	93.98%
4	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

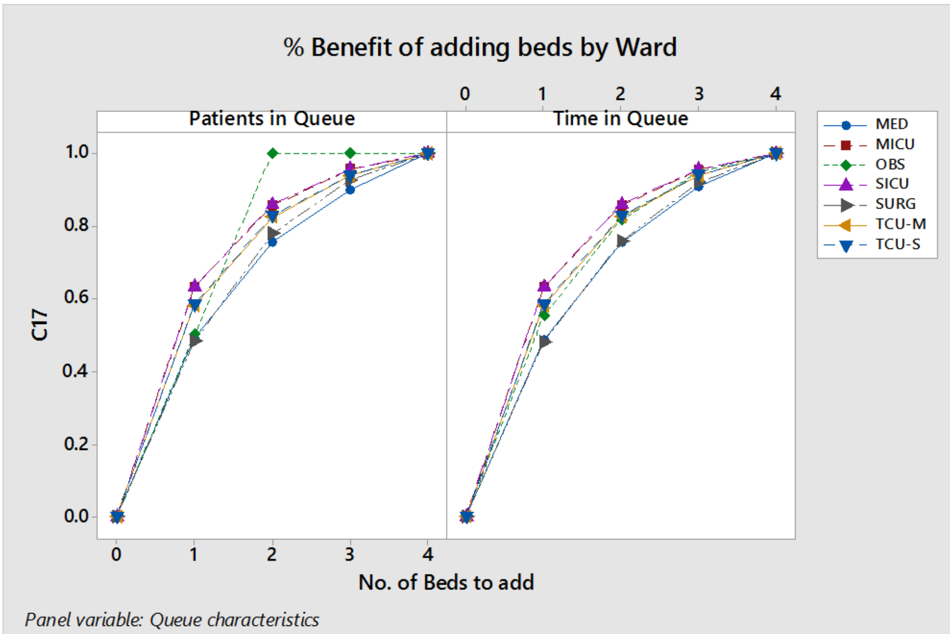


Figure 8.5. % of Benefit from adding beds to each ward.

8.2. SELECTION OF THE BEST SCENARIO

The analysis of the queues gave important information to determine which units could have larger benefit rates from adding beds, based on waiting time and Patients in queue. On this basis, it was possible to refine the search for the best combination of additional beds, including only ICU and TCU.

In the first part of the results it was established that, from evaluating each unit of care parameters, the benefit in waiting times and number of patients waiting from adding beds in MOS was considerably small in comparison with the benefit for ICU and TCU. Also it could be observed that the queues of the wards have similar behavior than the units they belong to. In this case, it is possible to use the conclusions obtained by the analysis of the units to make inferences about the wards.

One of the advantages of using DES models is the detailed information that can be collected. The representations of relationships between parameters allow a more complete and accurate analysis than the one that could result from only using queuing theory as specify in the literature review. In this point of the study, the inclusion of variables, like bed utilization and throughput, was useful to examine the impact throughout the system from the reduction in waiting times by adding beds in ICU and TCU.

Thus, to start with this part of the analysis it was necessary return to the initial outcomes of the experiment (Table 8.2) and also recall the benefit rates in waiting time presented in Table 8.4. From there the scenarios that involved adding beds to ICU and TCU were chosen. The summary of the results is presented in Table 8.7and Figure 8.6.

Table 8.7. Outcome parameters for Scenarios that involve adding beds to ICU and TCU

Scenario Name	No. Beds to Add in the scenario			Total beds to run the scenario			Avg. Time in Queue			% of Benefit Time in Queue		
	ICU	MOS	TCU	ICU	MOS	TCU	ICU	MOS	TCU	ICU	MOS	TCU
Current state	0	0	0	10	24	16	13.958	0.433	19.355	0%	0%	0%
Scenario 1	4	0	0	14	24	16	0.543	0.433	19.355	100%	0%	0%
Scenario 3	3	0	1	13	24	17	1.141	0.433	8.833	95.54%	0%	58.26%
Scenario 5	2	0	2	12	24	18	2.436	0.433	4.442	85.89%	0%	82.57%
Scenario 8	1	0	3	11	24	19	5.468	0.433	2.392	63.29%	0%	93.93%
Scenario 12	0	0	4	10	24	20	13.958	0.433	1.295	0%	0%	100%

To optimize the implementation of the four beds, it is reasonable to think that the best option would be the one that offered the larges benefits to both ICU and TCU at the same time. Observing the results, scenario 5 follows the logic of better benefits for both units; however, it is difficult to recognize the overall benefit when evaluating separated rates. It is noticeable that scenarios 5 and 8 qualified as good options from the benefit rates. Still, further analysis was required to confirm such assumption. Then, bed utilization rates and throughput were included in the analysis. Their measures will capture the impact of the additional beds and reduction in queue time across the system as mentioned above.

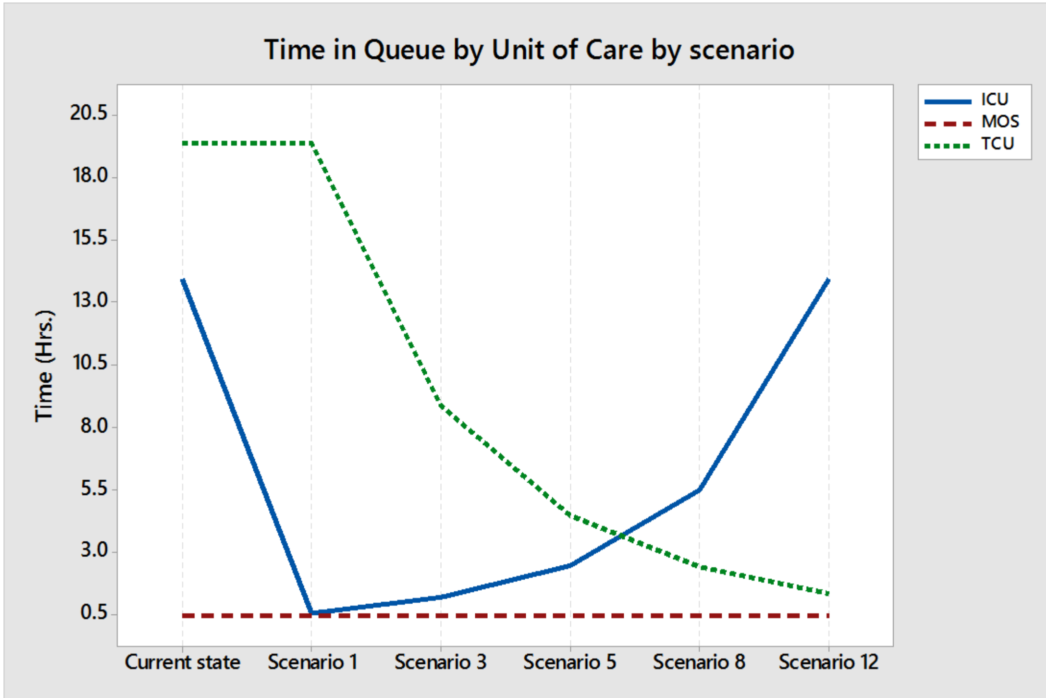


Figure 8.6. Waiting time by Unit of Care, by scenarios 1,3,5,8 and 12.

The identification of the changes in bed utilization and throughput for the selected scenarios allowed he identification of the best combination of beds. Increases in bed utilization rates and throughput (without considering changes in demand) indicate that the hospital has increased its capacity to serve patients.

Figure 8.7, Figure 8.8, and Table 8.8, present the distribution of daily rates of bed utilization and daily throughput for current state, scenario 5 and scenario 8.

The comparison between scenarios showed that scenario 8 represent the higher increase in utilization of beds and throughput, 1.6% and 1.375% respectively. This results indicated that adding 1 bed to ICU and 3 beds to TCU represented a larger increase in the capacity the hospital had to serve patients.

Table 8.8. Bed utilization rates and Throughput. Comparison by scenario.

Scenario	Daily Bed utilization rate		Daily Throughput	
	Mean	% of growth in the mean	Mean	% of growth in the mean
Current State	0.7561		13.09	
Scenario 5	0.7675	1.508%	13.2	0.840%
Scenario 8	0.7683	1.614%	13.27	1.375%

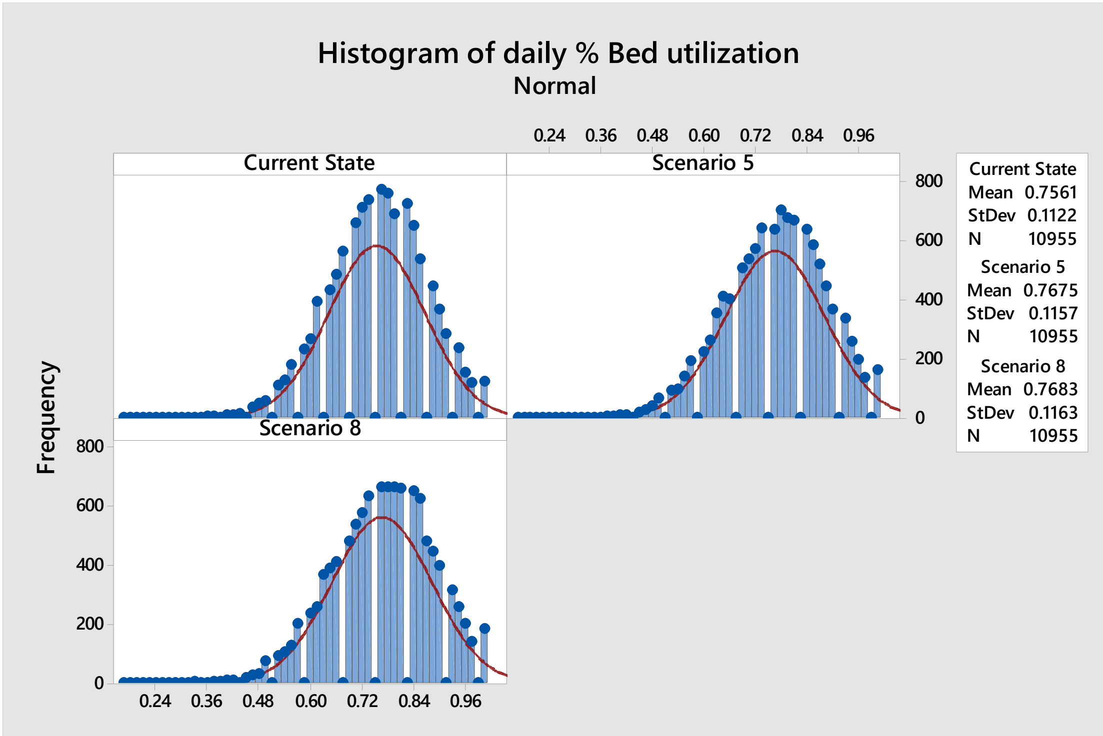


Figure 8.7. Histogram of daily %bed Utilization in the hospital.

