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Effect of Appointment Schedules on the Operational Performance of a University Medical Clinic

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EFFECT OF APPOINTMENT SCHEDULES ON THE OPERATIONAL PERFORMANCE OF A UNIVERSITY MEDICAL CLINIC

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ABSTRACT

Overall Healthcare cost in United States is one of the highest in the world. The per capita expenditure for hospital outpatients and physicians is the highest among other hospital expenses. High patient wait times, physician idle times, physician overtimes and patient congestion are some of the common problems encountered in outpatient clinics. Such performance measures mainly depend on the type of appointment system in a clinic. This research studies the effect of different appointment systems on the operational performance of a university medical clinic. The process at the medical clinic in the LSU Student Health Center (SHC) was modeled using the Rockwell Arena® simulation software. Four scheduling rules namely, the Individual block rule, Bailey rule, 3-Bailey rule, and the Two-at-a-time rule, were studied using the simulation model to understand their effect on the performance parameters of the SHC. The schedules were compared with respect to provider times (provider idle time, startup idle time, provider overtime, and provider utilization) and patient times (patient wait time and patient throughput time). The individual block rule was found to be the most patient friendly with the shortest patient times. The 3-Bailey rule was the most provider friendly rule with the least provider times. A KT (Kepner Tregoe) analysis of the rules showed that the Bailey rule was more suitable rule for the SHC, as it has a good trade-off between the patient and provider times. The Bailey rule has better provider times (Idle time – 31.8 min, Startup idle time – 6.5 min, Overtime – 6.9 min) and better provider utilization rate (92%) than the Individual block rule. However it has marginally higher patient times (throughput time – 41.4 min and wait time – 17.3 min). A test run with one provider for ten days in the clinic confirmed this behavior of the Bailey rule.

CHAPTER 1: INTRODUCTION

Healthcare cost in the United States is one of the highest in the world. In the last decade, the healthcare expenditures in the US have increased more than the individual income according to Holahan et al. (2011). Individual healthcare costs that averaged $147 in 1960 increased to $8860 in 2011 (Leavitt et al., 2014). Healthcare expenditures contributed to 17.9% of the gross domestic product of the US in 2011 ("Costs On the Rise," 2014). The public money used to finance the healthcare in United State, which is about 45% of all health expenditures, is expected to double by 2050 (Gupta et al., 2008). According to Holahan et al. (2011), the National Health Expenditures (NHE) increased at an annual average growth rate of 6.6% from 2000 to 2010, whereas the annual GDP growth rate was 4.1%. The NHE is forecasted to increase from $ 2.6 Trillion in 2010 to $ 4.5 Trillion in 2019 at a growth rate of 6.5% per year. This is higher than the forecasted GDP growth rate, which is about 5.1 % per year. Figure 1 shows the per capita health expenditure in the US by medical services category. Overall the per capita health expenses for the non-elderly population increased from $2873 in 2001 to $4037 in 2009. The "Physician and Outpatient" services experienced the highest increase when compared to other expenses. The increase rate was also substantially higher for the "Physician and Outpatient" services (44%) when compared to the other services (Blavin et al., 2012).

Making the outpatient departments cost effective is essential for organizations to be financially viable in the healthcare industry (Goldsmith, 1989). The spiraling healthcare costs and the growing public discontent calls for productivity improvements in the industry (Ho et al., 1992). There is a pressure on health care personnel to reduce costs and to improve the quality of services at the same time. Currently, there is an emphasis on reducing the length of hospital stays of patients, and thus outpatient care is becoming a vital component in healthcare (Cayirli et al., 2003).

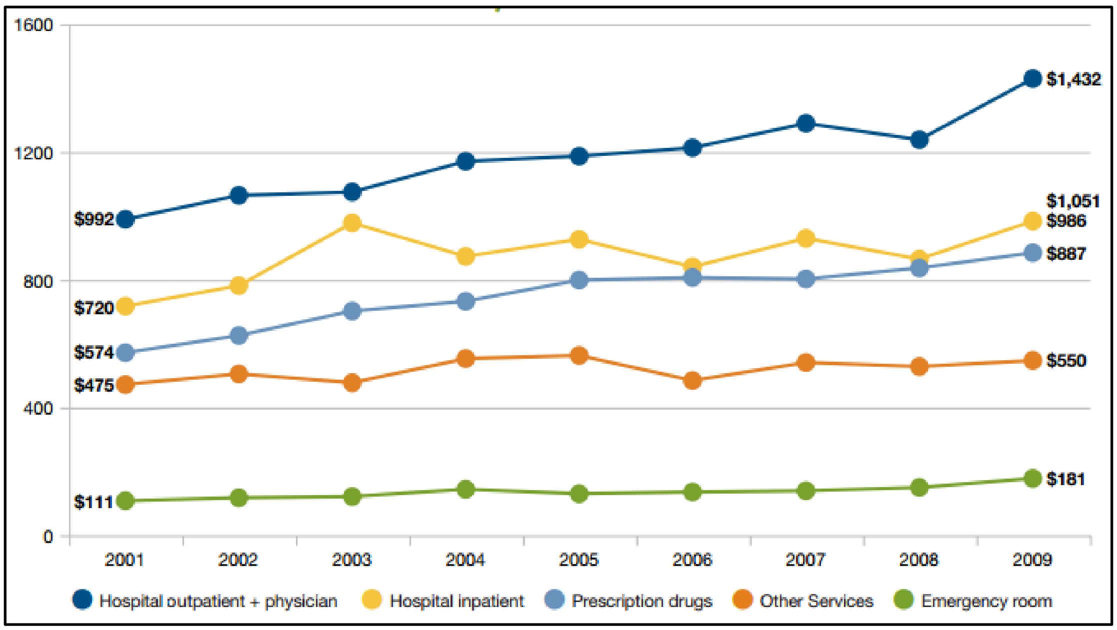

Figure 1: Per Capita Health Expenditures by Service Category, 2001–2009 (Blavin et al., 2012)

Some of the common issues that hinder the smooth operation of an outpatient clinic are provider idle times, patient wait times and patient congestions. Concerns such as long waiting times and waiting room congestion can also lead to patient dissatisfaction apart from hindering the operation of a clinic (Cayirli et al., 2003). Patients always desire to have less waiting times and congestion whereas providers tend to schedule more patients to incur less idle time (Klassen et al., 1996). Hence it is always important to have an appointment system that can minimize the idle time of doctors or providers, while reducing wait time of patients.

1.1. Importance of Appointment Systems

The primary objective of a well-designed appointment system is to deliver appropriate and timely health care service to the patients. An appointment system has to cater to the requirements of both the patients and providers by matching the supply with the demand. They also have the task of smoothening the work flow in clinics by reducing the crowding in the waiting rooms (Gupta et al., 2008). An appointment scheduling is a tradeoff between the patient wait time and provider idle time (Cayirli et al., 2012; Ho et al., 1992; Kaandorp et al., 2007). One of the major complaints by patients in outpatient clinics is the long wait times. A patient faces two types of wait times on scheduling an appointment, the direct and the indirect delay. Direct delay is the waiting time that the patient experiences upon arriving at the clinic (Gupta et al., 2008). The indirect delay is the period from the time of scheduling an appointment to the actual time of the appointment. This indirect delay that occurs in the clinic can cause a lot of dissatisfaction as it usually not known to patients beforehand.

Apart from minimizing the wait time of the patients, a good appointment system reduces the provider idle time and the provider overtime. Provider idle time is defined as the time when a provider is not consulting a patient because there are no patients waiting to be seen; and provider overtime is the difference between the desired end time of a clinic and the actual time the service is provided to the last patient (Cayirli et al., 2003). A bad appointment system can be a source of frustration for providers, as they are affected by the ambiguity in the number of appointments and also the mix of appointments on a given day. Most of the time providers manage the variations and priority demands by shrinking their lunch times, practicing double booking or working faster. Such factors usually affect the job satisfaction of the providers. According to Cayirli et al. (2003), well designed appointments systems should have the capability to increase the utilization of resources while minimizing the idle time of patients and the provider.

1.2 Methods for developing appointment systems

Appointment systems can be developed by analytical methods, simulations or case studies. Case studies are usually "before and after" type of studies, where researchers observe a system, make changes and observe again for improvements. Conclusions are drawn by analyzing both the before and after scenarios and further improvements are made. Case studies usually have a high degree of external validity, however they take longer time to implement and need more resources to execute. Analytical and simulation based studies provide the capability to model complex queuing systems, but it may not be feasible to factor all the parameters of a real setting. However, they usually require only less resources and time when compared to case studies. Analytical methods use queuing theory or mathematical programming methods, while simulation methods use computer based simulation packages to model the actual process. In simulation, the process is modeled by constructing the process flow and representing the process variables in the model.

1.3 Applications of Simulation

Simulations have a wide range of applications. They are used to model

1. Queuing and Servicing processes: Air traffic control, ambulance location and service, bank teller assignments, evacuation processes in stadiums and shopping centers, production processes, docking operations of ships.

2. Distribution processes: Warehouse location, material flow layout, mining operations, apparel supply and distribution, shipping and logistics simulation, supply chain simulation.
3. Scheduling processes: Job shop, construction, airlines, hospitals / health care, smelting operations in foundries, staffing requirements and forecasting in military, staffing optimization in call centers, staffing simulation in retail, etc.

Some advantages of simulation are:

1. New procedures or systems can be tested without disrupting the ongoing operations
2. The time of testing can be controlled
3. Modifications and what-if analysis are easy to do and less time consuming
4. Simulations allow for precise control of the parameters that are tested
5. Very cost effective for a large and complex system.

Discrete event simulations are commonly used in healthcare as the flow process in a hospital or clinic can be described by a set of individual events.

1.4 Discrete Event Simulation

The process of outpatient clinics can be considered as a queuing system that has a unique set of operating conditions (Cayirli et al., 2003). A very simple case would be a system with just one provider and patients arriving punctually. However, in reality there are a lot of other variables that can affect the process in a clinic. Discrete-event simulation software works on the principles of queuing theory and a model of the process can be created using any simulation software by considering the required variables of interest.

For this study, Arena simulation software by Rockwell automation will be used to model the patient flow process at the LSU Student Health Center (SHC). The objective of this study is to understand the effect of 5 different appointment systems on the operational performance of an SHC using the Arena simulation software.

CHAPTER 2: LITERATURE REVIEW

2.1 Types of Appointment rules

Appointment systems can be defined by the type of appointment rule that is used to schedule patients, patient classification and the adjustments made for special cases like no-shows, walk-ins and emergencies. An appointment rule sets the time interval for each visit and defines the number of patients scheduled for a particular time period. It can be described by (1) the time interval for each appointment called as blocks (2) number of blocks per session and (3) number of patients per block (Cayirli et al., 2003). Different appointment rules have been developed over the years for outpatient clinics. A classification of different appointment rules used by outpatient clinics is given in the literature review by Cayirli et al. (2003) . Commonly used appointment rules are described in the following sections.

1. Single block rule

This is probably the oldest of all appointment rules. It provides a date for the patients instead of specific time slots and patients are free to arrive at any time that day. They are seen on a first come first serve basis. Babes et al. (1991) studied the single block appointment system in public sector clinic in Algeria. It is understood that single block appointments have the advantage of low administrative work demand and are still used in public clinic settings in developing and under developed countries. However, there would be large waiting times for the patients and more idle time for providers due to the flexibility of arrival of the patients. Single block rule was the most prevalent rule before the 1950's in United States. Many studies about outpatient scheduling in 1950's and 1960's, such as Johnson et al. (1968) and Norman (1952) compared the single block system to the individual block system implying the shift from single block appointment rules. Figure 2 shows the design of different appointment schedule listed above.

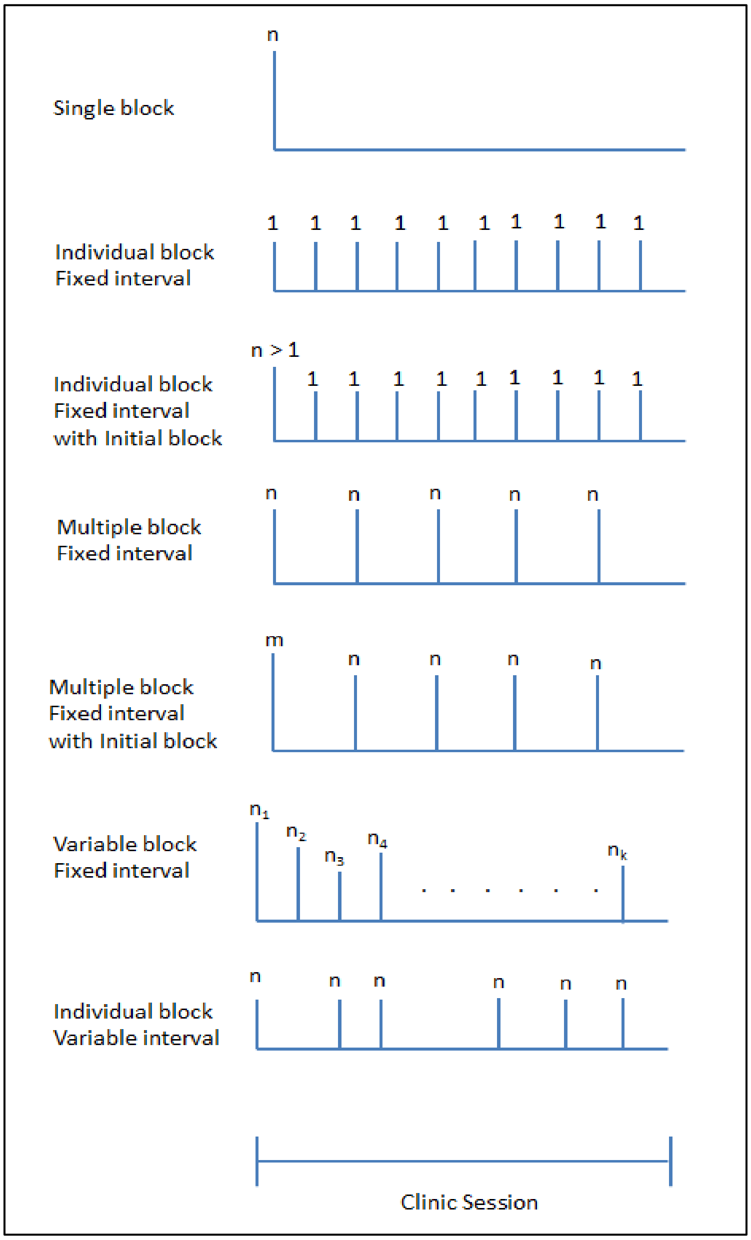

Figure 2: Different appointment rules, adapted from Cayirli et al. (2003)

2. Individual block and Fixed interval rule

This is the simplest of individual block rules. Every patient is provided an appointment block with a unique appointment time. Every block has the same time interval, usually the mean service time. The individual block and fixed interval rule has been studied as early as 1950's by Norman (1952). Norman (1952) made mathematical models to study the effect of individual appointment times given to patients on the patient wait time and provider idle time. He identified that individual blocks has less provider idle time and less patient waiting time when compared to the single block system. However, he emphasized that the effectiveness of such an appointment system is reduced if the appointment interval is not equal to the average consulting time. A study by Johnson et al. (1968) shows that single block appointment systems was prevalent even in 1968 and caused numerous problems to the patients and the physicians by increasing the waiting times and congestions. He performed a study on 5 voluntary and 3 municipal hospitals in New York and compared the time data of three hour sessions between a single block and individual block rule. He noticed that there is a steady waiting time for patients for individual block type appointments when compared to the single block appointment rule where some patients had to wait as high as more than two hours and some less than 10 minutes. Studies by Klassen et al. (1996) , Rohleder et al. (2000) and Cayirli et al. (2006) are some of the recent ones that dealt with individual block / fixed interval rule.