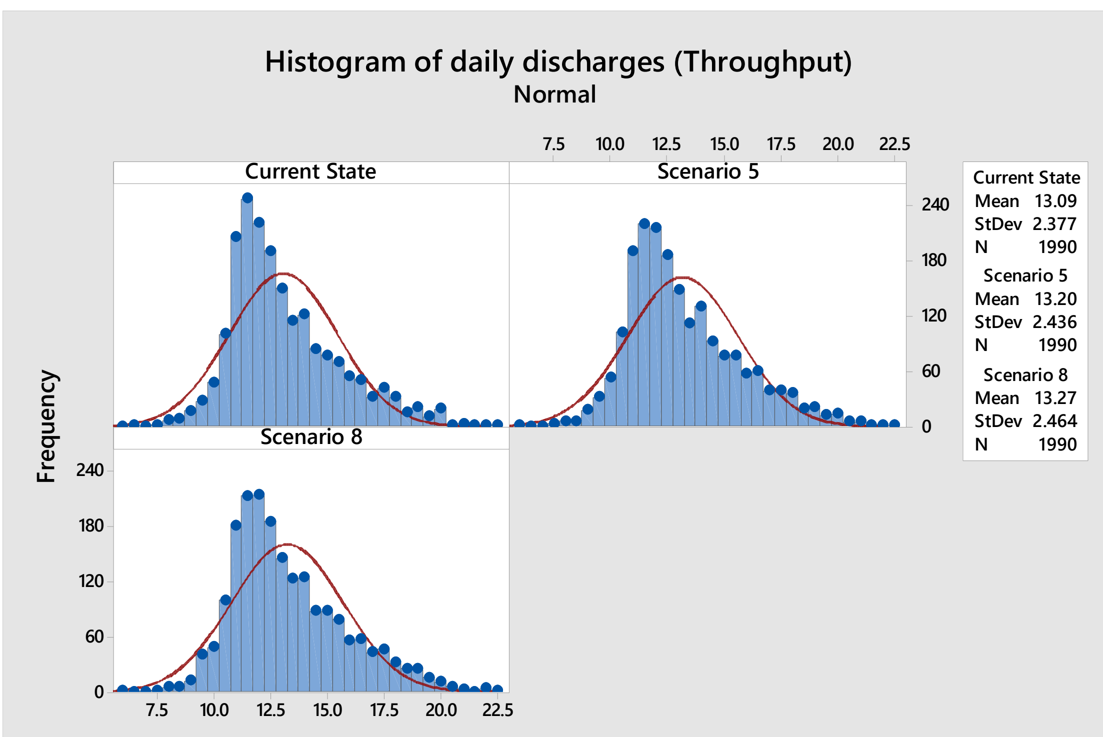


Figure 8.8. Histogram of daily discharges (Throughput) in the hospital.

9. CONCLUSIONS

This thesis described an application of DES for analyzing capacity. This was accomplished by testing different combination of beds in the units of care of VA Sacramento hospital.

In the initial phase of the research there is a special focus on stablishing accurate models that contemplate the quantitative characteristics of the variables from the original data. The arrival rates were defined by ward of admission, considering the admission day and time of the day. All wards fit a Poisson processes.

Since standard statistical models did not fit the LOS actual data, a set of non-parametric empirical distributions separated by patients with short stays (less or equal than 168 hours) and long stays (greater than 168 hours), were used. The LOS was classified in short and long with the purpose of constructing an accurate quantitative representation that account for the weighted tails showed by the data. In addition, the mixture of long and short stays (i.e. 90% of all patients having an LOS of 168 hours or less and 10% exceeding 168 hours to 66 days) within the data posed a unique set of issues, as a sole LOS statistical model cannot be found that can reproduce such a phenomenon.

The model was thoroughly validated. The comparison of the real data (arrivals and LOS) data against the simulation data did not show statistical differences. The effective validation provided confidence in the model to deliver accurate results from the experimentation phase. It also offers credibility in the hospital administrators to use the results for planning decisions that could impact in bed utilization rates and throughput.

The simulation can quantify the impact of different bed allocations on patient waiting times, one of the critical parameters measured in this study.

The number of beds to be added (1 to 4), used fin this analysis was determined from the specifications of space available expressed by the hospital managers.
The analysis of various configurations for additional 4 beds provided quantitative information about:

1. The benefits offered by adding one up to four beds in each unit of care (ICU, MOS, TCU) based on waiting time and number of patients in queue. ICU showed

the highest rate of benefit (refer to Table 8.7). It was also found that the highest % of benefit, and bed utilization rates in ICU were consequence of the influence of the average ICU patients LOS (also the highest measured from the units).

The analysis of the queues gave important information about the benefit from adding beds to each unit of care based on waiting time and Patients in queue. The evaluation of the individual queues, allowed to focused the study on ICU and TCU.

The current distribution of beds in the units is disproportionate in comparison with bed utilization.

2. The inclusion in the analysis of variables, like bed utilization and throughput, was useful to examine the impact throughout the system from the reduction in waiting times by adding beds in ICU and TCU. Increases in bed utilization rates and throughput (without considering changes in demand) indicate that the hospital has increased its capacity to serve patients. Based on this premise, it could be determined that adding 1 bed to ICU and 3 beds to TCU was the combination of beds that represented the most positive impact on hospital capacity This scenario showed an increase of 1.6% and 1.4% in bed utilization and throughput respectively.

In the following section it is presented a description of some limitations within the development of this DES and recommendations on future work.

10. LIMITATIONS AND FUTURE WORK

10.1. LIMITATIONS

Across the work, several limitations were found, included:

- The collection of the data was not made specifically for the development of a DES model. From the information available it was possible to obtain general rates of patient admissions and discharges, but information about patient transfers between the wards was misleading. This data made it difficult to capture desirable outcomes. However, it is valuable to highlight that the data obtained from the simulation was accurately validated for arrivals and LOS.
- The model assumes unconstrained waiting times. In reality, there is a limit in the time the patients can wait in queue depending on their level of acuteness and hospital occupancy rates. The consideration of this parameter would have allowed the study of other aspects such as rejection rates.

10.2. FUTURE WORK

- Currently, it is planned to use the simulation model to forecast Occupancy rates within a 24-hour period, based on the time a patient has been in a hospital ward. In an effort to determine a patient's or cohort of patients' discharge probability within the next 24 hours.
- The inclusion of patient flow rates between the wards would allow the use of the model for different purposes. The inclusion of transfer rates between wards can reduce the variability of simulation. For example, it will open the possibility to study the impact in occupancy from the implementation of changes in the discharge policies.
- The analysis of the current state of the hospital, suggested an inadequate distribution of beds between the units of care. Hence, it will be of important use to stablish the optimal allocation of beds per unit. For this matter, the inclusion of the evaluation of policies, qualitative details, and an optimization algorithm to complement the simulation model.

The goodness of the implementation of optimization to increase the benefits of the simulation results has been describe in publicized studies like Wang et al., [10] and Mallor et al. [13].

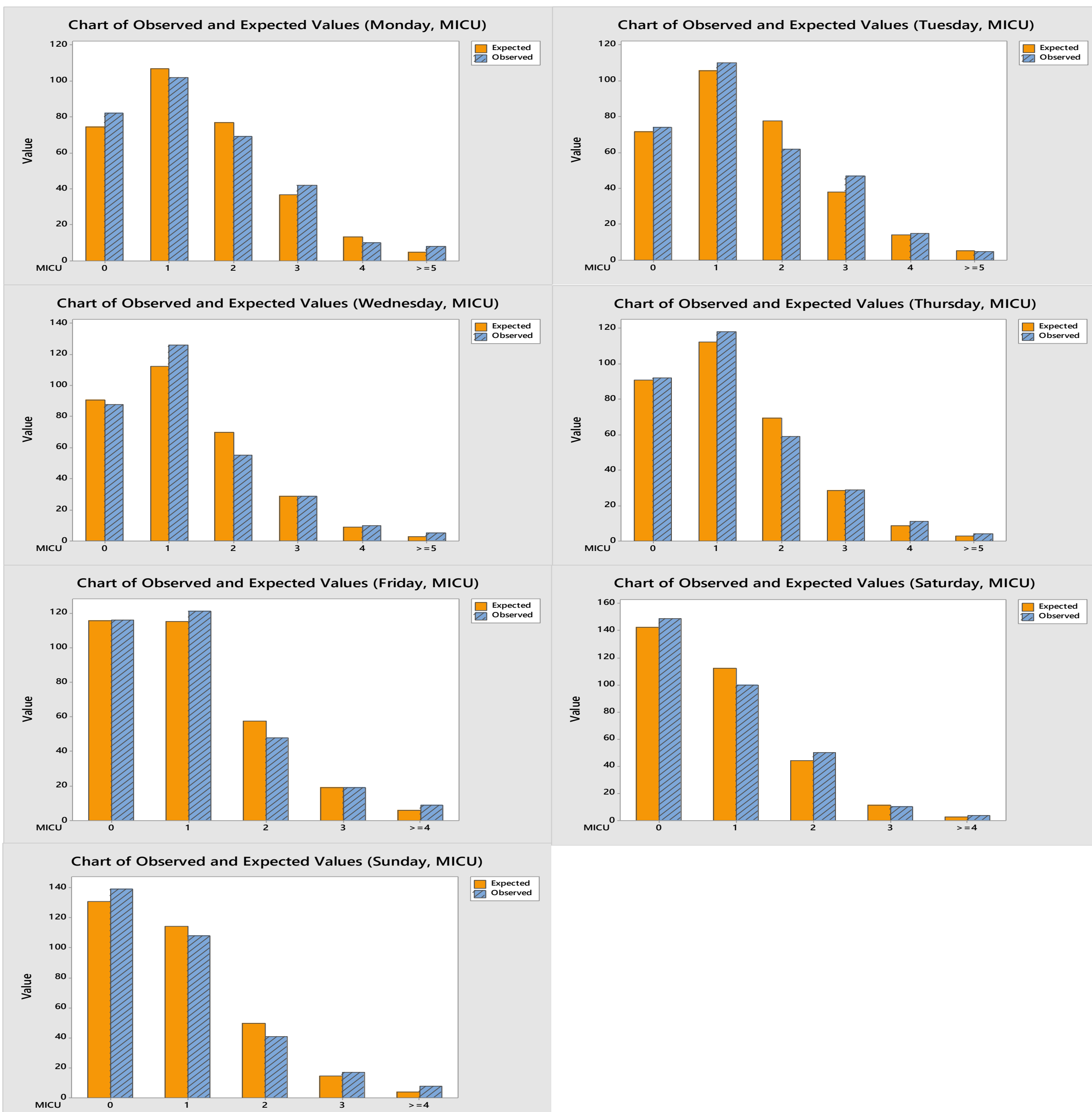
APPENDIX

DISTRIBUTION FIT FOR ARRIVALS AND LOS

VA SACRAMENTO MEDICAL CENTER

ARRIVALS: A histogram with both the observed (real-data) versus the Poisson function (expected) by day of the week is provided for each ward.

MICU



SICU

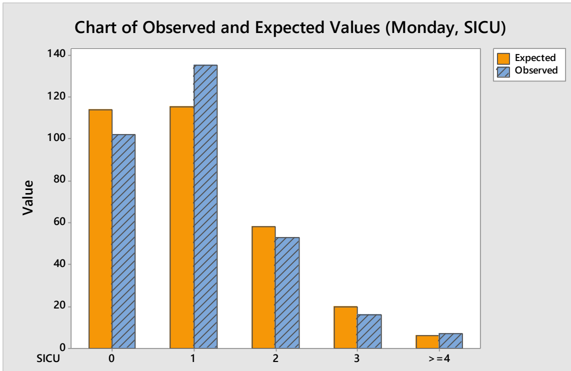


Chart of Observed and Expected Values (Monday, SICU)
Expected
Observed
Value
140
120
100
80
60
40
20
0
SICU
0
1
2
3
> =4

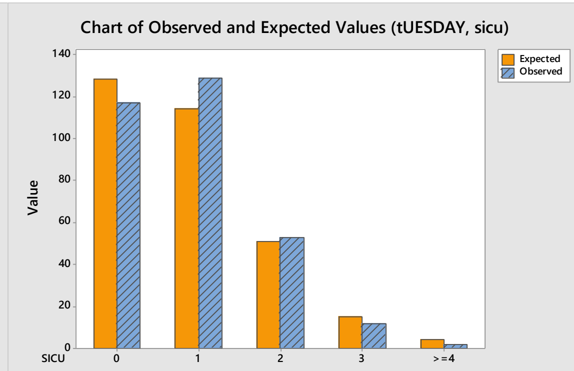


Chart of Observed and Expected Values (tUESDAY, sicu)
Expected
Observed
Value
140
120
100
80
60
40
20
0
SICU
0
1
2
3
> =4

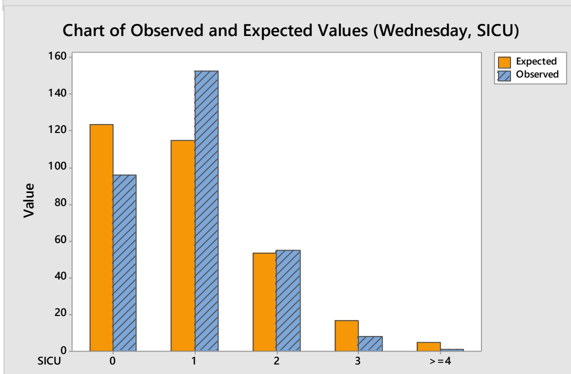


Chart of Observed and Expected Values (Wednesday, SICU)
Expected
Observed
Value
160
140
120
100
80
60
40
20
0
SICU
0
1
2
3
> =4

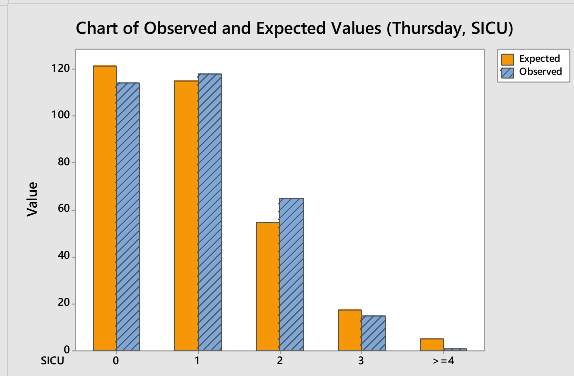


Chart of Observed and Expected Values (Thursday, SICU)
Expected
Observed
Value
120
100
80
60
40
20
0
SICU
0
1
2
3
> =4

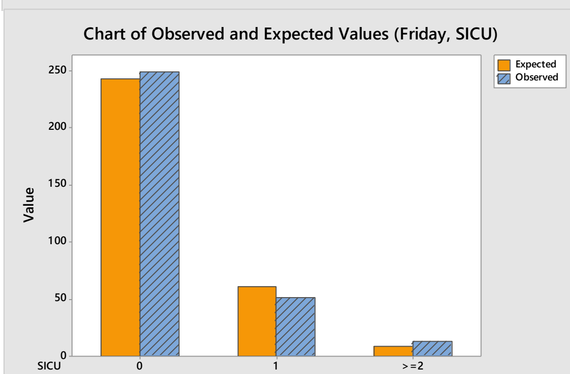


Chart of Observed and Expected Values (Friday, SICU)
Expected
Observed
Value
250
200
150
100
50
0
SICU
0
1
> =2

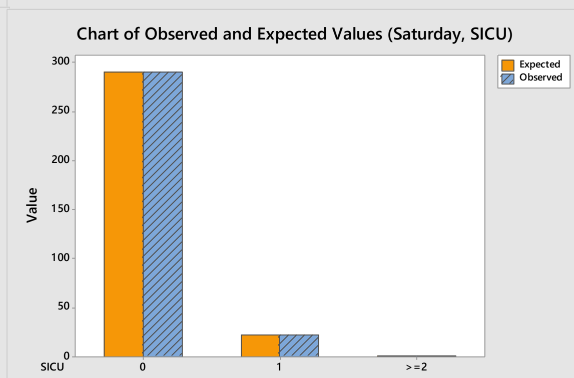


Chart of Observed and Expected Values (Saturday, SICU)
Expected
Observed
Value
300
250
200
150
100
50
0
SICU
0
1
> =2

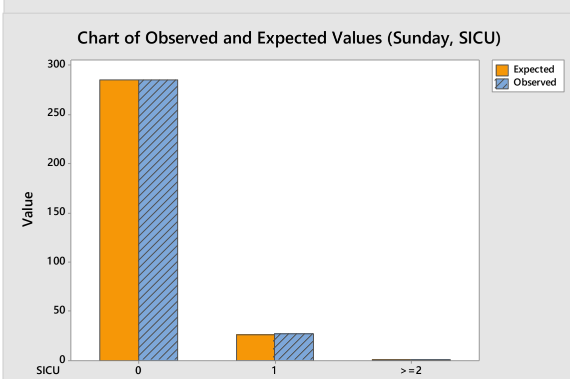


Chart of Observed and Expected Values (Sunday, SICU)
Expected
Observed
Value
300
250
200
150
100
50
0
SICU
0
1
> =2

OBS

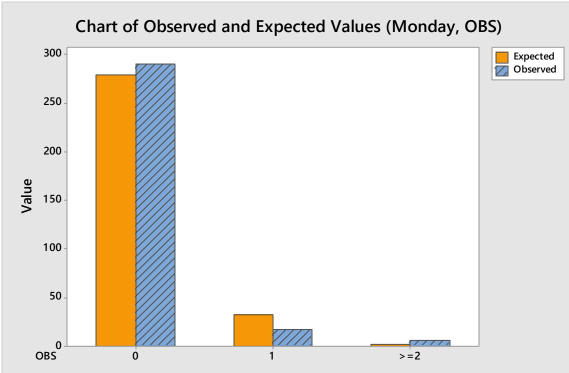


Chart of Observed and Expected Values (Monday, OBS)
Value
300
250
200
150
100
50
0
OBS
0
1
> =2
Expected
Observed

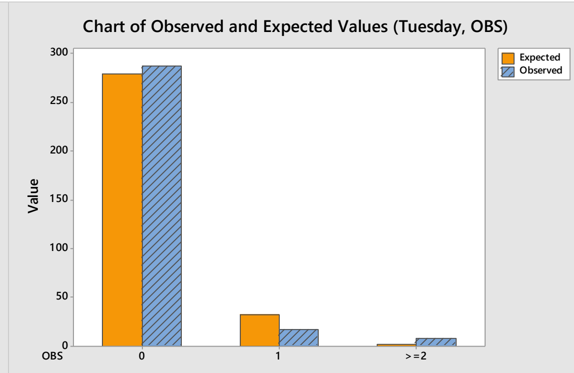


Chart of Observed and Expected Values (Tuesday, OBS)
Value
300
250
200
150
100
50
0
OBS
0
1
> =2
Expected
Observed

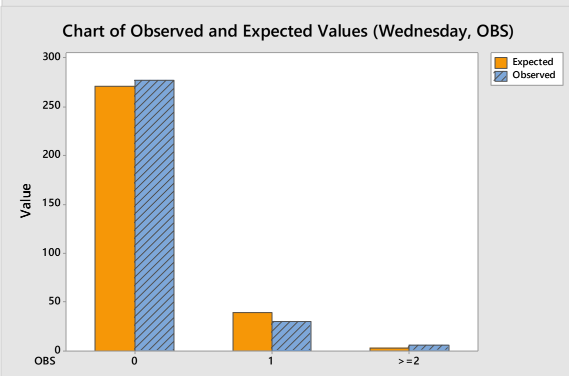


Chart of Observed and Expected Values (Wednesday, OBS)
Value
300
250
200
150
100
50
0
OBS
0
1
> =2
Expected
Observed

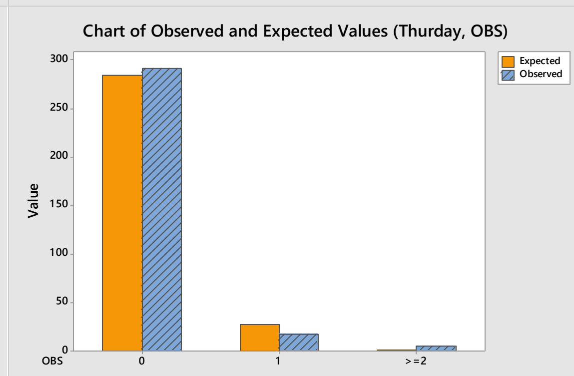


Chart of Observed and Expected Values (Thurday, OBS)
Value
300
250
200
150
100
50
0
OBS
0
1
> =2
Expected
Observed