3. Individual block and Fixed interval rule with an initial block

Otherwise known as the Bailey rule, this rule was introduced by Norman Bailey in 1952; it has an initial block with two patients continued by one patient in each block as in the individual block/fixed interval rule. The objective of the Bailey rule is to have an inventory of patients to reduce the idle time of the provider in cases where the first patient fails to come or arrives late. Cayirli et al. (2006), Rohleder et al. (2000) and Cayirli et al. (2008) evaluated this rule in the studies. Modifications of the Bailey rule such as 3-Bailey rule, with three initial patients were proposed by Brahimi et al. (1991) and tested by Wijewickrama et al. (2008).

4. Multiple-block/Fixed-interval rule

The multiple block fixed interval rule is designed to have more than one patient arrive at the same time. For example a "Two-at-a-Time" design assigns two patients to one block with twice the mean consultation time (Soriano, 1966).

5. Multiple-block/Fixed-interval rule with an initial block

This is a variation of the Multiple-block/Fixed interval rule with just an initial block. However there are not many studies that have investigated this rule.

6. Variable-block/Fixed-interval rule

Variable block/Fixed interval rule has different number of patients arrive during the same time intervals. Rising et al. (1973) investigated having multiple blocks of appointments within every hour on a given day. Fries et al. (1981) analyzed a generalized single server multiple block system (m-at-a-time), with variable sized blocks. They observe that there are some difficulties in designing such a system even though there are advantages in performance. It is understandable that these types of rules would demand more administrative efforts when compared to other rules.

7. Individual-block/Variable-interval rule

This rule suggests scheduling individual patients for different intervals of time. Ho et al. (1992) studied different Individual-block-Variable-interval rules. They noticed that increased appointment interval towards the end of the session improved the performance of the clinic. The pattern of scheduling with an increase in arrivals during the middle of the session represents a dome shaped pattern which has been studied by Wang (1993). This rule would also require additional administrative efforts, because of the variation in the times of different types of appointment reasons.

2.2 Use of Simulation in Healthcare

Simulation has found a variety of applications in healthcare. One of the main advantages of simulation is its ability to model complex queuing systems and various environment variables that would be difficult to evaluate using analytical methods. Simulation also provides the capability to perform "what-if" scenarios to understand the relationship between the appointment systems and the environment variables. Simulation has been used increasingly use in health care as cost control and efficiency improvements in hospitals and clinics has become more important (Rohleder et al., 2011). A literature review by Jun et al. (1999) reviews over 100 articles that use simulation in healthcare for process improvements. Use of simulation in Healthcare is described in the following section.

1. Improving Patient flow

Effective patient flow has advantages like reduced waiting time, effective utilization of resources, shorter throughput time for patients and less patient congestion. Simulation studies have concentrated on patient scheduling and admissions, patient routing and resource scheduling to improve patient flow.

Patient scheduling and admissions deal with the length of individual appointments and how appointments are scheduled in a given day. It defines the proper appointment rule for scheduling patients. Su et al. (2003) developed a scheduling system using simulation for a mixed-registration type outpatient clinic setting. They used “Windows” based discrete event simulation software “MedModel” to model the process of clinics in “Su-Ten Hospital” in Taiwan. The model was used to evaluate different scheduling policies of walk-in and appointment patients. Rohleder et al. (2011) used simulation to identify an appropriate scheduling system for patients in an outpatient orthopedic clinic. Based on the simulated improvements, a 40 minute reduction in patient time was observed. An example of the simulation model of the orthopedic clinic by Rohleder et al. (2011) is shown in Figure 3

Patient routing and flow schemes deal with how the flow of patients inside a hospital affects the operation of a clinic. A lot of studies regarding routing have been done to refine the patient flow in emergency departments. Medeiros et al. (2008) developed a new patient flow method in an emergency department using simulation. The objective of their study was to develop and implement a new approach to the patient flow process in an emergency department. They tested a Provider Directed Queuing (PDQ) system which places an emergency care physician at triage.

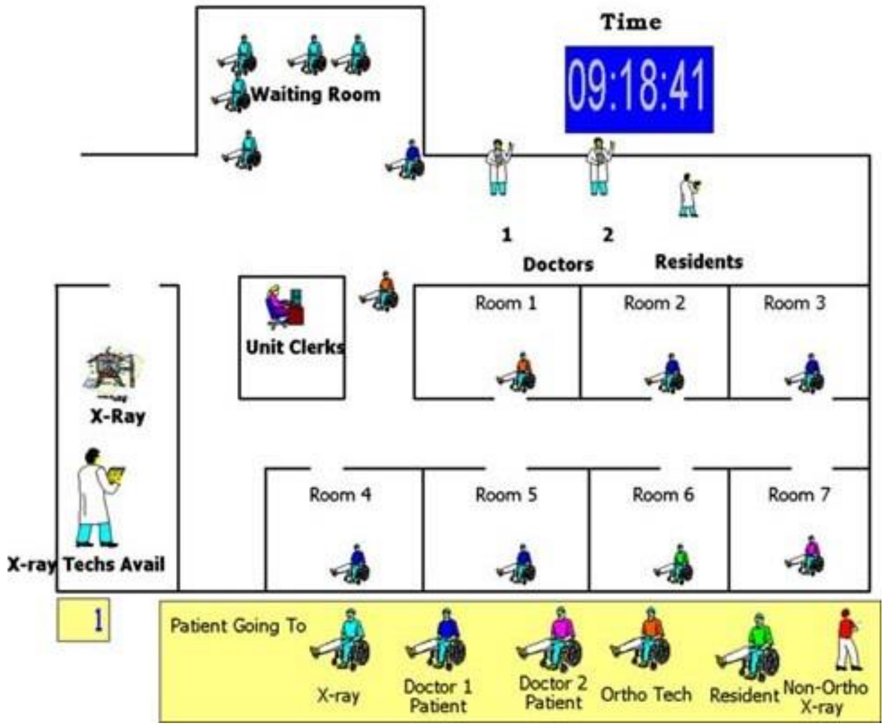

Figure 3: Simulation representation of Orthopedic Clinic in Florida by Rohleder et al. (2011)

Scheduling and availability of resources kind of studies aim at matching the resources like the number of nurses and providers with the arrival of patients. This type of study is mostly done for walk-in type applications. Giachetti et al. (2005) studied the viability of having an open access policy in an outpatient clinic using discrete-event and continuous simulation modelling. The authors built a simulation model of the clinic using Arena software and identified an Open Access scheduling system to perform better in such conditions. Rohleder et al. (2011) used discrete-event simulation to improve patient flow in an outpatient orthopedic clinic, which had an average monthly volume of 1000 appointments. The simulation model was made using the Arena software. Scheduling solutions were given to increase the utilization of the x-ray equipment.

2. Allocation of resources

The high cost of operation in health care demands effective utilization of all resources. It is important to have a clear idea of the requirements before purchase of additional resources. It is also important for hospitals clinics to effectively utilize the existing resources to reduce wait times, patient throughput times, etc. The simulation studies that deal with effective allocation of resources can be classified under bed sizing, room sizing and staff sizing studies.

Studies related to bed sizing deals with determining the optimal number of beds required for hospitals with the objective of having reasonable utilization rates. Cohen et al. (1980) used simulation to present a bed planning model in a progressive care hospital. Dumas (1985) used a simulation model to evaluate bed usage performance and develop different bed allocation plans in a hospital at New York city.

Room sizing deals with identifying requirements like the number of operation theatres needed or the number of people present to understand the space requirements, etc. Kwak et al. (1975) describes a simulation procedure used for determining the number of patients that would need a recovery room, given the number of operating rooms present in a hospital. Kuzdrall et al. (1981) determined facility needs for different scheduling policies in an operating facility.

Staff sizing deals with determining the number of staffs required for a particular task or operation to have minimum downtime. A lot of work balancing, job rotation studies have been conducted in this regard to determine optimum staffing requirements. Takakuwa et al. (2008) developed a discrete-event simulation model to examine congestion and the schedules of doctors in the outpatient ward at Nagoya University hospital, Japan. They analyzed the performance measures like the weighted average patient waiting time to evaluate alternate staffing schedules by changing the number of doctors in the system. The optimum solution reduced waiting time by 40.34% by deploying 105 doctors. Hashimoto et al. (1996) identified bottlenecks in an internal outpatient clinic using simulation. They identified that having more doctors slowed down the operation in clinic and suggested adding two more dischargers and limiting the doctors to four numbers.

2.3 Discrete event simulation software in Healthcare

There have been tremendous improvements in simulation software over the years to add more features to increase usability and to make it more user-friendly. One of the main improvements has been the visual oriented graphic output that has not only helped in presenting the model but also in verification of the process flow. Introduction of Object Oriented Paradigm (OOP) in simulation software has added the functionality that enables people to model the process without writing codes. The simplicity of these software has improved over the years because of the drag and drop options, making it more user friendly when compared to the older versions (Jun et al., 1999). Some of the common software that have been used for modelling healthcare systems are: “MedModel”, which was used by Su et al. (2003) to evaluate different scheduling policies; “Arena” simulation software, used in a number of studies, examples of which is provided already; “See-Why” software, used by Jones et al. (1987) for a visualization study; and “CLINSIM” software, used by Paul et al. (1995). Arena® simulation software by Rockwell Automation is used in this study. SIMUL8 from SIMUL8 Corporation, Anylogic from

Anylogic Company and “FlexSim” from FlexSim Software Products, Inc. are some of the some other software available in the market for simulation of healthcare processes.

CHAPTER 3: RATIONALE AND OBJECTIVE

3.1 Rationale

Simulation studies in the past have been conducted on general outpatient clinics to develop appointment systems. However, from the extensive literature review, it appears that there is no research on the study of appointment systems for University clinics. Since this research focuses on studying the effect of appointment times on the operation of a University Medical Clinic, it is important to understand how they differ from general outpatient clinics.

Student Health Centers (SHC) are the primary option for the students studying in a University for Non-emergency Medical problems. SHC's are present in most of the Higher Education Institutions (HEI) in the US. There are more than 2700 HEI's in the United States with SHC's, catering to the needs of over 12.5 Million students (Brindis et al., 1997). These SHC's handle 20 to 25 million visits every year which amounts to a cost of about $ 1.4 billion (Brindis et al., 1997). According to a survey conducted by McBride et al. on 172 SHC's, medical services was the most common service provided in an SHC.

Figure 4 shows the availability of different programs in an SHC, and Figure 5 shows the percentage of the various services provided under the Medical clinic programs. Ninety eight percent of the Medical services in SHC provide outpatient care to the students.

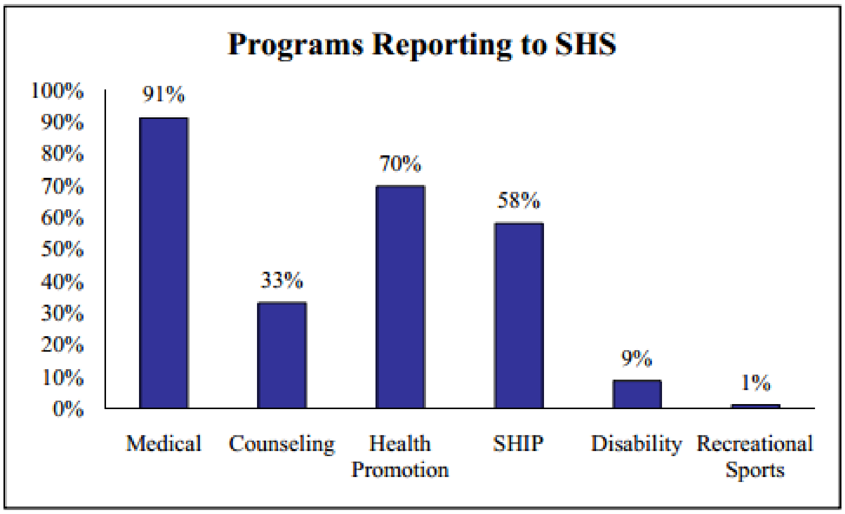

Figure 4: Services reporting to the SHS's. Medical services is most prevalent (McBride et al.)