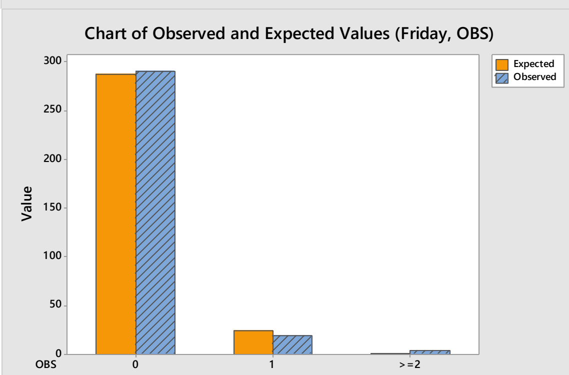


Chart of Observed and Expected Values (Friday, OBS)
Value
300
250
200
150
100
50
0
OBS
0
1
> =2
Expected
Observed

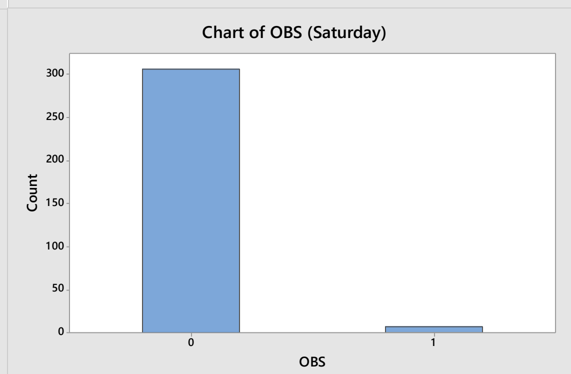


Chart of OBS (Saturday)
Count
300
250
200
150
100
50
0
0
1
OBS

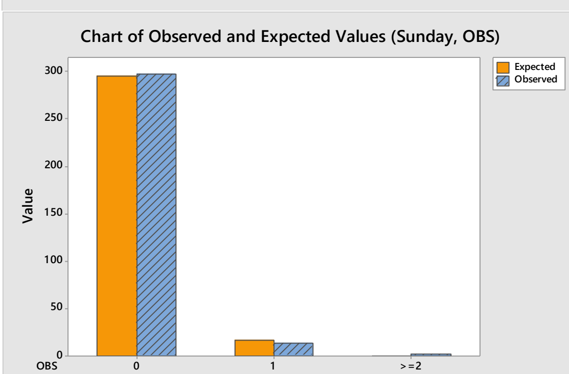


Chart of Observed and Expected Values (Sunday, OBS)
Value
300
250
200
150
100
50
0
OBS
0
1
> =2
Expected
Observed

MED

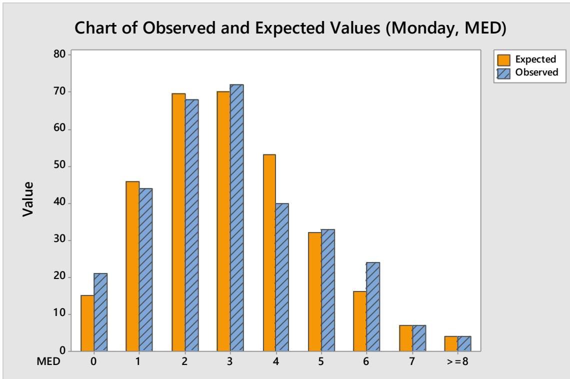


Chart of Observed and Expected Values (Monday, MED)
Expected
Observed
Value
MED
0 1 2 3 4 5 6 7 >=8

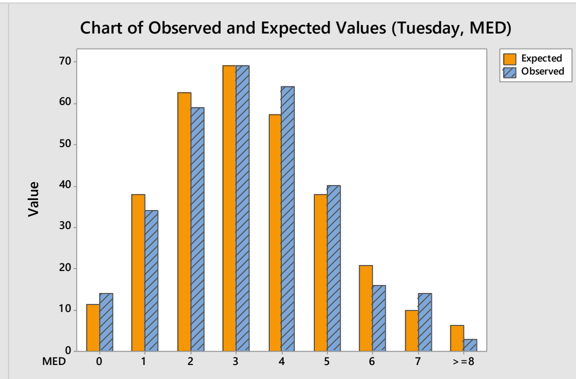


Chart of Observed and Expected Values (Tuesday, MED)
Expected
Observed
Value
MED
0 1 2 3 4 5 6 7 >=8

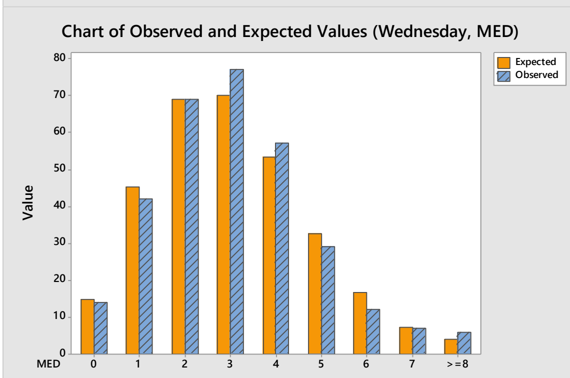


Chart of Observed and Expected Values (Wednesday, MED)
Expected
Observed
Value
MED
0 1 2 3 4 5 6 7 >=8

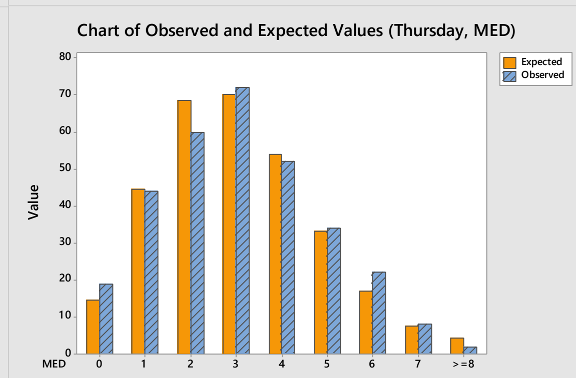


Chart of Observed and Expected Values (Thursday, MED)
Expected
Observed
Value
MED
0 1 2 3 4 5 6 7 >=8

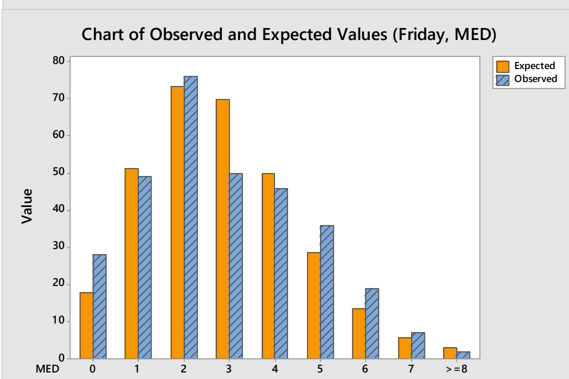


Chart of Observed and Expected Values (Friday, MED)
Expected
Observed
Value
MED
0 1 2 3 4 5 6 7 >=8

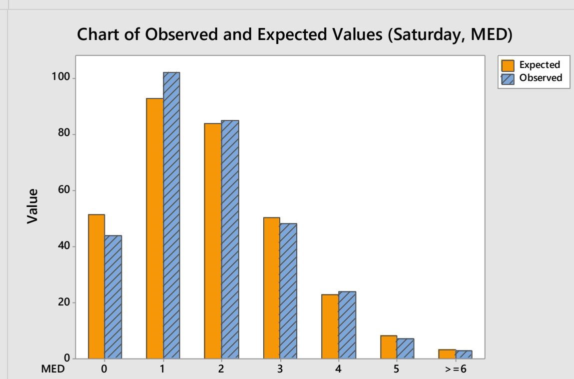


Chart of Observed and Expected Values (Saturday, MED)
Expected
Observed
Value
MED
0 1 2 3 4 5 >=6

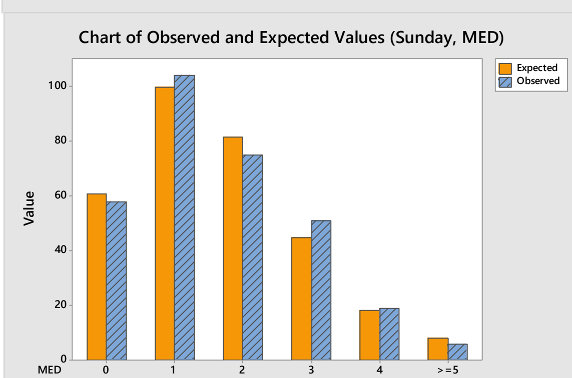


Chart of Observed and Expected Values (Sunday, MED)
Expected
Observed
Value
MED
0 1 2 3 4 >=5

SURG

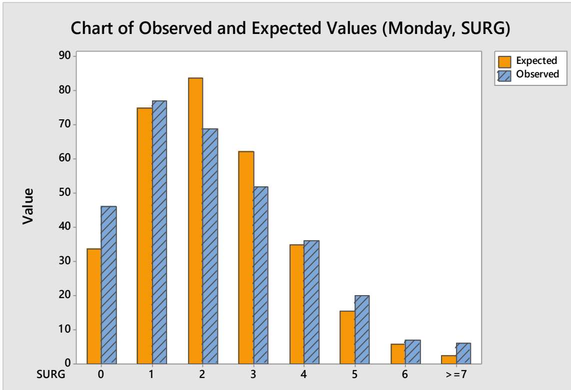


Chart of Observed and Expected Values (Monday, SURG)
Expected
Observed
Value
0
10
20
30
40
50
60
70
80
90
SURG
0
1
2
3
4
5
6
>=7

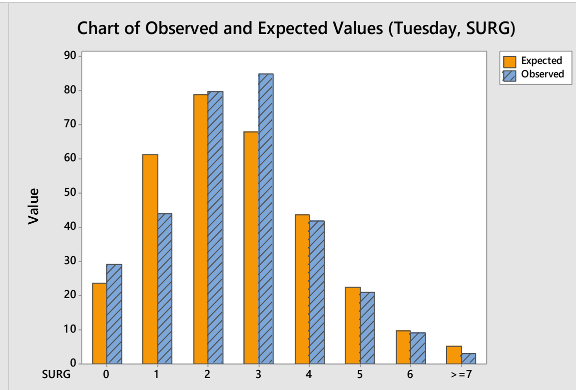


Chart of Observed and Expected Values (Tuesday, SURG)
Expected
Observed
Value
0
10
20
30
40
50
60
70
80
90
SURG
0
1
2
3
4
5
6
>=7

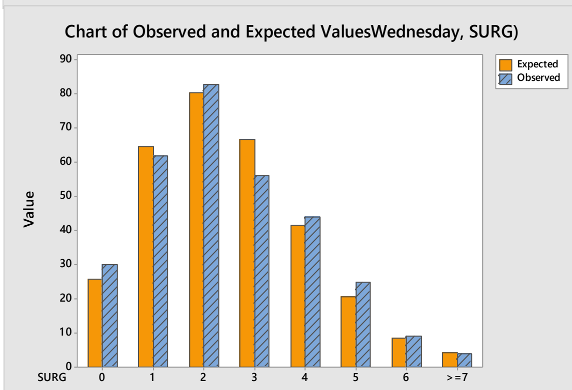


Chart of Observed and Expected ValuesWednesday, SURG)
Expected
Observed
Value
0
10
20
30
40
50
60
70
80
90
SURG
0
1
2
3
4
5
6
>=7

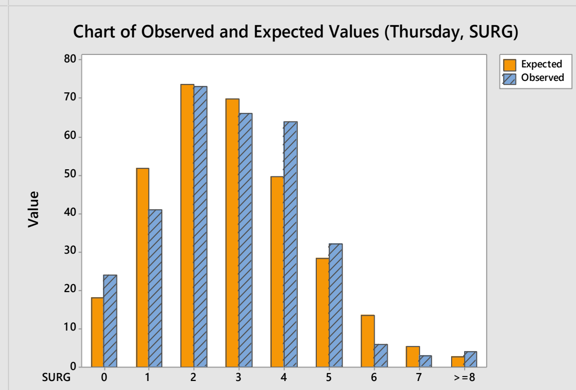


Chart of Observed and Expected Values (Thursday, SURG)
Expected
Observed
Value
0
10
20
30
40
50
60
70
80
SURG
0
1
2
3
4
5
6
7
>=8

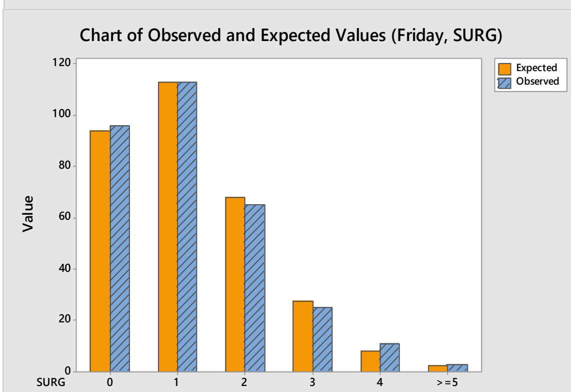


Chart of Observed and Expected Values (Friday, SURG)
Expected
Observed
Value
0
20
40
60
80
100
120
SURG
0
1
2
3
4
>=5

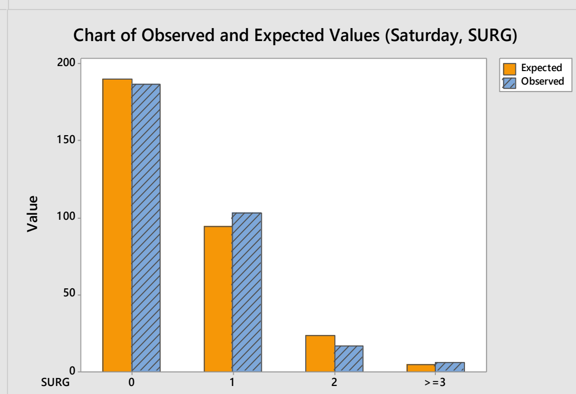


Chart of Observed and Expected Values (Saturday, SURG)
Expected
Observed
Value
0
50
100
150
200
SURG
0
1
2
>=3

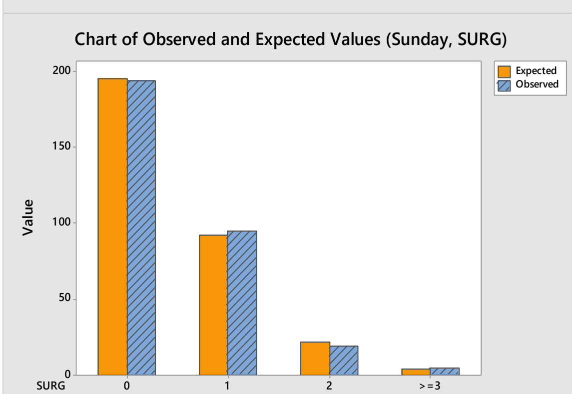


Chart of Observed and Expected Values (Sunday, SURG)
Expected
Observed
Value
0
50
100
150
200
SURG
0
1
2
>=3

TCU-M

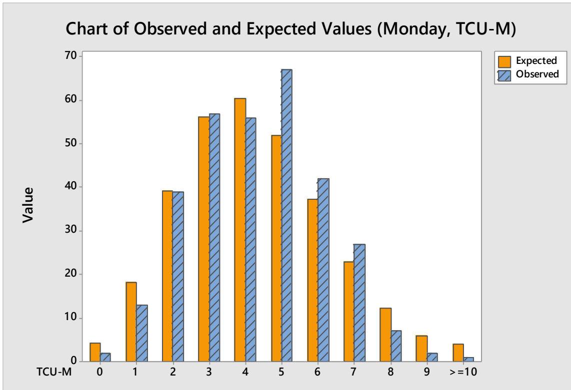


Chart of Observed and Expected Values (Monday, TCU-M)
Expected
Observed
Value
TCU-M

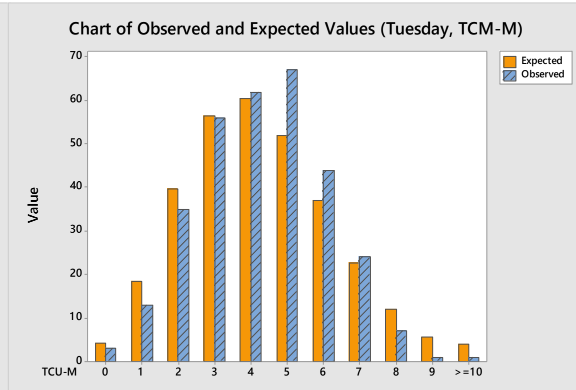


Chart of Observed and Expected Values (Tuesday, TCM-M)
Expected
Observed
Value
TCU-M

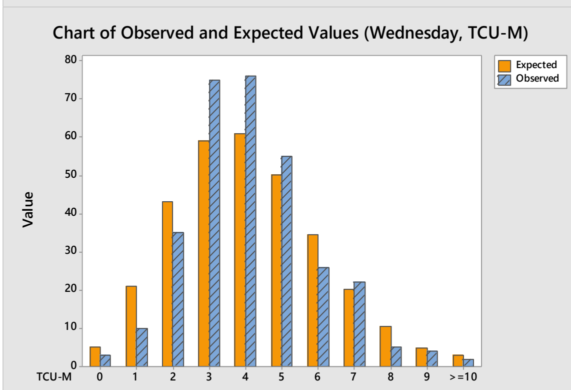


Chart of Observed and Expected Values (Wednesday, TCU-M)
Expected
Observed
Value
TCU-M

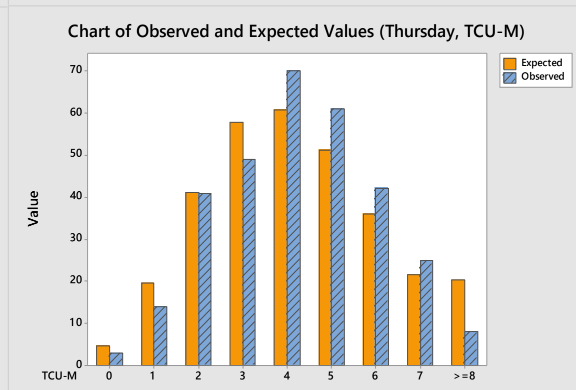


Chart of Observed and Expected Values (Thursday, TCU-M)
Expected
Observed
Value
TCU-M

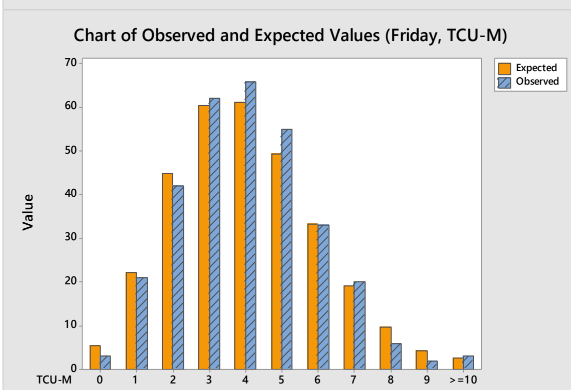


Chart of Observed and Expected Values (Friday, TCU-M)
Expected
Observed
Value
TCU-M

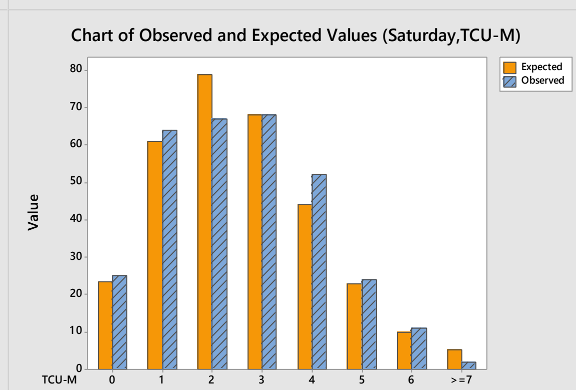


Chart of Observed and Expected Values (Saturday,TCU-M)
Expected
Observed
Value
TCU-M