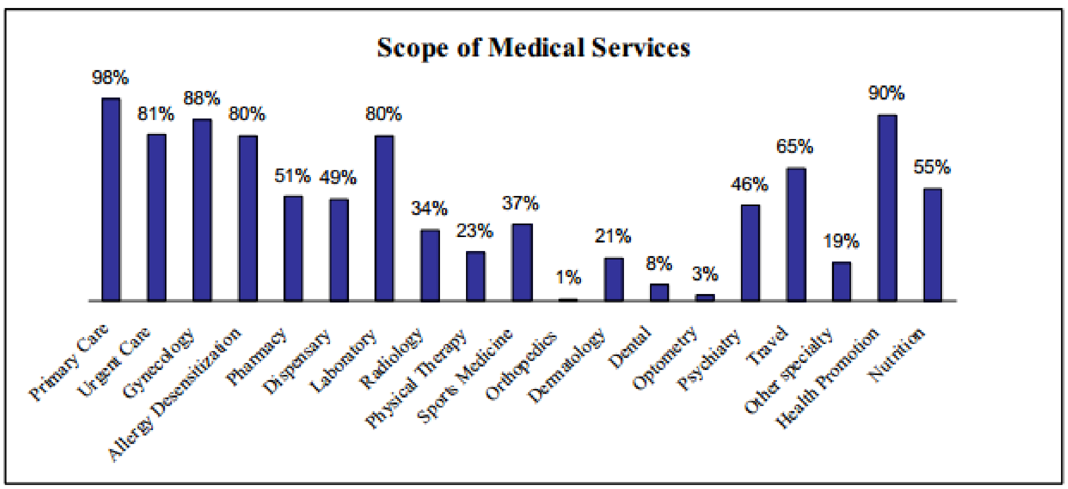

Figure 5: Scope of the Medical Services in SHS (McBride et al.)

The demography of the patients makes the outpatient clinic at the SHC different from the general outpatient clinics. One of the major differences is that the University clinics tend to patients of a narrow age range, typically young adults of 18 to 24 years. The young students have a tendency to delay seeking medical treatment and fail to provide important information to the medical staffs (Brindis et al., 1997). The threshold level for waiting for young students is usually low as they have a need for timely and urgent appointments. Due to these urgent appointments, the students tend to see any available doctor in the clinic and do not see the same doctor all the time. Since most of the students seek attention for urgent problems, it is also preferable that they are seen without delay. It is also difficult for a student to find appointment slots with the same provider between their class schedules, which leads to the student scheduling appointments with any available provider. This inconsistency of not staying with the same provider leads to a weak relationship between the provider and the patient when compared to a regular outpatient clinic. The physicians also have to give some parenting advice to the students during visits as most of them are in the beginning stages of self-care. Patient wait time is a major concern for the students as they usually tend to schedule appointments between class hours and any delay would affect their attendance. Most of these SHC operate in full scale only during the major semester periods (Funderburk et al., 2012). Such characteristics of the patient population and the settings in SHC make the outpatient clinics within a university unique from other general clinics.

The Student Health Center at the Louisiana State University (LSU) is chosen for this study. Long patient wait times and provider idle times have also been a concern at the SHC at LSU. There are about 25000 visits every year in the medical clinic at the LSU SHC. Apart from the medical clinic, the LSU SHC also provides other services through its Mental Health clinic, Women's clinic, Specialty clinic and through various wellness programs. A good appointment system for a Student Health Center is thus necessary to have an organized process flow with minimum wait times and idle times. It would also be interesting to see how different appointment schedules perform in this type of setting. Most of the simulation studies in the past researches on general outpatient clinics were done under ideal conditions and did not consider environment factors like patient unpunctuality, variation in service time and presence of supporting lab processes that can affect operation of a clinic. This study considers these variabilities in the model to mimic the actual scenarios.

3.1.1 Research Question

Since the outpatient clinics in student health centers differ from general outpatient clinics, there is a need to understand how different appointment systems perform in an SHC. To understand this, an appropriate research question would be: How do different appointment schedules affect the operational performance parameters such as provider idle time, patient wait time, patient throughput time, provider startup idle time and provider overtime in a University medical clinic?

3.2 Objective

The objective of this study is to understand the effect of different appointment systems on the operational performance of a University Medical Clinic using simulation. Louisiana State University's Student Health Center will serve as the case environment by which different appointment systems can be evaluated. The process at Louisiana State University's SHC is modeled using Arena Simulation software from Rockwell Simulation. The following appointment systems are studied.

1. Individual block/Fixed interval (Existing appointment system – one patient per block)

2. Bailey rule (Individual block/Fixed interval with two initial blocks)
3. 3-Bailey (Individual block/Fixed interval with three initial blocks)
4. Two at a time (Two patients appointed together with twice the mean service time)

		Individual Block Rule		Bailey Rule		3 Bailey Rule		2-at-a-time	
Hours	Minute	8Hr	10Hr	8Hr	10Hr	8Hr	10Hr	8Hr	10Hr
		Shift Begin	Shift Begin	Shift Begin	Shift Begin	Shift Begin	Shift Begin	Shift Begin	Shift Begin
0	0	**1**	**1**	**2**	**2**	**3**	**3**	**2**	**2**
0.25	15	1	1	1	1	1	1		
0.5	30	1	1	1	1	1	1	2	2
0.75	45	1	1	1	1	1	1		
1	60	1	1	1	1	1	1	2	2
1.25	75	1	1	1	1	1	1		
1.5	90	1	1	1	1	1	1	2	2
1.75	105	1	1	1	1	1	1		
2	120	1	1	1	1	1	1	2	2

Figure 6: Appointment Schedules modeled in Arena

The following performance variables were measured to compare the different appointment systems: provider idle time, provider startup idle time, provider Overtime, provider utilization, patient wait time, and patient throughput time. The patient throughput time is defined as the total time spent by a patient in the clinic. Patient wait time is the time that is spent by the patient other than the time with provider, nurse or in other value added activities. The provider idle time is the time during which the provider has scheduled patients but there have no patients to see, because of which the provider is rendered idle. The time spent in charting is not considered as idle time. The provider startup idle time is the time from the start of the shift to the time the provider sees the first patient. This does not include the administrative time allocated to each provider at the beginning of the shift. The provider overtime is defined as the time the provider spends after the office hours in seeing patients. Provider utilization is the ratio of the busy times by the total scheduled time available to the provider. Environment variables like no-shows and unpunctuality of patients were also considered when modeling the process of the SHC.

3.2.1 Experimental design

The dependent variables for this study are the six performance variables, namely the patient throughput time, patient wait time, provider idle time, provider startup idle time, provider overtime and provider utilization. The independent variables are the four appointment rules, namely the Individual block rule, Bailey rule, 3-Bailey rule and Two-at-a-time rule. The null and alternate hypothesis for the study is as follows for each for the performance measure.

1. Hypothesis for Patient throughput time

Null hypothesis: H0: There is no difference in patient throughput times of the four appointment schedules.

Alternative hypothesis: H1: The patient throughput time of at least one schedule is different.

2. Hypothesis for Patient wait time

Null hypothesis: H0: There is no difference in patient wait times of the four appointment schedules.

Alternative hypothesis: H1: The patient wait time of at least one schedule is different.

3. Hypothesis for Provider Idle time

Null hypothesis: H0: There is no difference in provider idle times of the four appointment schedules.

Alternative hypothesis: H1: The provider idle time of at least one schedule is different.

4. Hypothesis for Provider Startup idle time

Null hypothesis: H0: There is no difference in startup idle times of the four appointment schedules.

Alternative hypothesis: H1: The startup idle time of at least one schedule is different.

5. Hypothesis for Provider overtime

Null hypothesis: H0: There is no difference in provider overtimes of the four appointment schedules.

Alternative hypothesis: H1: The provider overtime of at least one schedule is different.

6. Hypothesis for Provider utilization

Null hypothesis: H0: There is no difference in provider utilizations of the four appointment schedules.

Alternative hypothesis: H1: The provider utilization of at least one schedule is different.

CHAPTER 4: METHODS AND PROCEDURE

The objective of this study was to understand the effect of different appointment schedules on the operational performance of an SHC. The Louisiana State University's SHC was used for this study. A simulation model of the SHC was created using the Arena simulation software. A deep understanding of the process at the SHC was required to create the simulation model. The first step of this study was to determine the process flow of the SHC. This was done by direct observation and by discussions with the clinicians. The important input variables required for the model were identified from the process flow study. Then next step was the data collection for these input variables which were the input for the Arena model. Data collection was done by either direct observation or by analyzing the historical data from fall and spring semesters of 2014. In the third step, the simulation model of the SHC was created using Arena simulation software. A model was created for each the four schedules. The models were run for 100 replications and the output data for each model was recorded in MS-Excel files. The model was then validated by comparing the results of the individual block rule with the actual data from the clinic. In the final step of the study, the schedules were compared with each other for the performance parameters. After the comparisons, a Kepner-Tregoe (KT) analysis was performed to decide the best schedule for the SHC and a test run of the Bailey rule was also done to check the face value of the results. A detailed explanation of the methods in this study is described in the following sections.

4.1 Determination of Process flow SHC

The objective of this step was to understand the flow of the patients at the SHC. The patients coming to the health center were followed for one week from arrival to exit to understand the process. A process flow diagram was made based on the observations and discussions with the clinicians at SHC.

Figure 7 shows the process flow of patients at LSU SHC. There are basically two types of patients who come to the SHC: (a) Appointment patients, who are patients with scheduled appointments and (b) Walk in patients, who directly walk in to the clinic for urgent appointments, also called as triage patients. Triage patients are seen by dedicated providers and are not considered for this study as they do not affect the appointment process. Figure 8 shows the typical appointment screen of the Medicat EMR system, used for scheduling patients. The column headings show the name of the provider and the row headings show the time slot for appointments. The green blocks are for dedicated for walk-ins and the purple blocks are for appointment patients. The orange and red blocks are scheduled for administrative purposes and breaks. The blue blocks are extra reservation slots. Students can schedule appointments at the SHC through the online website or telephone or by speaking directly to a front desk receptionist. Students can schedule appointments with any of the 6 providers at the SHC medical clinic based on their convenience and availability of appointment slots.

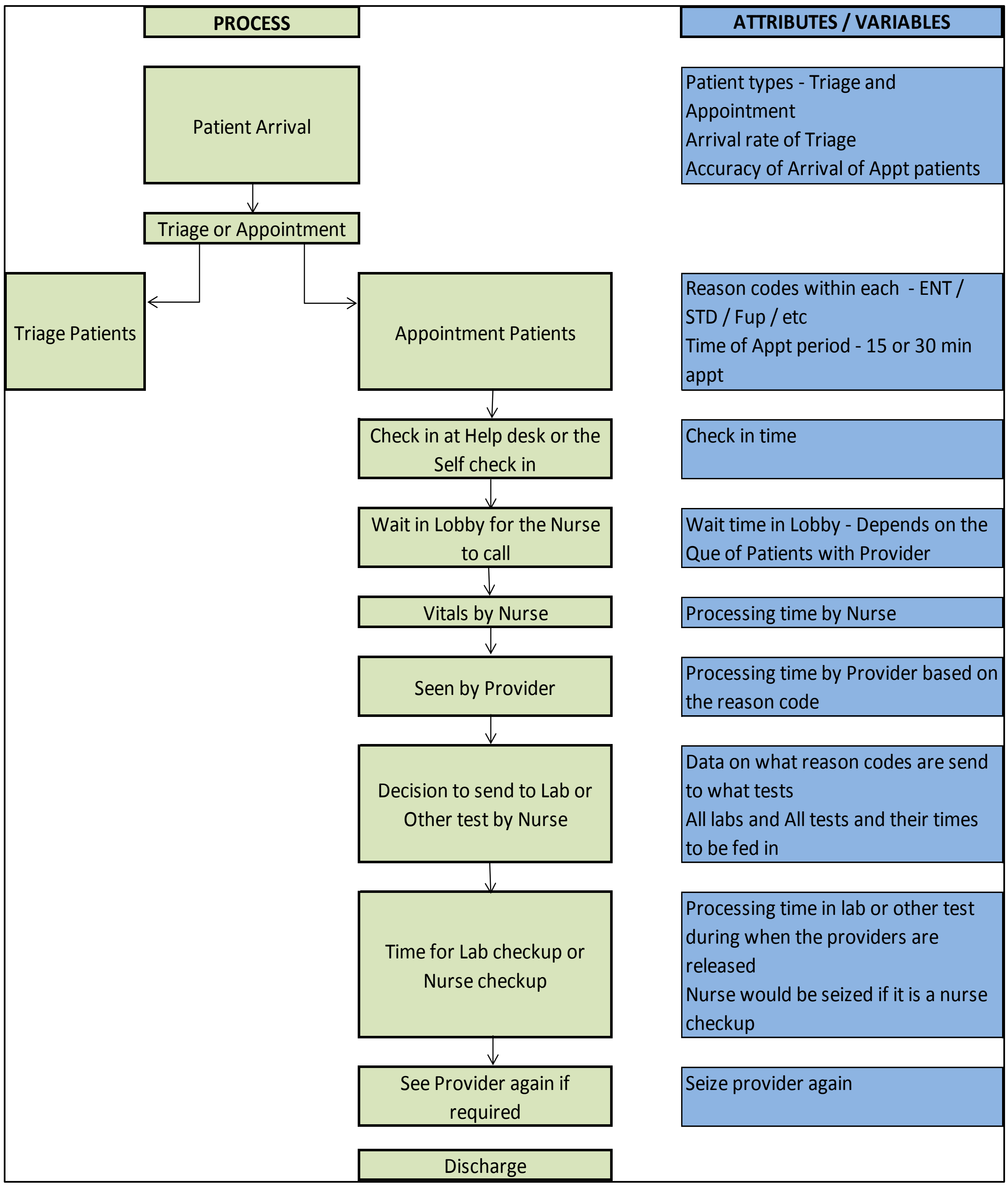

Figure 7: Process flow of patients at the LSU Student Health Center

Reset	Provider 1		Provider 2	
08:30 AM	Admin Block	----------	----------	----------
08:45 AM	----------	----------	----------	----------
09:00 AM	----------	----------	Admin Block	----------
09:15 AM	----------	----------	----------	----------
09:30 AM	[MCAbdomial]	----------	[PEother]	----------
09:45 AM	----------	----------	Medical Clinic Ap	----------
10:00 AM	[MCAnxiety]	----------	[MCRxRefill]	----------
10:15 AM	----------	----------	Medical Clinic Ap	----------
10:30 AM	[MCHEENT]	----------	[MCUndis15]	----------
10:45 AM	[MCRxRefill]	----------	[MCAnxiety]	----------
11:00 AM	[MCRxRefill]	----------	----------	----------
11:15 AM	[MCSkin]	----------	[MCGenital]	----------
11:30 AM	[MCHEENT]	----------	LUNCH Block	----------
11:45 AM	BLOCK Reservat	----------	----------	----------
12:00 PM	LUNCH Block	----------	----------	----------
12:15 PM	----------	----------	----------	----------
12:30 PM	----------	----------	[TRIAGE]	----------
12:45 PM	----------	----------	[TRIAGE]	[TRIAGE]
01:00 PM	[MCAnxiety]	----------	[TRIAGE]	BLOCK Reserva
01:15 PM	----------	----------	[TRIAGE]	[TRIAGE]
01:30 PM	[MCAbdomial]	----------	[TRIAGE]	BLOCK Reserva
01:45 PM	[MCVaginal]	----------	TRIAGE Reserv	----------
02:00 PM	----------	----------	[TRIAGE]	----------
02:15 PM	[MCAnxiety]	----------	[TRIAGE]	----------
02:30 PM	----------	----------	[TRIAGE]	----------
02:45 PM	[MCVaginal]	----------	[TRIAGE]	----------
03:00 PM	----------	----------	[TRIAGE]	----------
03:15 PM	[MCHEENT]	----------	TRIAGE Reserv	----------
03:30 PM	[MCSTDScrnF]	----------	[TRIAGE]	----------
03:45 PM	----------	----------	[TRIAGE]	----------
04:00 PM	[MCBodyInj]	----------	[TRIAGE]	----------
04:15 PM	Medical Clinic Ap	----------	TRIAGE Reserv	----------
04:30 PM	----------	----------	----------	----------
04:45 PM	BLOCK Reservat	----------	----------	----------
05:00 PM	Admin Block		Admin Block	