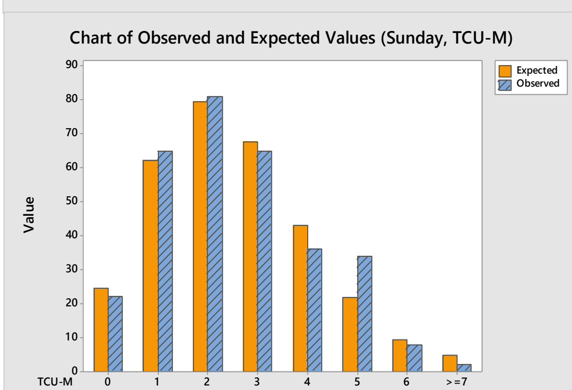


Chart of Observed and Expected Values (Sunday, TCU-M)
Expected
Observed
Value
TCU-M

TCU-S

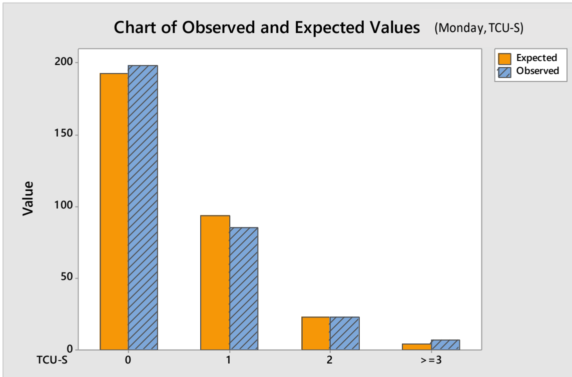


Chart of Observed and Expected Values (Monday, TCU-S)
Expected
Observed
Value
0
50
100
150
200
TCU-S
0
1
2
>=3

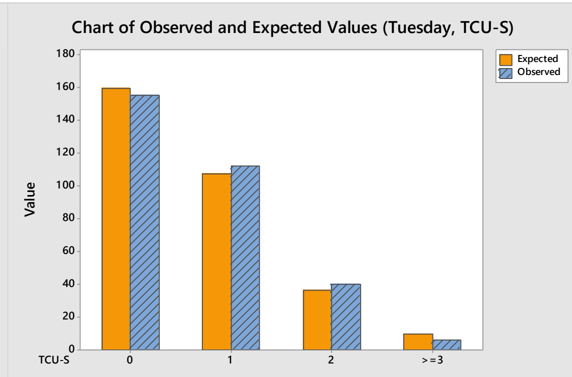


Chart of Observed and Expected Values (Tuesday, TCU-S)
Expected
Observed
Value
0
20
40
60
80
100
120
140
160
180
TCU-S
0
1
2
>=3

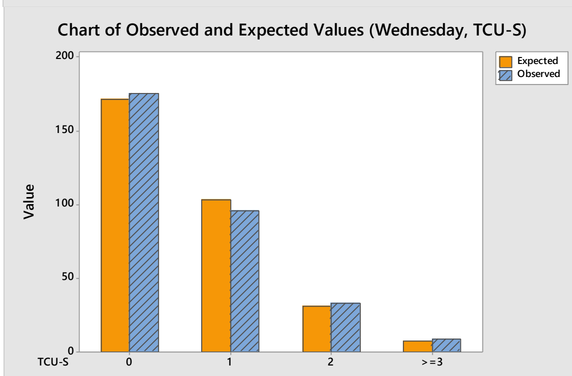


Chart of Observed and Expected Values (Wednesday, TCU-S)
Expected
Observed
Value
0
50
100
150
200
TCU-S
0
1
2
>=3

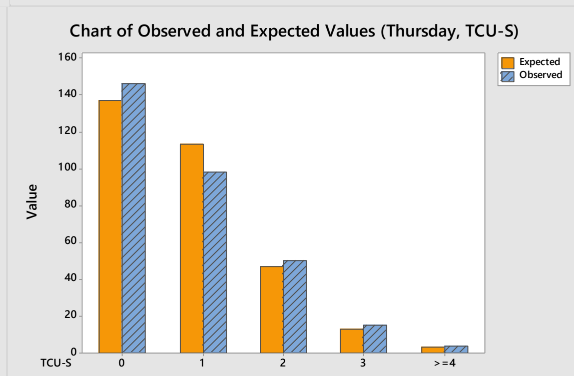


Chart of Observed and Expected Values (Thursday, TCU-S)
Expected
Observed
Value
0
20
40
60
80
100
120
140
160
TCU-S
0
1
2
3
>=4

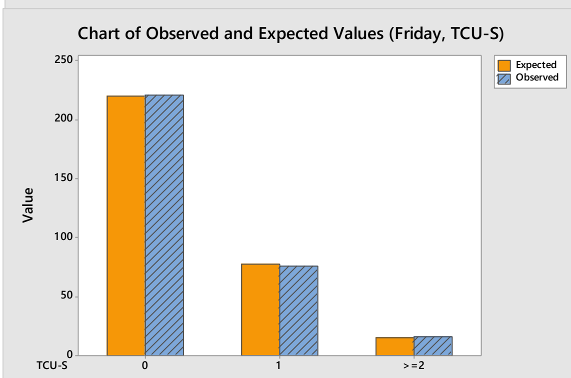


Chart of Observed and Expected Values (Friday, TCU-S)
Expected
Observed
Value
0
50
100
150
200
250
TCU-S
0
1
>=2

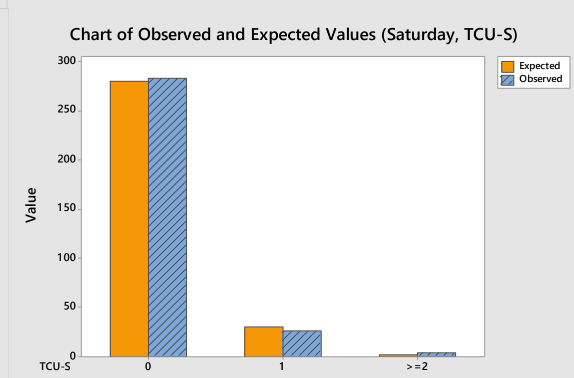


Chart of Observed and Expected Values (Saturday, TCU-S)
Expected
Observed
Value
0
50
100
150
200
250
300
TCU-S
0
1
>=2

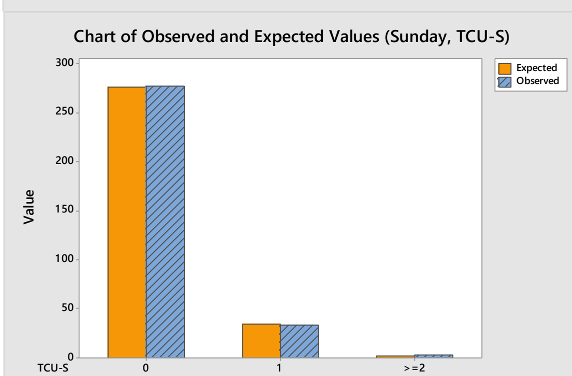
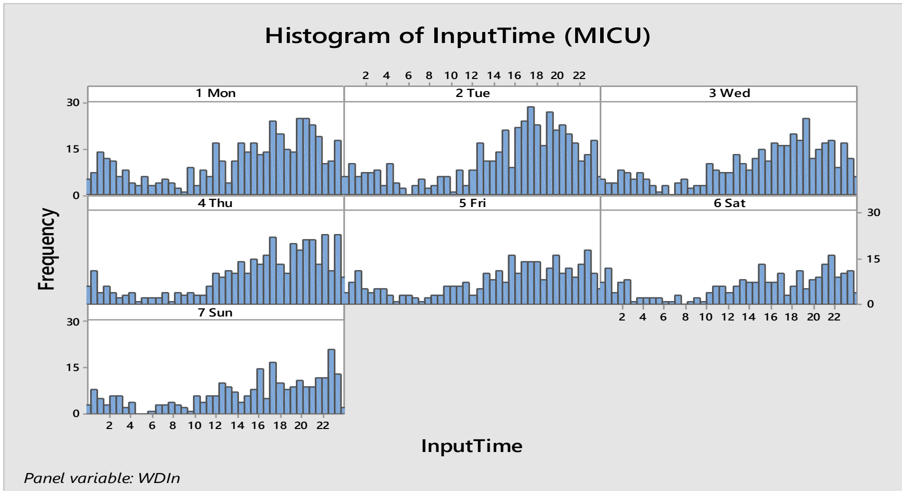
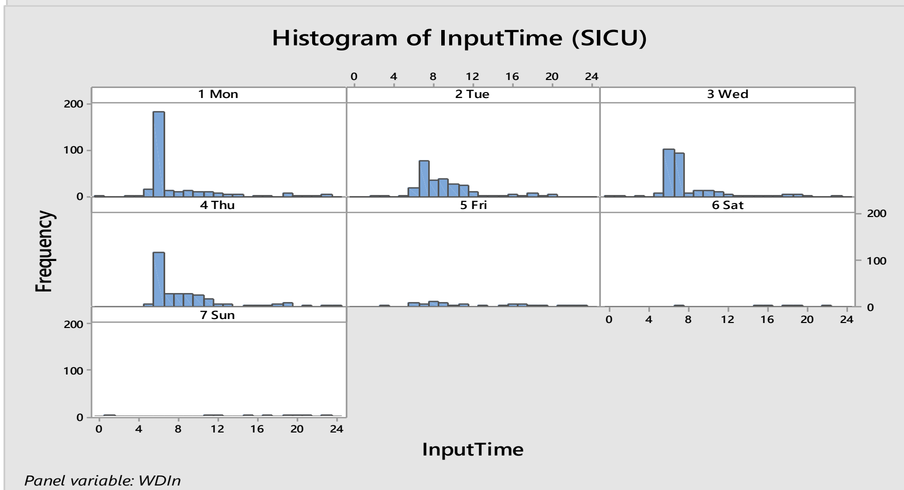
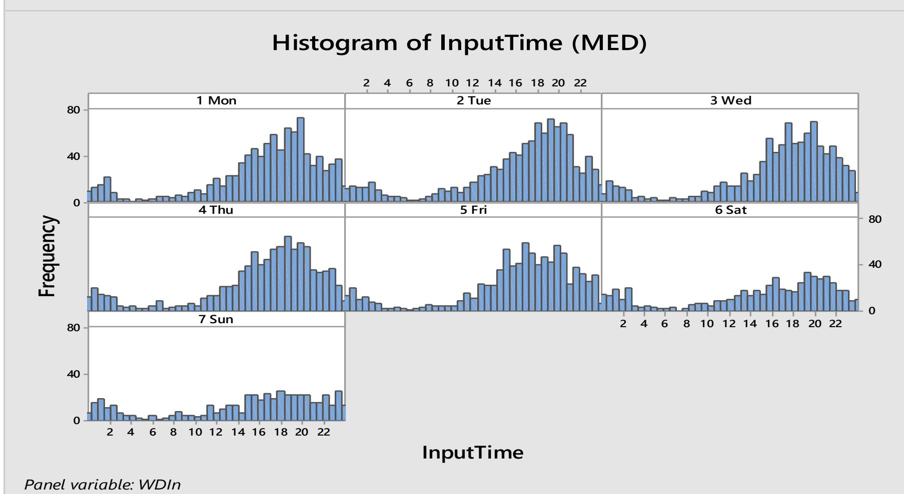