Figure 8: Appointment screen of Medicat EMR

4.1.1 Process flow of patients at the SHC

Appointments for TriageNur1

Appt Time	End Time	Pat...	Provider	Appt Note	Reason	Arrived	Ready	Admitted	Seen By...	Discharged
09:30 AM	09:45 AM	Wil...	TriageNur1	vomitting, sick for the last 3 ...	TRIAGE	09:28 AM	09:31 AM	09:39 AM	09:39 AM	09:39 AM
09:45 AM	10:00 AM	Me...	TriageNur1	congestion, cough	TRIAGE	09:44 AM	09:47 AM	09:54 AM	09:54 AM	09:54 AM
10:00 AM	10:15 AM	Sa...	TriageNur1	sinus	TRIAGE	09:52 AM	09:53 AM	10:09 AM	10:09 AM	10:09 AM
11:15 AM	11:30 AM	Wil...	TriageNur1	left knee problem	TRIAGE	11:10 AM	11:10 AM			

Figure 9: EHR screen with time stamps on the patient name in every step

The “Electronic Health Records” (EHR) screen, shown in Figure 9 is used by the nurses and providers for charting and recording the flow of patients in the SHC. Once the appointment is scheduled, students are required to arrive 10 minutes before the appointment time. Upon arrival, the students check-in using their ID card at one of the four self-check-in stations. The student’s name is marked as “Arrived” in the EHR screen when they swipe their ID card in the self-check-in station. The name is displayed in blue color when it’s marked as “Arrived”. When the patient completes the self-check-in process, the patient’s status is marked as “Ready”, which is indicated in pink color. The nurse calls the patient into one of the examination rooms for taking the vitals on seeing this status change. Every provider has a dedicated nurse for taking vitals. After taking the vitals, the nurse changes the patient’s status to “Admitted” in the EHR system, which changes the color from pink to purple. This color change is the indication for the provider that the patient is ready for examination. There are two examination rooms for every provider. Before starting the examination process, the provider changes the patient’s status as “Seen by provider”, which is indicated by orange color. After examination, the patient is directed to a lab if needed, otherwise the patient is discharged. In most cases, the provider sees the patient again after lab results. However there are some cases where the provider discharges the patient and the lab results are communicated later through e-mail or telephone. The provider changes the patient’s status to “Discharged”, after discharging the patient. The name is indicated in green color when the patient is discharged. After getting discharged, a patient may go to the pharmacy or accounts department before leaving the SHC. Since this does not affect the time of the provider or the wait time of the patient for the appointment, it is not considered in the Arena model.

Figure 10 shows the flow of patients inside the health center. The blue line indicates a case with a lab checkup and the red line indicates a case without a lab checkup.

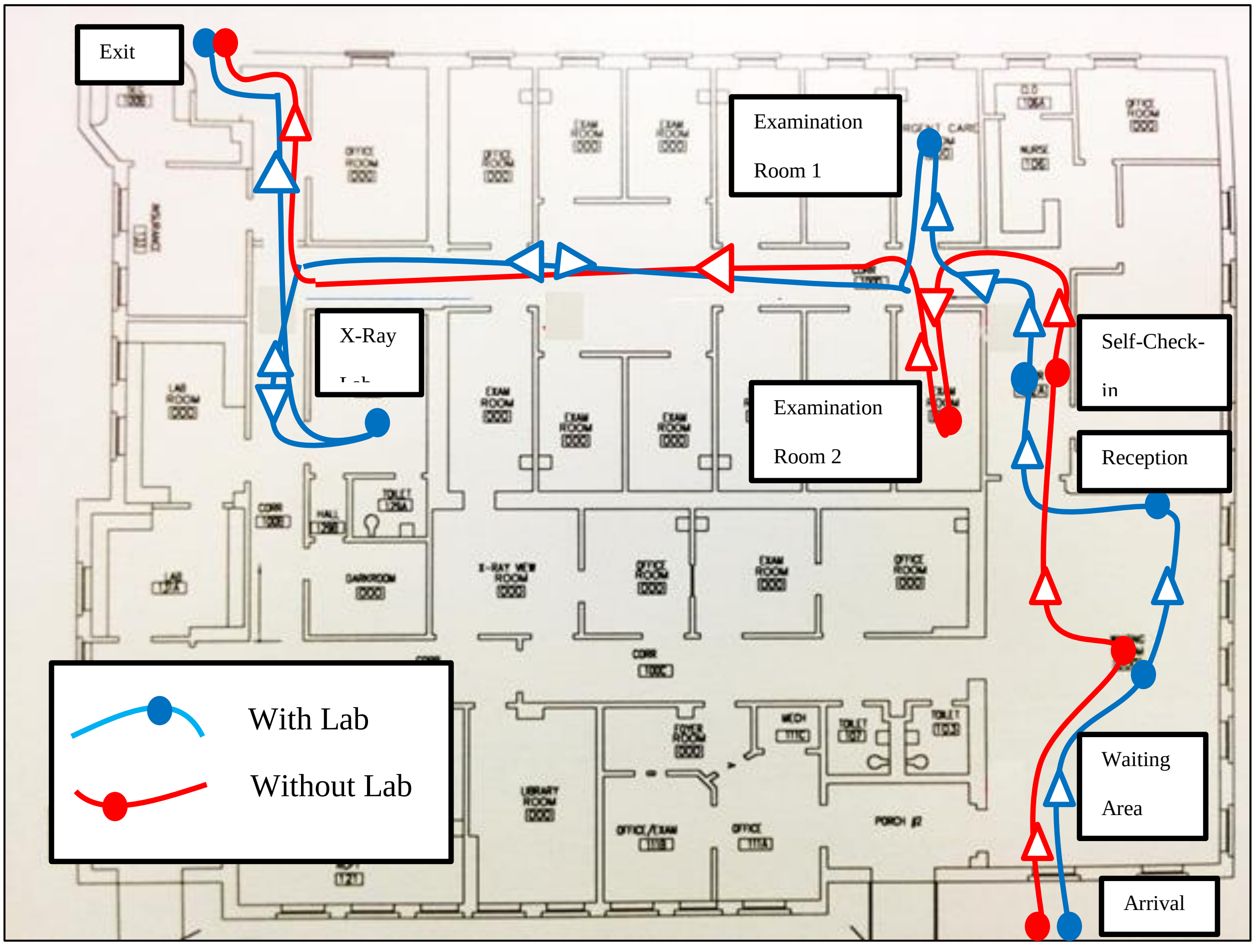

Figure 10: Spaghetti diagram of patient flow at the SHC

4.2 Data Collection

Critical variables required for modeling the process in Arena were identified from the process flow study. Data was collected for these variables by time studies through direct observation and using the past data from the EMR software. The time studies were done during the spring and fall semesters of 2014. The time data was analyzed using the "Arena Input Analyzer" software to create distributions for the simulation model. The input parameters that are considered for the model and their distributions are shown in Table 1. The line items in the table were verified with providers and clinicians. The graphs for the frequency distributions of input data are attached in Appendix A.

Table 1: Input parameters for Arena model

Sl.No	Data required for modelling	Measurement method	Value
1	Punctuality of arrival of the patients before 9:30	EMR software	96% - NORM(-6.3, 10.5), 4% - UNIF(28,130))
2	Punctuality of arrival of the patients after 9:30	EMR software	92% - Time+Norm(-10.3,10), 8% - 2)
3	No show-rate and unscheduled appointments	EMR software	14%
4	Number of self-check in counters	Observation	4
5	Service time at the self-check-in station	EMR software	GAMM(7.04, 0.241)
6	Number of nurses for each providers	Observation	1
7	Service time of the nurses	Observation	3 + 4 * BETA(1.85, 2.35)
8	Number of providers at a given time on a given day	EMR software	6
9	Schedule of providers on a given day considering lunch time and administrative times	EMR software	Shown in Figure 6
10	Service time of the providers for 15 min appointment without lab	Observation	9% - UNIF(5,12), 79% - TRIA(12, 15.1, 18.9), 12% - UNIF(19,24)
11	Service time of the providers for 15 min appointment with lab, before lab	Observation	5 + 5 * BETA(0.823, 0.68)
12	Service time of the providers for 15 min appointment with lab, after lab	Observation	5 + 5 * BETA(0.716, 0.615)
13	Percentage of 30 minute appointments	EMR software	6%
14	Service time of the providers for 30 min appointment	Observation	TRIA(24, 27, 33)
15	Percentage of patients routed to labs	Observation	6%
16	Service time of the labs	Observation	UNIF(14,26)

(Table 1 continued)

Sl.No	Data required for modelling	Measurement method	Value
17	Percentage of patients discharged by the nurse	Observation	3%
18	Service time of the nurse discharge	Observation	TRIA(2, 2.75, 5)

During the direct observation of the service times, the walk times of the nurses and providers to receive the patients were considered as a part of their service time. Hence this time was also accounted in the throughput times of the patient. The lab service times were calculated as the time of return from lab minus the time of departure to lab for the patients. Hence the walk times to and from the labs were also considered as a part of the lab service time.

The output parameters required to validate the model were also collected. The different output parameters that were required to validate the model are in Table 2. Data for the output parameters was collected by direct observation and using the EMR

Table 2: Output parameters for validation of the model

Sl.No	Output data for validation	Measurement Method
1	Throughput time of the patient	EMR software
2	Idle time of the provider	Observation
3	Startup Idle time of provider	EMR software
4	Overtime of the patient	Observation

4.3 Arena modelling

Arena simulation software from Rockwell Automation was used to create the virtual process model of the SHC. The process was created using the ‘Basic Process’ and ‘Advanced Process’ modules in Arena. The model consists of two main parts: Control block, shown in Figure 11 and Main block, shown in Figure 12. The Main block contains the process of the medical clinic from arrival to exit of the patient. The Control block has control loops to record the idle times of providers.

The processes for six providers were constructed in the main block. Five providers work in 8hr shifts while one provider works in 10 hour shift at the SHC. Hence the model was constructed with a run time of 11.5 hours with 1 hour assigned before the start of the morning session and 0.5 hours assigned after the end of the shift. The extra times are allocated to capture early arrivals and late discharges. The administrative times for providers at the beginning and the end of each shift were not considered in the model as they don't have any scheduled patient arrivals during that time. A lunch time of 1 hour was allocated to each provider in between the shift as per the SHC's schedule.

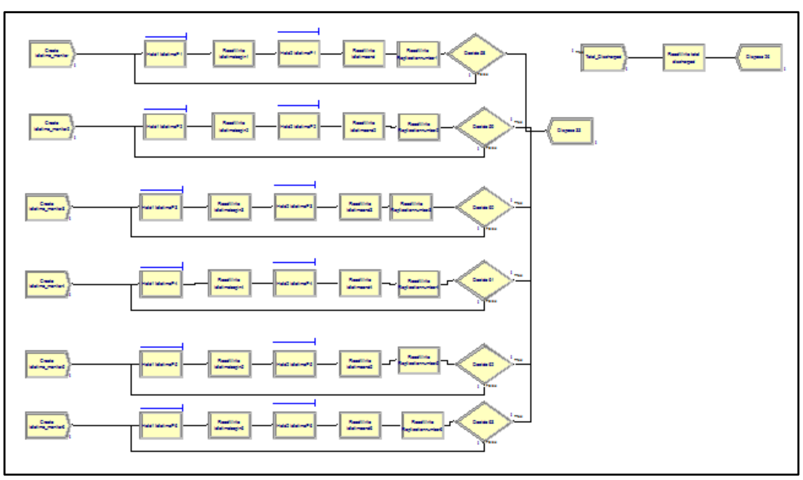

Figure 11: Control block of the Arena Model

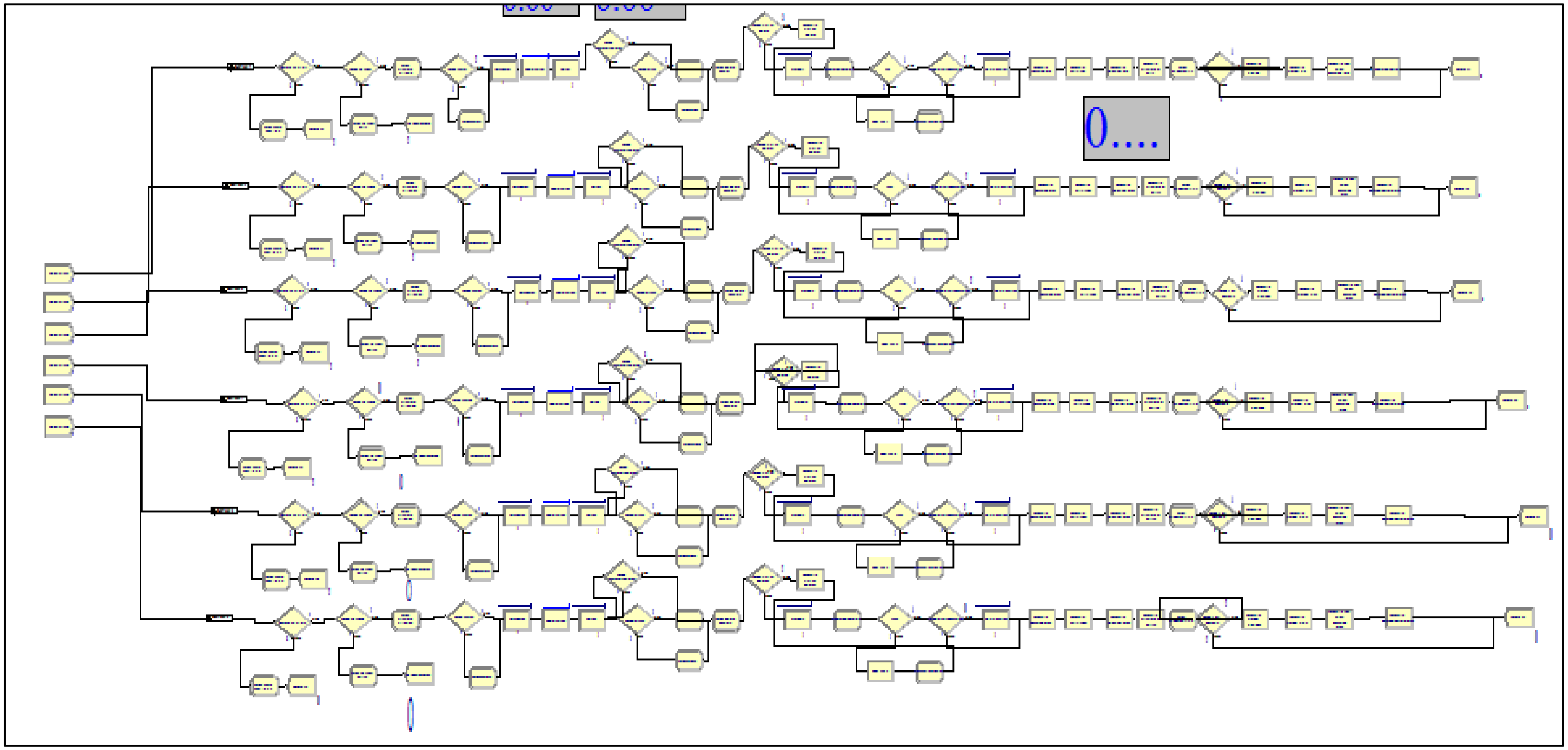

Figure 12: Main block of the Arena Model

4.3.1 Arena Modelling - Main Block

The Main block has the process for six providers which consist of patient arrivals, self-check-in process, nurse process, provider examination process, lab process and discharge process. The patient arrival process in the model is shown in Figure 13. A “Create” block was used to create 30 entities at time 0 in the 8hr shift and 38 entities for the 10 hour shift providers. The entities are then routed to a “Submodel” in which they are assigned specific appointment times with the punctuality error. The process in the Submodel is shown in Figure 14. Inside the Submodel, the entity is routed to a “Decide” block. The 30 entities are routed to different “Delay” blocks which assign the punctuality for the patient as per the distribution. The entities are also assigned the entity type with a unique identification number for the shift. After exiting the “Submodel” process, the entity goes to a Decide block which removes the current entity if the previous appointment was a 30 minute appointment. This is done to replicate the real situation where another patient cannot schedule an appointment immediately after the 30 minute appointment. After that the entity goes to another “Decide” block, which removes the entities for no shows and unscheduled appointments. The third “Decide” block routes entities to Assign blocks that assign attributes to them as 30 minute appointments or 15 minute appointments. After this process, entities are routed to the “Self-check-in” process.

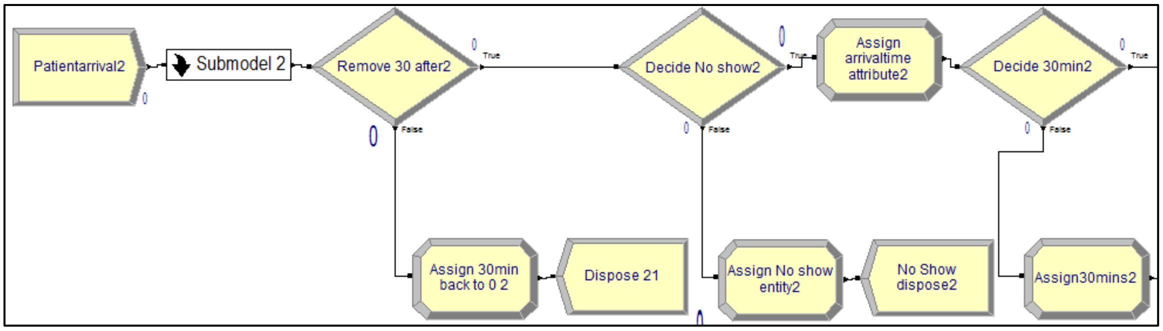

Figure 13: Patient arrival process

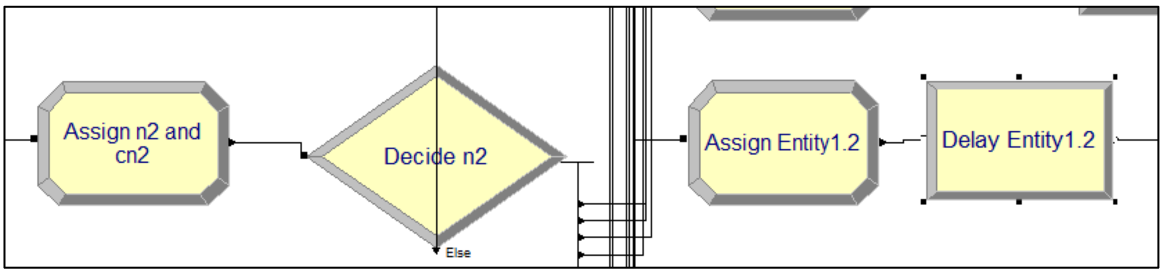

Figure 14: Submodel Process of assigning the appointment time and unpunctuality for patients

After the arrival process, the entity is routed to the “Selfcheck-in” process block, shown in Figure 15. Here the entity seizes one of the four “Check-in” resources and releases it after the self-check-in process. After self-check-in, the entity is routed to a “Hold” block that holds the entity until the condition “(NQ(Provider.Queue) <= 1) && (Nurse.WIP < 1)” is satisfied. This condition is necessary to ensure that the provider queue is empty and the nurse is not attending to another patient. Once the condition is satisfied, the patient moves into the “Nurse” process block, where it seizes the nurse resource for the particular provider. After the nurse process, the entity is routed to a Decide block to figure if it’s a 30 minute or 15 minute appointment. If the entity has a 30 minute appointment, it is routed to the provider. If the entity has a 15 minute appointment, then it is routed to another decide block, “DecideforLab”. Here 6% of the patients are routed to an “Assign” block which assigns an attribute for lab visits. The assignment to lab is done by assigning the attribute “Labvisit” to 0 or 1. If “Labvisit” is assigned to 0, the entity does not go through the lab process and if “Labvisit” is assigned to 1, the entity goes through the lab process. The service time of the provider is also assigned in this step. The service times are provided in the Table 1.

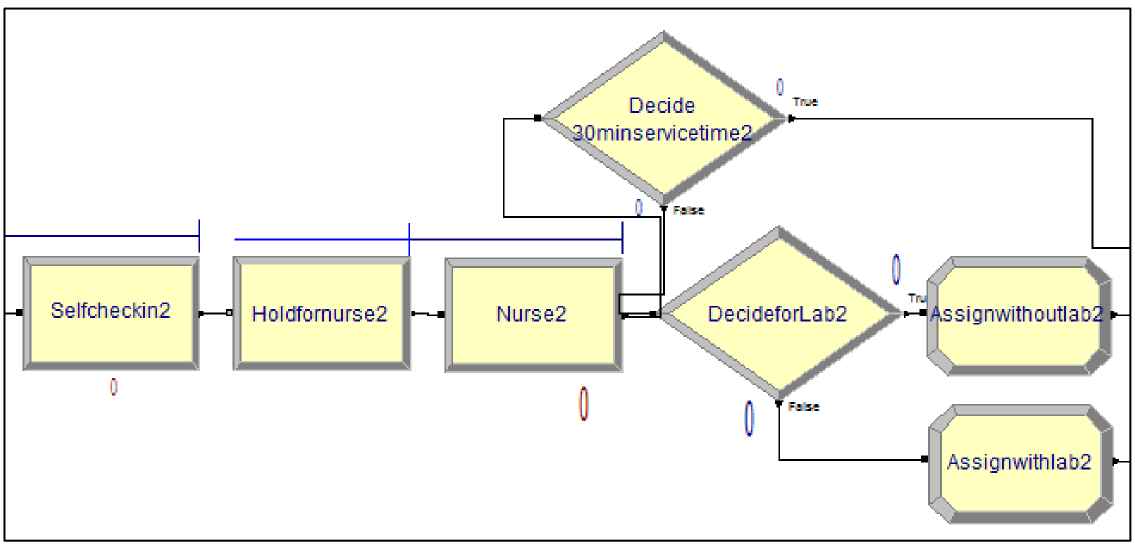

Figure 15: Check-in and Nurse Process

After the service time is assigned to the entity, the entity enters the “Assign Idletime counter” block, shown in Figure 16. It records a variable “Idletimecounter”, which is used in later stages to record the idletime statistics of the provider. The entity is then routed to a Decide block, “Decide startup idletime” to decide if it is the first patient for the provider. If it is the first patient for the provider, then it is routed to a “ReadWrite” block to record the current time using “TNOW” statement. This gives the time at which the first patient is available for the provider, from which the startup idle time is calculated as “TNOW-60”. The next block is a process block for the “Provider” process. Here the entity seizes the provider resource for a time equal to the attribute “Servicetime”. After the provider process is over, the entity enters an “Assign” block, “Assign_Provider_over_time” which assigns an attribute “Overtime” to TNOW. Even though it assigned for every entity, this attribute is recorded only for the last entity to obtain the overtime of the particular provider for the shift.

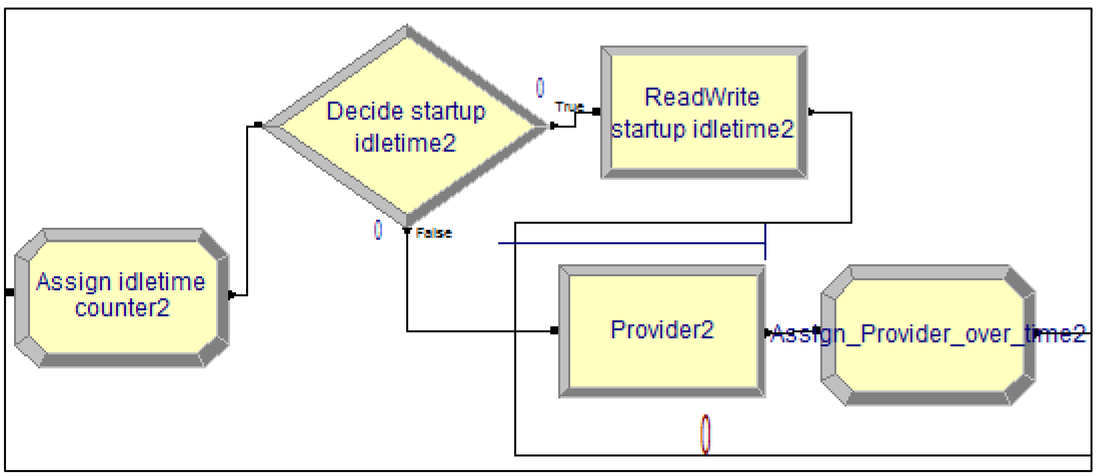

Figure 16: Provider process

After the provider process, the entity enters the lab process, shown in Figure 17. A “Decide” block checks if the “Labvisit” attribute is equal to 1 and sends the entity to a “Delay” block which delays the entity for “UNIF(14,26)” minutes to recreate the time for lab. If the attribute “Labvisit” is equal to 0, then the entity bypasses the lab process. After the lab process, the entity is sent back to the provider process with a new service time and the “Labvisit” attribute assigned to 0 so the entity can bypass the lab process next time. After the lab process, the entity enters a Decide block which routes 3% of the entities back to the nurse for discharge. This is done to replicate the real scenario, where some patients are discharged by the nurse.

After the lab process, the entities are routed to a series of “ReadWrite” blocks to record the output parameters, shown in Figure 18. The “ReadWrite Dischargetime” records the discharge time of the entity using “TNOW” statement. The “ReadWrite Entitytype” writes the unique number of the entity. “ReadWrite Patientwaittime” block writes the wait time of the entity in the system. The time other than that spent with nurse, provider, lab and self-check-in process is considered as patient wait time. The “ReadWrite arrivaltime of entity” block records the arrival time of the entity into the system which is later used in calculating the throughput time. In the next block, “Assign lastelement”, a variable assigned to identify the last entity in the system.

After the ReadWrite blocks, the entity then arrives at a Decide block “Decide if last element”, shown in Figure 19, which checks if it is the last entity in the system. The decision is made by checking whether the count of all the entities that have exited from the system is equal to 29 for 8hr shift providers and 37 for 10 hour shift provider. If the condition is satisfied, the entity goes to the next ReadWrite block, otherwise it is routed to the Dispose block. The first Readwrite block “ReadWrite provider utilization” records the utilization of the provider. The second Readwrite block, “ReadWrite provider util” records the replication number. The third ReadWrite block “ReadWrite Final patient discharge time” records the discharge time of the last entity using “TNOW” statement. This discharge time provides the exit time of the last patient from the system. The final ReadWrite block, “ReadWrite _Provider_Over_time” records the attribute “Overtime”, which gives the time when the provider released the last patient. “Overtime” minus the scheduled completion time of the provider gives the overtime of the provider for the shift.