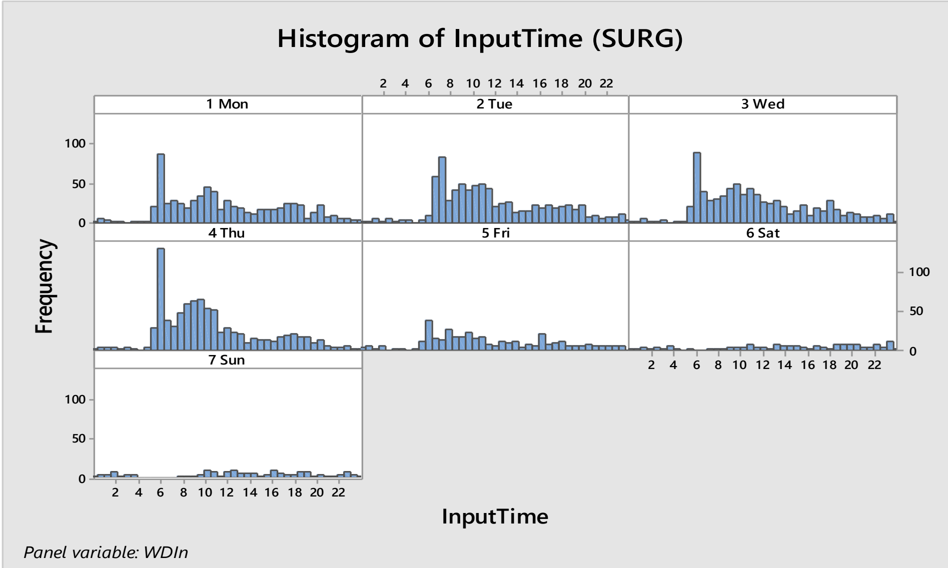
Chart of Observed and Expected Values (Sunday, TCU-S)
Expected
Observed
Value
0
50
100
150
200
250
300
TCU-S
0
1
>=2

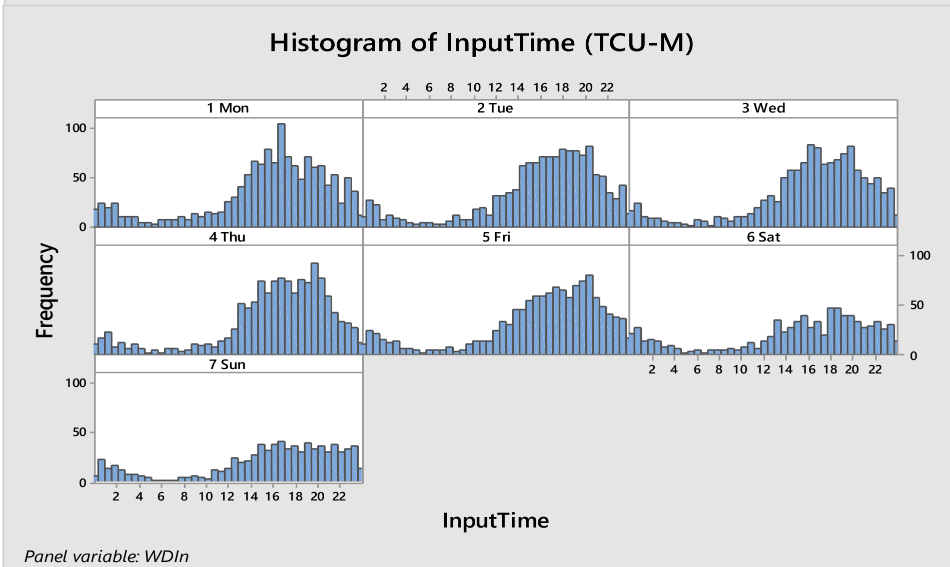
ARRIVAL TIME OF THE DAY: A histogram of arrivals distribution by time of the day for each day of the week, is provided for each ward.

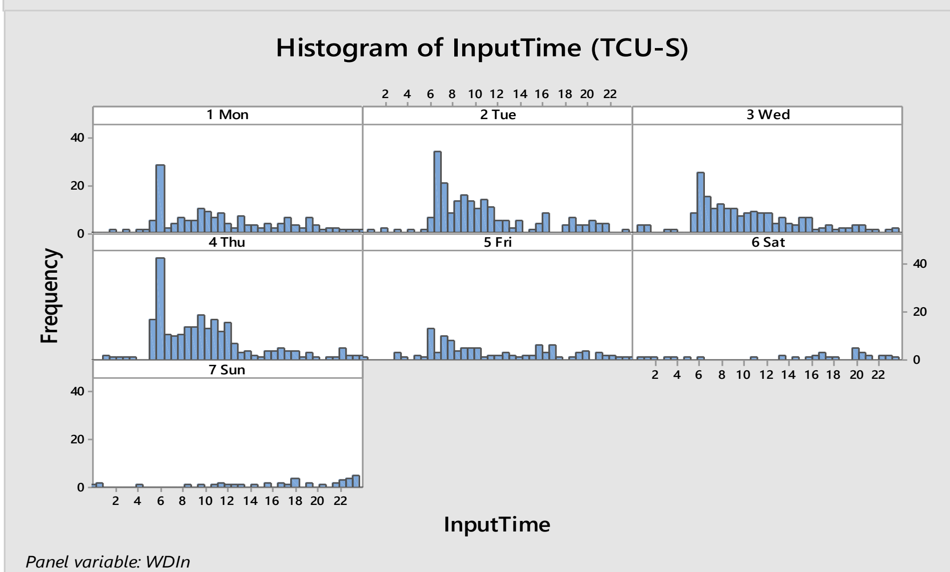




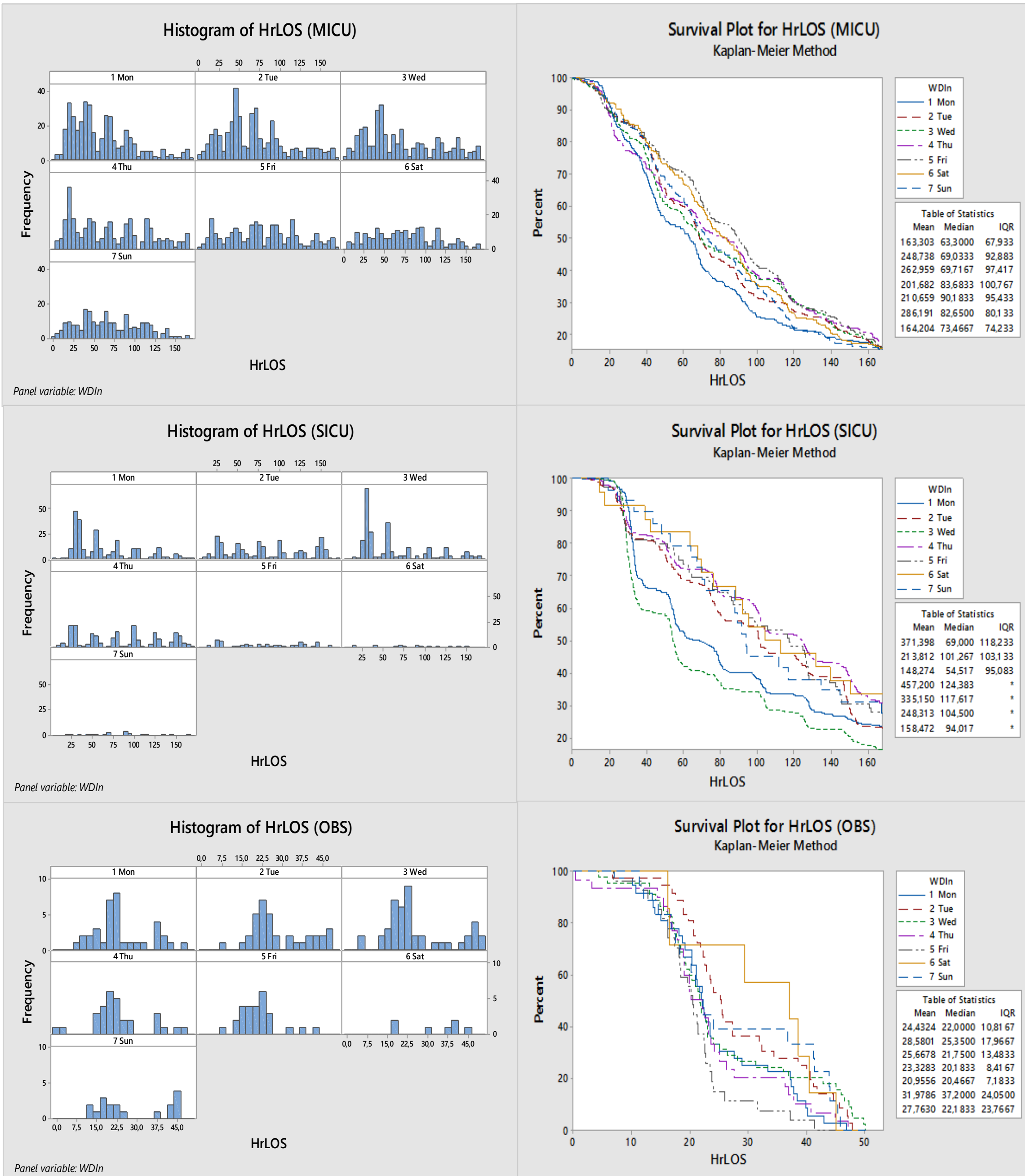


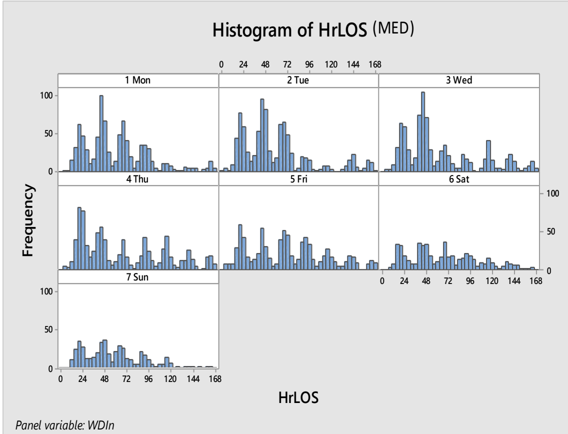

Histogram of InputTime (SURG)
1 Mon
2 Tue
3 Wed
4 Thu
5 Fri
6 Sat
7 Sun
Frequency
InputTime
Panel variable: WDIn