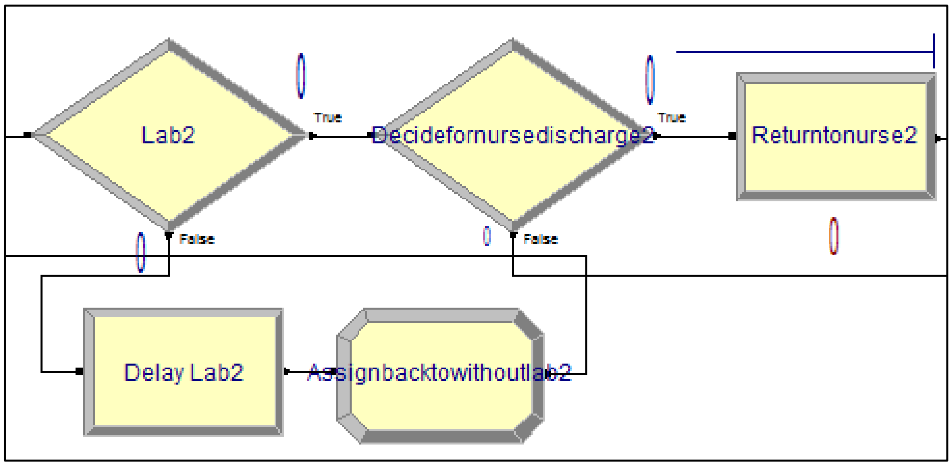

Figure 17: Lab Process

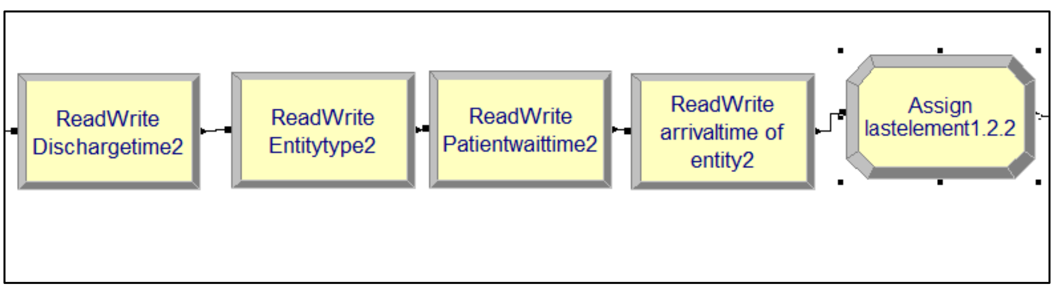

Figure 18: Read Write Processes

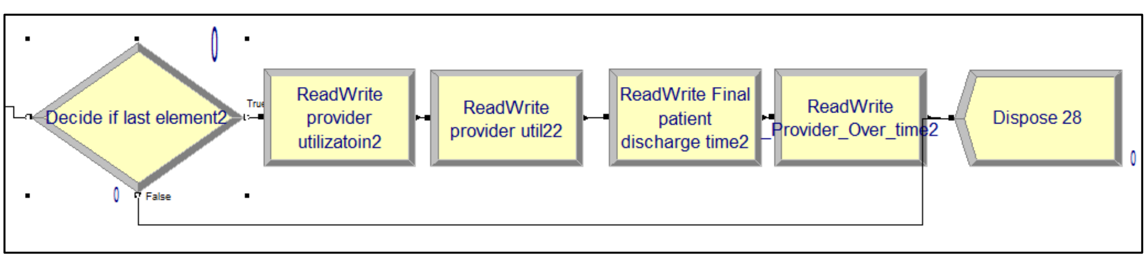

Figure 19: Recording parameters for Last entity and dispose

		Individual Block Rule		Bailey Rule		3 Bailey Rule		2-at-a-time	
Hours	Minute	8Hr	10Hr	8Hr	10Hr	8Hr	10Hr	8Hr	10Hr
		Shift Begin	Shift Begin	Shift Begin	Shift Begin	Shift Begin	Shift Begin	Shift Begin	Shift Begin
0	0	**1**	**1**	**2**	**2**	**3**	**3**	**2**	**2**
0.25	15	1	1	1	1	1	1		
0.5	30	1	1	1	1	1	1	2	2
0.75	45	1	1	1	1	1	1		
1	60	1	1	1	1	1	1	2	2
1.25	75	1	1	1	1	1	1		
1.5	90	1	1	1	1	1	1	2	2
1.75	105	1	1	1	1	1	1		
2	120	1	1	1	1	1	1	2	2
2.25	135	1	1	1	1	1	1		
2.5	150	1	1	1	1	1	1	2	2
2.75	165	1	1	1	1	1	1		
3	180	1	1	1	1	1	1	2	2
3.25	195	1	1	1	1	1	1		
3.5	210	1	1	1	1		1	2	2
3.75	225	1	1		1				
4	240	Lunch	1	Lunch		Lunch		Lunch	1
4.25	255	Lunch	Lunch	Lunch	Lunch	Lunch	Lunch	Lunch	Lunch
4.5	270	Lunch	Lunch	Lunch	Lunch	Lunch	Lunch	Lunch	Lunch
4.75	285	Lunch	Lunch	Lunch	Lunch	Lunch	Lunch	Lunch	Lunch
5	300	1	Lunch	2	Lunch	3	Lunch	2	Lunch
5.25	315	1	Lunch	1	Lunch	1	Lunch		Lunch
5.5	330	1	1	1	2	1	3	2	2
5.75	345	1	1	1	1	1	1		
6	360	1	1	1	1	1	1	2	2
6.25	375	1	1	1	1	1	1		
6.5	390	1	1	1	1	1	1	2	2
6.75	405	1	1	1	1	1	1		
7	420	1	1	1	1		1	2	2
7.25	435	1	1		1		1		
7.5	450	Shift End	1	Shift End	1	Shift End	1	Shift End	2
7.75	465		1		1		1		
8	480		1		1		1		2
8.25	495		1		1		1		
8.5	510		1		1		1		2
8.75	525		1		1		1		
9	540		1		1				2
9.25	555		1						
9.5	570		Shift End		Shift End		Shift End		Shift End
9.75	585								
10	600								
10.25	615								
10.5	630								
10.75	645								
11	660								
11.25	675								

Figure 20: Appointment systems modeled in Arena

4.3.2 Arena Modelling - Control Block

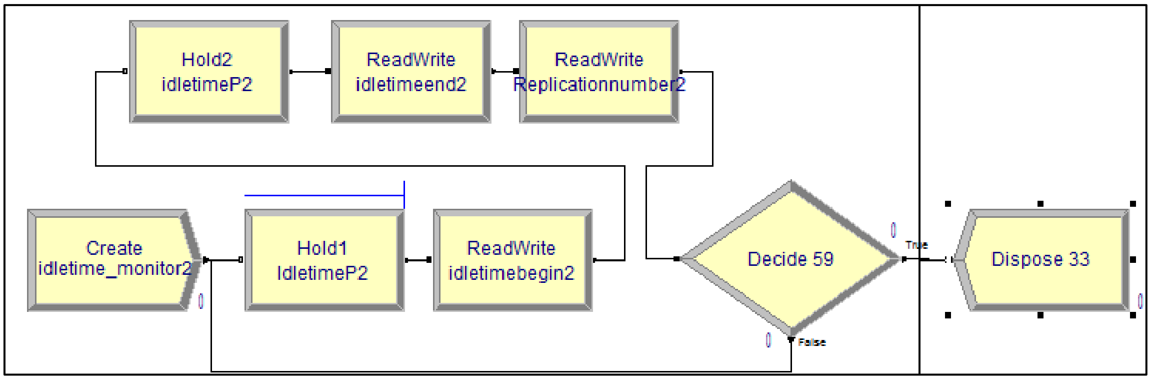

Figure 21: Control Block process for recording idle time

The control block consists of different loops with ReadWrite blocks to record the idle time of the providers, as shown in Figure 21. A control entity is created for every provider using the “Create Idletime_monitor” block at time 0. The entity goes to a “Hold” block, “Hold1 IdletimeP”, where it waits for the situation until the provider resource is idle. If the provider resource becomes idle, the entity moves on to the “ReadWrite Idletimebegin” block which records the current time using “TNOW” statement. This gives the start time of the idle period for the provider. The entity then moves to another hold block, “Hold2 IdletimeP” which scans if the provider resource’s status changes to busy. If the condition is satisfied, the entity is released to the next block “ReadWrite Idletimeend”, which records the current time using “TNOW” statement. The difference between the two TNOW times at the start and end gives the idle time of the provider. The entity is routed to “ReadWrite Replicationnumber” to write the replication number against the idle time in an excel file. This replication number is used to compile the idle time of the provider per replication. The Decide block then checks for the end of the shift and routes the entity to a dispose block. If the shift is not over, then the entity is routed into the same loop and continues recording the idle times of the provider until the end of the run.

4.4 Comparison of Schedules

The performance parameters were recorded in MS-Excel files for each provider, which were then compiled under different schedules and the shift timings. The performance of the four appointment systems was evaluated by comparing the Patient throughput time, Patient wait time, Provider Idle time, Provider startup idle time, Provider Overtime and Provider Utilization. For each of the dependent variables, Kruskal-Wallis test was performed to test for difference between the four schedules. Post-hoc analysis was done using Tukey-Kramer pairwise comparison to further understand how the schedules differed with each other.

4.5 Kepner-Tregoe (KT) analysis and Test run

A KT analysis was performed in order to facilitate the decision making process of the schedule selection. KT analysis involves weighing important criteria to decide between alternatives (Kepner et al., 2013). A weight is given for each criterion and the alternatives are scored based on the performance. This score is then multiplied with the weights to get a weighted score. The weighted scores of different criteria are added up for every alternative. The alternative with the highest total is usually chosen, however in this case the alternative with the lowest total is chosen as the patient and provider times are used as scores and it is desirable to have the lowest times.

The performance parameters considered for the analysis were: (1) patient throughput time, (2) patient wait time, (3) provider idle time, (4) provider startup idle time and (5) provider overtime. The provider utilization was not considered as it is just another measure of the provider idle time. A survey was conducted with the providers to decide the weights for the criteria in the KT analysis. The average of the weights for each criterion from the surveys was calculated and used as the weights for the analysis. The best schedule from the KT analysis was then tested in the SHC with one provider for ten days and the results were compared with the past values for the same provider.

CHAPTER 5: RESULTS

After creating the Arena model of the SHC, the performance measures were collected in Excel files. In order to check whether the simulation model is a close representation of the real setting, the model was first validated by comparing the output parameters of the individual block rule with the real values from clinic. The results of the validation are shown in section 5.1. After validation the different schedules were compared with respect to the six performance measures, namely the patient throughput time, patient wait time, provider idle time, provider startup idle time, provider overtime and provider utilization. The comparisons of schedules are shown in the section 5.2. The decision analysis to determine the best rule and the results of the test run of the Bailey rule are shown in section 5.3.

5.1 Validation of the individual block rule

The Arena model was first validated by comparing the output of the individual block model with the actual output parameters from the real setting. The output parameters analyzed were: provider idle time, provider startup idle time, provider overtime and patient throughput time. The Mann-Whitney test was used for the statistical comparison between the two scenarios.

Table 3 provides *p*-values from the comparison for both scenarios and Figure 22 shows the comparison of means and standard deviations of the model. The provider idle time and provider startup idle time predicted by the model are 10% more than that of the real setting. The provider overtime predicted by the model for the individual block rule is higher by 5%. However, the *p* -values of provider idle time, provider startup idle time and provider overtime are greater than 0.05, which shows that there is no significant difference between the real setting and arena model. Even though the provider over time and provider startup idle times are different by 5% and 10% respectively, the actual difference in means is less than 1 minute. The provider idle time of the model is higher by 5 minutes, which may be due to fact that some provider disturbances by clinicians or other providers and their activities like hand wash were not considered as a part of idle time in the real setting. Not considering these activates might be the reason for the difference in provider idle times. However no significant difference is observed between the idle times of the model and real setting.

The p -value for the patient throughput time was less than 0.05, which meant that there was a statistically significant difference. Upon further examination, it was observed that the median of the model is only higher by 2.8 minutes. Even though it was statistically significant, it was not considered practically significant for this study. Also this difference can be attributed to two deviations in the capturing of the throughput time in the real setting. (1) The EMR software calculates the throughput time by subtracting the discharge and arrival time of patients. Although the patient is discharged in the system, there are many cases where the patient goes back to the nurse for information on pharmacy and insurance related issues and then exits the system. Thus the patient is still in the system even though the EMR shows that they left the system. This results in early discharges in the system even though the patient is still in the process and can contribute for lower values. For this study, the combined time of patient examination and charting is considered as service time, which adds to the patient throughput time, so (2) there are cases where the provider discharges the patient before completing the EMR notes and may go back to completing the notes at a later time. Such cases can again attribute for under reporting of throughput time of the patient in the real setting. So while the difference between the model and the actual data are different, the practical significance is small and thus the model can be assumed to be representative of the actual system.