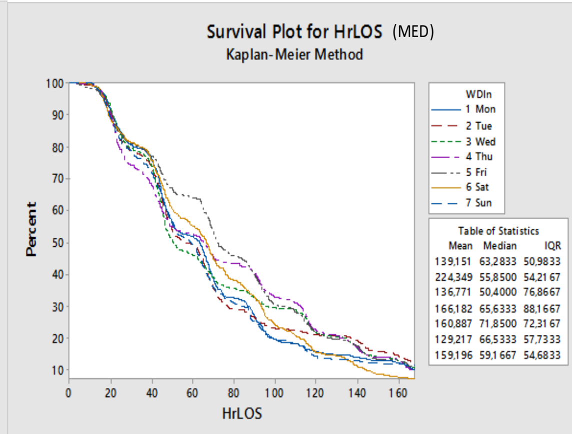

Histogram of InputTime (TCU-M)
1 Mon
2 Tue
3 Wed
4 Thu
5 Fri
6 Sat
7 Sun
Frequency
InputTime
Panel variable: WDIn

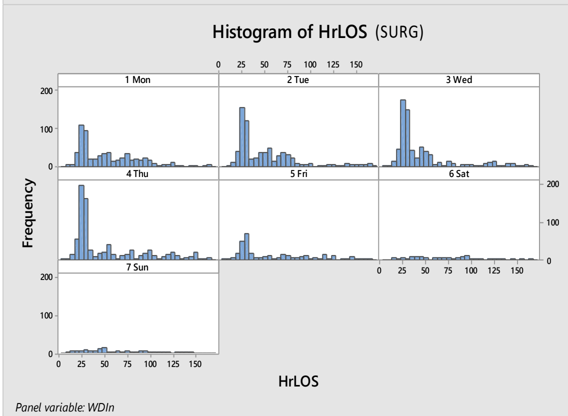

Histogram of InputTime (TCU-S)
1 Mon
2 Tue
3 Wed
4 Thu
5 Fri
6 Sat
7 Sun
Frequency
InputTime
Panel variable: WDIn

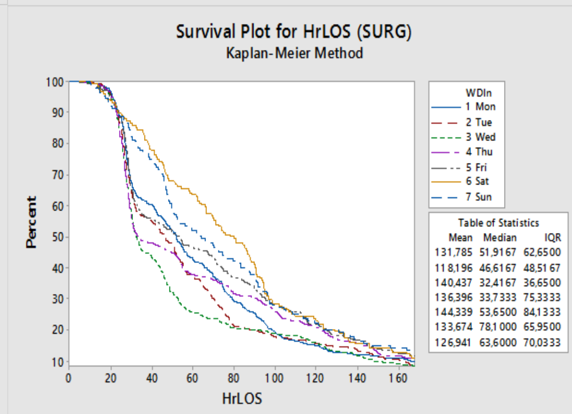
LOS: A histogram and a survival plot of the LOS by day of the week are provided for each ward. Also a table with the summary of the results for the fitting test is presented. Notice that in all figures the decimal, which is commonly displayed as ".", will be represented with a ",". Hence, the number of 2.5 will be displayed in the graphic as 2,5.

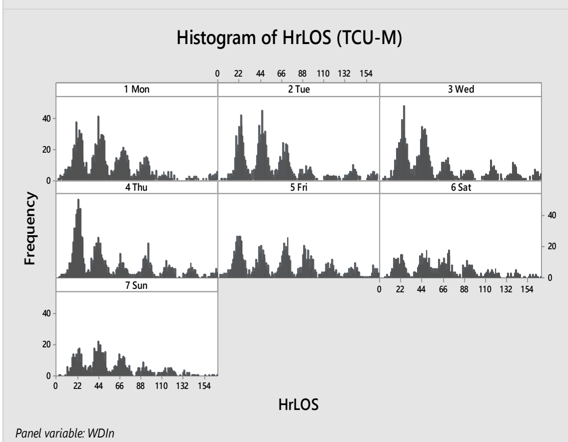


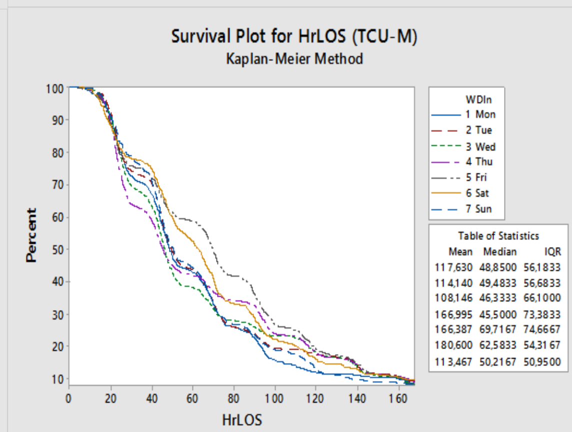

Histogram of HrLOS (MED)
1 Mon
2 Tue
3 Wed
4 Thu
5 Fri
6 Sat
7 Sun
Frequency
HrLOS
Panel variable: WDIn

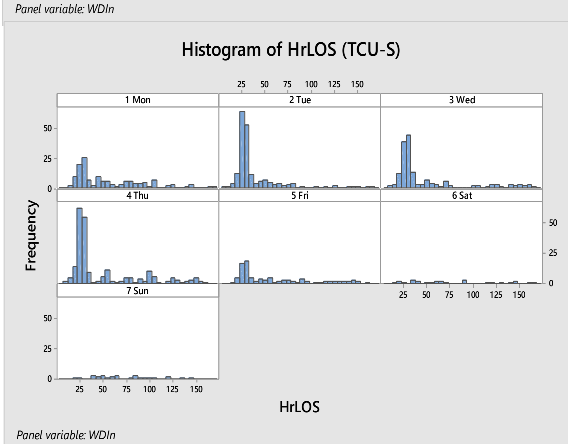

Survival Plot for HrLOS (MED)
Kaplan-Meier Method
Percent
HrLOS
WDIn
1 Mon
2 Tue
3 Wed
4 Thu
5 Fri
6 Sat
7 Sun
Table of Statistics
Mean Median IQR
139,151 63,2833 50,9833
224,349 55,8500 54,2167
136,771 50,4000 76,8667
166,182 65,6333 88,1667
160,887 71,8500 72,3167
129,217 66,5333 57,7333
159,196 59,1667 54,6833

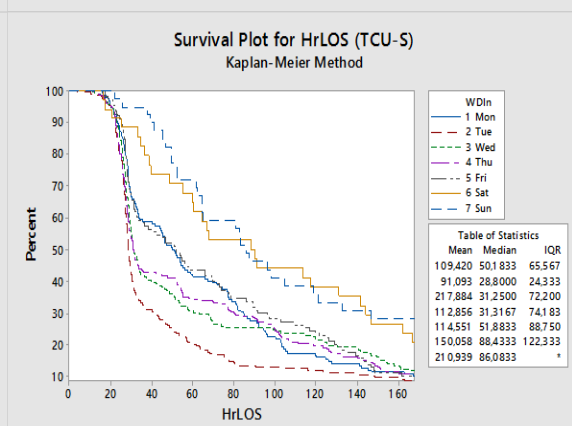

Histogram of HrLOS (SURG)
1 Mon
2 Tue
3 Wed
4 Thu
5 Fri
6 Sat
7 Sun
Frequency
HrLOS
Panel variable: WDIn


Survival Plot for HrLOS (SURG)
Kaplan-Meier Method
Percent
HrLOS
WDIn
1 Mon
2 Tue
3 Wed
4 Thu
5 Fri
6 Sat
7 Sun
Table of Statistics
Mean Median IQR
131,785 51,9167 62,6500
118,196 46,6167 48,5167
140,437 32,4167 36,6500
136,396 33,7333 75,3333
144,339 53,6500 84,1333
133,674 78,1000 65,9500
126,941 63,6000 70,0333


Histogram of HrLOS (TCU-M)
1 Mon
2 Tue
3 Wed
4 Thu
5 Fri
6 Sat
7 Sun
Frequency
HrLOS
Panel variable: WDIn


Survival Plot for HrLOS (TCU-M)
Kaplan-Meier Method
Percent
HrLOS
WDIn
1 Mon
2 Tue
3 Wed
4 Thu
5 Fri
6 Sat
7 Sun
Table of Statistics
Mean Median IQR
117,630 48,8500 56,1833
114,140 49,4833 56,6833
108,146 46,3333 66,1000
166,995 45,5000 73,3833
166,387 69,7167 74,6667
180,600 62,5833 54,3167
113,467 50,2167 50,9500


Histogram of HrLOS (TCU-S)
1 Mon
2 Tue
3 Wed
4 Thu
5 Fri
6 Sat
7 Sun
Frequency
HrLOS
Panel variable: WDIn


Survival Plot for HrLOS (TCU-S)
Kaplan-Meier Method
Percent
HrLOS
WDIn
1 Mon
2 Tue
3 Wed
4 Thu
5 Fri
6 Sat
7 Sun
Table of Statistics
Mean Median IQR
109,420 50,1833 65,567
91,093 28,8000 24,333
217,884 31,2500 72,200
112,856 31,3167 74,183
114,551 51,8833 88,750
150,058 88,4333 122,333
210,939 86,0833 *

	LOS Fitting test results by Ward	
WDIn	**Wilcoxon test**	**Conclusion**
MICU	P-Value = 0.001	Observed data (real-data) and Poisson function data are significantly different.
SICU	P-Value = 0.000	Observed data (real-data) and Poisson function data are significantly different.
OBS	P-Value = 0.081	Observed data (real-data) and Poisson function data are <u>not</u> significantly different.
MED	P-Value = 0.000	Observed data (real-data) and Poisson function data are significantly different.
SURG	P-Value = 0.000	Observed data (real-data) and Poisson function data are significantly different.
TCU-M	P-Value = 0.000	Observed data (real-data) and Poisson function data are significantly different.
TCU-S	P-Value = 0.000	Observed data (real-data) and Poisson function data are significantly different.

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