Table 3: Validation of the Arena Model

	Mean		Percentage Difference	Standard Deviation		*p*-Value
	Real	Model		Real	Model	
Provider idle time	45.73	50.50	10%	27.82	28.39	0.4505
Provider Startup idle time	9.49	10.41	10%	10.67	10.79	0.5356
Provider Overtime	15.42	16.18	5%	17.01	17.77	0.8784
Patient Throughput time	38.9	39.56	2%	23.76	19.97	<.0001

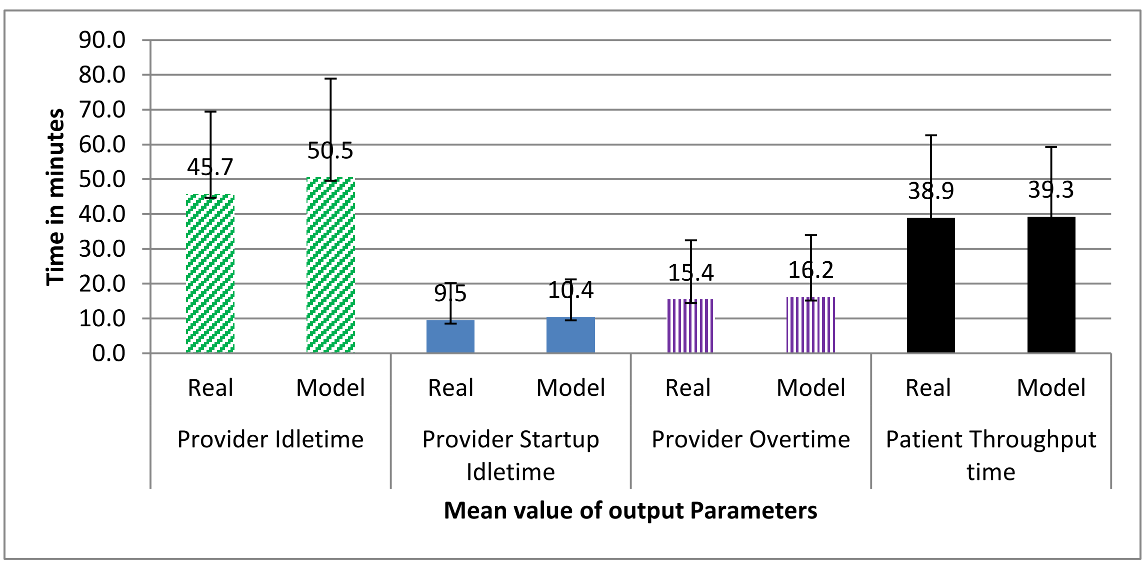

Figure 22: Comparison of means and standard deviations of output parameters

5.2 Comparison of Schedules

The comparison of the schedule methods was done for each of the performance parameters namely the patient throughput time, patient wait time, provider idle time, provider startup idle time, provider overtime and provider utilization. The statistical analysis of the schedules was done using the Kruskal Wallis test. Tukey-Kramer test was performed for the post hoc analysis of the different schedules. All statistical analysis was done using SAS 9.4 statistical software. This analysis was performed in consultation with the LSU Experimental Statistic department. Each performance measures will be discussed and then a holistic evaluation will be completed to determine which scheduling method results in the best overall system for both patients and providers.

5.2.1 Patient throughput time

The total time spent by the patient in the clinic is considered as throughput time. It was calculated by subtracting the discharge time from the arrival time of an entity. Figure 23 shows the comparison of means of throughput time for the four schedules. The individual block rule resulted in the least throughput time for both the 8hr and 10hr shift providers and the 3-Bailey rule had the highest throughput time. Table 4 shows the comparison of the means, medians and standard deviations of the throughput times of the four schedules. Table 5 shows the results of the Tukey Kramer test from SAS. A *p*-value less than 0.05 signifies that the schedules are significantly different.

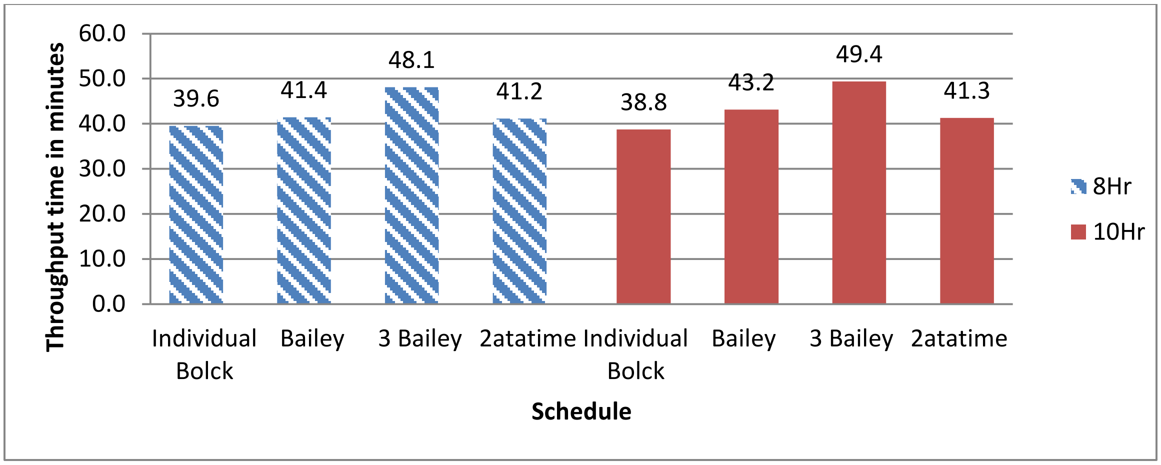

Figure 23: Comparison of patient throughput time

Table 4: Comparison of patient throughput time

Throughput time	**Mean**		**Median**		**Standard Deviation**	
	8hr	**10hr**	**8hr**	**10hr**	**8hr**	**10hr**
Individual Block	39.6	38.8	34.9	36.1	20.4	16.4
Bailey	41.4	43.2	38.1	39.9	18.6	19.9
3 Bailey	48.1	49.4	45.5	46.4	20.1	21.5
2atatime	41.2	41.3	37.4	38.3	19.5	18.9

Table 5: Result of Tukey-Kramer test for patient throughput time

Least Squares Means for effect Schedule
Pr > |t| for H0: LSMean(i)=LSMean(j)
Dependent Variable: Time

i/j	**Individual block 8hr**	**Individual block 10hr**	**Bailey 8hr**	**Bailey 10hr**	**3-Bailey 8hr**	**3-Bailey 10hr**	**Two-at-a-time 8hr**	**Two-at-a-time 10hr**
Individual block 8hr		0.8683	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Individual block 10hr	0.8683		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Bailey 8hr	<.0001	<.0001		0.0005	<.0001	<.0001	0.0692	0.9998
Bailey 10hr	<.0001	<.0001	0.0005		<.0001	<.0001	<.0001	0.0044
3-Bailey 8hr	<.0001	<.0001	<.0001	<.0001		0.5213	<.0001	<.0001
3-Bailey 10hr	<.0001	<.0001	<.0001	<.0001	0.5213		<.0001	<.0001
Two-at-a-time 8hr	<.0001	<.0001	0.0692	<.0001	<.0001	<.0001		0.8537
Two-at-a-time 10hr	<.0001	<.0001	0.9998	0.0044	<.0001	<.0001	0.8537	

Table 6: Tukey Kramer grouping of schedules for patient throughput times

Obs	Schedule	Estimate	Standard Error	Letter Group
1	3-Bailey 10hr	32978	293	A
2	3-Bailey 8 hr	32340	148.26	A
3	Bailey 10 hr	27785	294.18	B
4	Bailey 8hr	26376	148.22	C
5	Two-at-a-time 10 hr	26228	293.37	C
6	Two-at-a-time 8 hr	25765	147.9	C
7	Individual Block 10 hr	24119	295.6	D
8	Individual Block 8 hr	23666	144.53	D

5.2.2 Patient wait time

The time, spent by the patient other than the time with the nurse, provider, lab and the self-check-in process, is counted as wait time. The total wait times of the entity in the system was added up and considered as the patient wait time. Figure 24 shows the comparison of means of patient wait time for the four schedules. The individual block rule had the least patient wait time for both the 8hr and 10hr shift providers. The 3-Bailey rule had the highest patient wait time. Table 7 provides the mean, median and standard deviation values of the patient wait times for the different schedules. Table 8 shows the results of the Tukey Kramer test from SAS. A p-value less than 0.05 shows that schedules are significantly different.

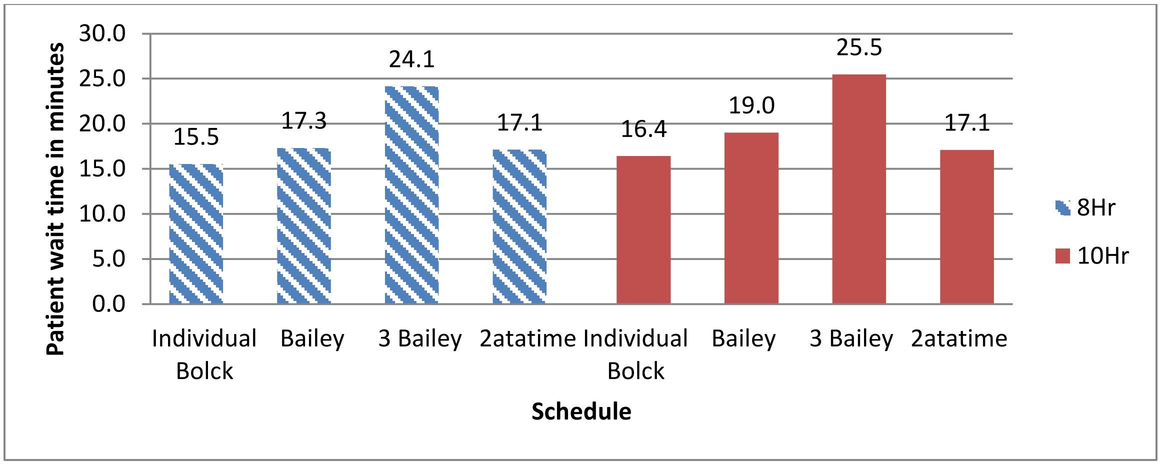

Figure 24: Comparison of patient wait time

Table 7: Comparison of patient wait time

Wait time	Mean		Median		Standard Deviation	
	8hr	10hr	8hr	10hr	8hr	10hr
Individual Block	15.5	16.4	11.3	12.7	18.3	18.3
Bailey	17.3	19.0	14.6	15.6	16.3	17.9
3 Bailey	24.1	25.5	21.8	22.7	18.1	19.4
2atatime	17.1	17.1	13.7	14.6	17.5	16.6

Table 8: Result of Tukey-Kramer test for patient wait time

Least Squares Means for effect Schedule Pr > |t| for H0: LSMean(i)=LSMean(j) Dependent Variable: Time								
i/j	Individual block 8hr	Individual block 10hr	Bailey 8hr	Bailey 10hr	3-Bailey 8hr	3-Bailey 10hr	Two-at-a-time 8hr	Two-at-a-time 10hr
Individual block 8hr		0.0041	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Individual block 10hr	0.0041		<.0001	<.0001	<.0001	<.0001	0.0209	0.0053
Bailey 8hr	<.0001	<.0001		0.0005	<.0001	<.0001	0.0121	0.9898
Bailey 10hr	<.0001	<.0001	0.0005		<.0001	<.0001	<.0001	0.0012
3-Bailey 8hr	<.0001	<.0001	<.0001	<.0001		0.4	<.0001	<.0001
3-Bailey 10hr	<.0001	<.0001	<.0001	<.0001	0.4		<.0001	<.0001
Two-at-a-time 8hr	<.0001	0.0209	0.0121	<.0001	<.0001	<.0001		0.876
Two-at-a-time 10hr	<.0001	0.0053	0.9898	0.0012	<.0001	<.0001	0.876	

Table 9: Tukey Kramer grouping of schedules for patient wait times

Obs	Schedule	Estimate	Standard Error	Letter Group
1	3-Bailey 10hr	33590	291.5	A
2	3-Bailey 8 hr	32896	147.34	A
3	Bailey 10 hr	27729	292.67	B
4	Bailey 8hr	26328	147.46	C
5	Two-at-a-time 10 hr	26048	291.87	CD
6	Two-at-a-time 8 hr	25604	147.14	D
7	Individual Block 10 hr	24521	291.98	E
8	Individual Block 8 hr	23295	143.79	F

5.2.3 Provider idle time

Any time when the provider resource is not busy is considered as the provider idle time. This time was calculated using the control loop in the Arena model. An entity scanned for the utilization of the provider resource and recorded all idle times the resource experienced during the run. Figure 25 shows the comparison of means of provider idle time for the four schedules. The 3 Bailey schedule had the least provider idle time for both the 8hr and 10hr shift providers. The individual block rule had the highest provider idle time. Table 10 shows the comparison of the means, medians and standard deviations of the provider idle time for the four schedules. Table 11 shows the results of the Tukey Kramer test from SAS. A *p*-value less than 0.05 shows that schedules are significantly different.

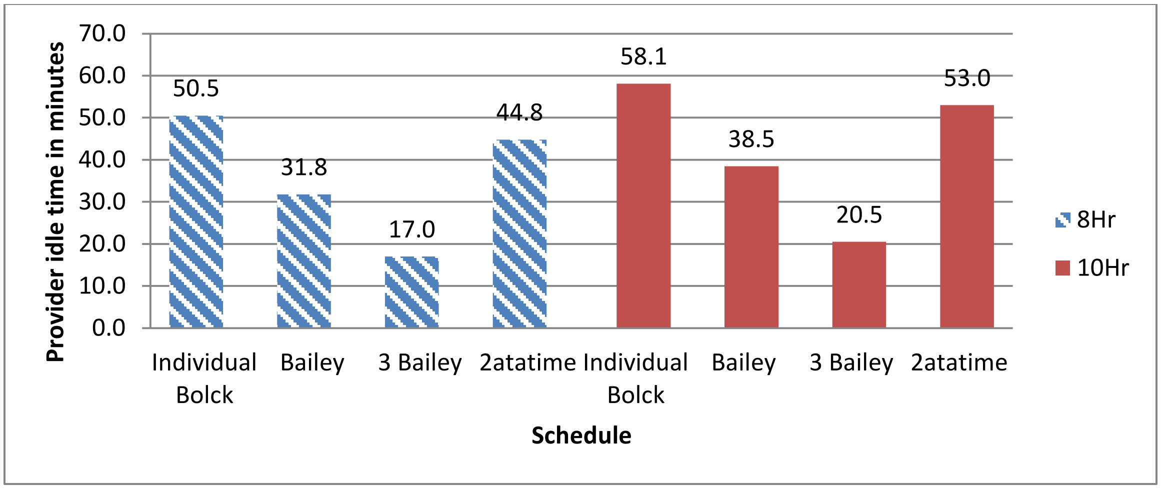

Figure 25: Comparison of means of provider idle time

Table 10: Comparison of provider idle time

Provider Idle time	Mean		Median		Standard Deviation	
	8hr	10hr	8hr	10hr	8hr	10hr
Individual Block	50.5	58.1	48.7	56.4	28.4	25.1
Bailey	31.8	38.5	28.9	35.6	21.9	26.4
3 Bailey	17.0	20.5	11.6	18.4	19.2	16.4
2atatime	44.8	53.0	40.9	52.1	28.3	30.4

Table 11: Result of Tukey-Kramer pairwise comparison of provider idle time

Least Squares Means for effect Schedule Pr > |t| for H0: LSMean(i)=LSMean(j) Dependent Variable: Time								
i/j	Individual block 8hr	Individual block 10hr	Bailey 8hr	Bailey 10hr	3-Bailey 8hr	3-Bailey 10hr	Two-at-a-time 8hr	Two-at-a-time 10hr
Individual block 8hr		0.0597	<.0001	0.0004	<.0001	<.0001	0.0079	0.9995
Individual block 10hr	0.0597		<.0001	<.0001	<.0001	<.0001	<.0001	0.5647
Bailey 8hr	<.0001	<.0001		0.2604	<.0001	0.0001	<.0001	<.0001
Bailey 10hr	0.0004	<.0001	0.2604		<.0001	<.0001	0.3282	0.0045
3-Bailey 8hr	<.0001	<.0001	<.0001	<.0001		0.54	<.0001	<.0001
3-Bailey 10hr	<.0001	<.0001	0.0001	<.0001	0.54		<.0001	<.0001
Two-at-a-time 8hr	0.0079	<.0001	<.0001	0.3282	<.0001	<.0001		0.1583
Two-at-a-time 10hr	0.9995	0.5647	<.0001	0.0045	<.0001	<.0001	0.1583	

Table 12: Tukey Kramer grouping for provider idle time

Obs	Schedule	Estimate	Standard Error	Letter Group
1	Individual Block 10 hr	1659.36	57.6274	A
2	Two-at-a-time 10 hr	1505.34	58.2125	AB
3	Individual Block 8 hr	1471.71	25.7976	A
4	Two-at-a-time 8 hr	1339.91	26.0069	BC
5	Bailey 10 hr	1197.71	57.9177	CD
6	Bailey 8hr	1047.31	26.4135	D
7	3-Bailey 10hr	739.43	62.1412	E
8	3-Bailey 8 hr	609.73	26.8689	E

5.2.4 Provider Startup idle time

The startup idle time is calculated as "Examination start time of first patient" minus the "Scheduled start time for the provider". The examination start time of the first patient for every provider was recorded by the Arena software in MS-Excel files for every run. This was subtracted from the shift start time to calculate the provider startup idle time. Figure 26 shows the comparison of means of provider startup idle time for the four schedules. The 3 Bailey schedule had the least provider startup idle time for both the 8hr and 10hr shift providers and the individual block rule had the highest provider startup idle time. Table 13 shows the comparison of the means, medians and standard deviation of the provider startup idle times for the four schedules. Table 14 shows the results of the Tukey Kramer test from SAS. A *p*-value less than 0.05 shows that schedules are significantly different.

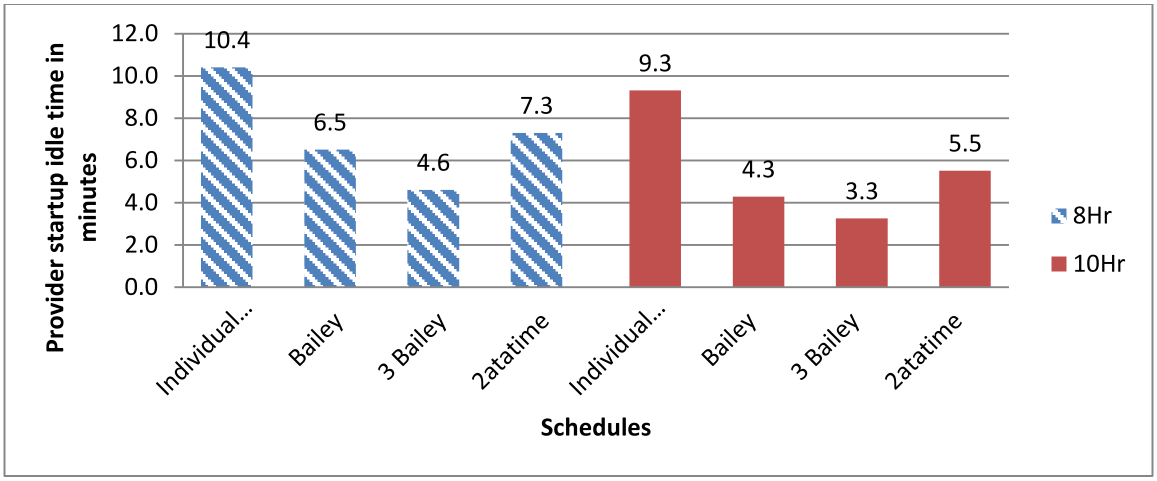

Figure 26: Comparison of means of provider startup idle time

Table 13: Comparison of provider startup idle time

Provider Startup Idle time	Mean		Median		Standard Deviation	
	8hr	10hr	8hr	10hr	8hr	10hr
Individual Block	10.4	9.3	7.1	5.5	10.8	9.3
Bailey	6.5	4.3	4.4	3.8	7.9	5.3
3 Bailey	4.6	3.3	3.8	3.8	5.7	3.8
2atatime	7.3	5.5	4.7	4.2	8.7	7.6

Table 14: Result of Tukey-Kramer pairwise comparison for provider startup idle time

Least Squares Means for effect Schedule Pr > |t| for H0: LSMean(i)=LSMean(j) Dependent Variable: Time								
i/j	Individual block 8hr	Individual block 10hr	Bailey 8hr	Bailey 10hr	3-Bailey 8hr	3-Bailey 10hr	Two-at-a-time 8hr	Two-at-a-time 10hr
Individual block 8hr		0.7207	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Individual block 10hr	0.7207		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Bailey 8hr	<.0001	<.0001		0.1014	0.0005	0.0002	0.6168	0.8939
Bailey 10hr	<.0001	<.0001	0.1014		1	0.8792	0.0034	0.9499
3-Bailey 8hr	<.0001	<.0001	0.0005	1		0.4493	<.0001	0.9438
3-Bailey 10hr	<.0001	<.0001	0.0002	0.8792	0.4493		<.0001	0.203
Two-at-a-time 8hr	<.0001	<.0001	0.6168	0.0034	<.0001	<.0001		0.2636
Two-at-a-time 10hr	<.0001	<.0001	0.8939	0.9499	0.9438	0.203	0.2636	

Table 15: Tukey Kramer grouping for provider startup idle time

Obs	Schedule	Estimate	Standard Error	Letter Group
1	Individual Block 10 hr	3010.18	93.8308	A
2	Individual Block 8 hr	2840.77	41.9624	A
3	Two-at-a-time 8 hr	2441.4	41.9624	B
4	Bailey 8hr	2334.29	41.9624	BC
5	Two-at-a-time 10 hr	2199.23	93.8308	BCD
6	3-Bailey 8 hr	2080.3	41.9624	D
7	Bailey 10 hr	2049.02	93.8308	CD
8	3-Bailey 10hr	1869.79	93.8308	D

5.2.5 Provider Overtime

The discharge time of the last patient minus the scheduled end time of the session for provider was considered as the provider overtime. If it is negative, it means that the provider has completed the work before the scheduled end time and is considered as an early closure. Provider overtimes for such early closures were considered 0 instead of a negative value as it counts as idle time. Figure 27 shows the comparison of means of provider overtime for the four schedules. The 3 Bailey schedule had the least provider overtime for 8hr shift provider and the Bailey rule had the least overtime for the 10 hour provider. The individual block rule had the highest provider overtime for both the 8 hour and 10 hour shift providers. Table 16 shows the comparison of the means, medians and standard deviations of the provider overtime for the four schedules. Table 17 shows the results of the Tukey Kramer test from SAS. A *p*-value less than 0.05 shows that schedules are significantly different.

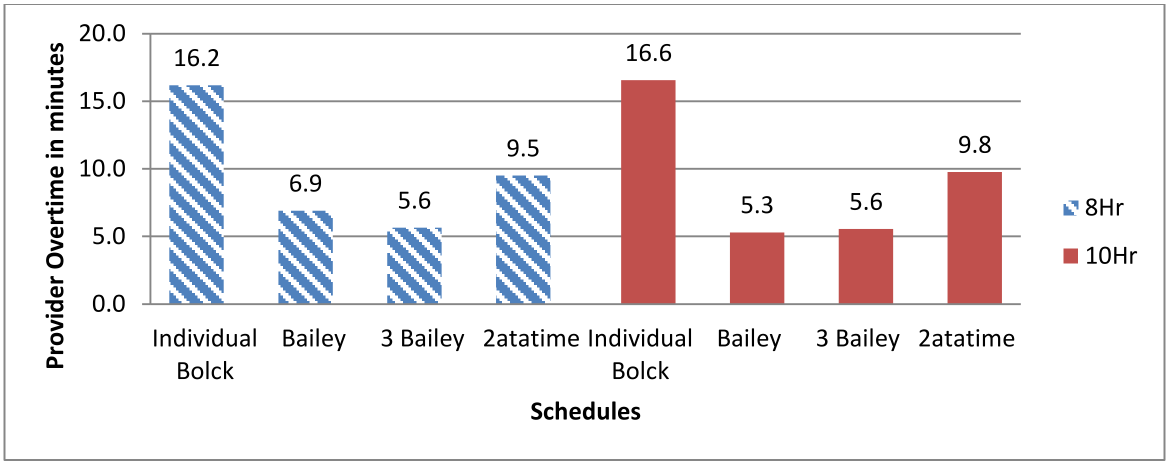

Figure 27: Comparison of means of provider overtime

Table 16: Comparison of provider overtime

Provider Overtime	Mean		Median		Standard Deviation	
	8hr	10hr	8hr	10hr	8hr	10hr
Individual Block	16.2	16.6	12.8	14.1	17.8	13.7
Bailey	6.9	5.3	0.0	0.0	13.2	7.1
3 Bailey	5.6	5.6	0.0	0.0	11.5	10.9
2atatime	9.5	9.8	5.4	6.5	12.8	11.4

Table 17: Result of Tukey-Kramer pairwise comparison for provider overtime

Least Squares Means for effect Schedule Pr > |t| for H0: LSMean(i)=LSMean(j) Dependent Variable: Time								
i/j	Individual block 8hr	Individual block 10hr	Bailey 8hr	Bailey 10hr	3-Bailey 8hr	3-Bailey 10hr	Two-at-a-time 8hr	Two-at-a-time 10hr
Individual block 8hr		0.9335	<.0001	<.0001	<.0001	<.0001	<.0001	0.0021
Individual block 10hr	0.9335		<.0001	<.0001	<.0001	<.0001	<.0001	0.0021
Bailey 8hr	<.0001	<.0001		1	0.5311	0.7123	<.0001	0.0023
Bailey 10hr	<.0001	<.0001	1		0.9859	0.9519	0.0173	0.0442
3-Bailey 8hr	<.0001	<.0001	0.5311	0.9859		0.9994	<.0001	<.0001
3-Bailey 10hr	<.0001	<.0001	0.7123	0.9519	0.9994		<.0001	0.0004
Two-at-a-time 8hr	<.0001	<.0001	<.0001	0.0173	<.0001	<.0001		0.9986
Two-at-a-time 10hr	0.0021	0.0021	0.0023	0.0442	<.0001	0.0004	0.9986	

Table 18: Tukey Kramer grouping of schedules for provider overtime

Obs	Schedule	Estimate	Standard Error	Letter Group
1	Individual Block 10 hr	1697.81	66.2375	A
2	Individual Block 8 hr	1611.52	28.7199	A
3	Two-at-a-time 10 hr	1330.75	65.2052	B
4	Two-at-a-time 8 hr	1287.23	26.2394	B
5	Bailey 8hr	1051.52	28.8065	C
6	Bailey 10 hr	1039.99	68.4584	C
7	3-Bailey 8 hr	972.95	28.8065	C
8	3-Bailey 10hr	934.59	64.2197	C

5.2.6 Provider Utilization

The provider utilization is calculated by dividing the "Sum of provider busy times" by "Total scheduled time for the provider". The provider busy time is obtained by subtracting the "provider idle time" from the "total scheduled time". Figure 28 shows the comparison of means of provider utilization for the four schedules. The individual block schedule had the least provider utilization for 8hr and the 10hr shift provider. The 3-Bailey rule had the highest provider utilization. Table 19 shows the values of means, medians and standard deviations of provider utilizations of the four schedules. Table 20 shows the results of the Tukey Kramer test from SAS. A *p*-value less than 0.05 shows that schedules are significantly different.

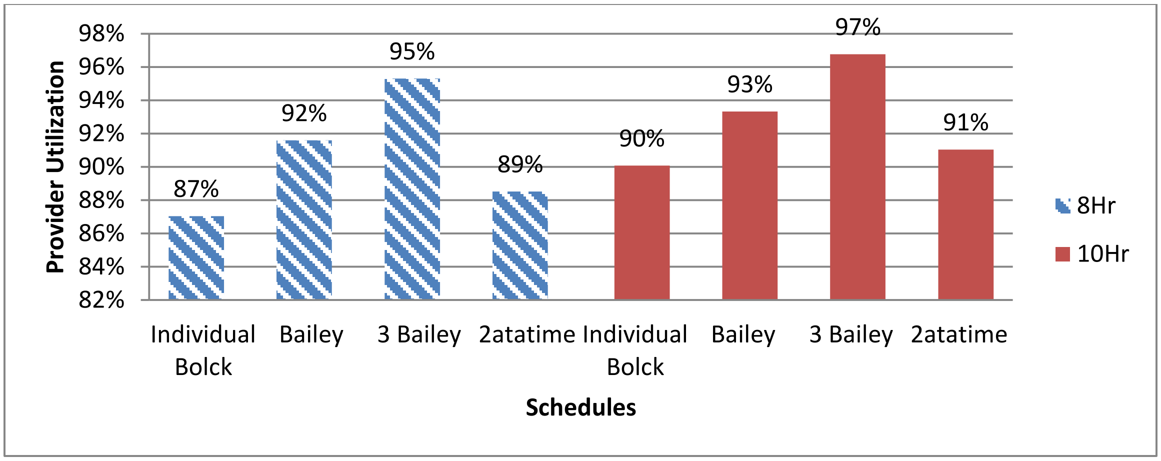

Figure 28: Comparison of provider utilization

Table 19: Comparison of Provider Utilization

Provider Utilization	Mean		Median		Standard Deviation	
	8hr	10hr	8hr	10hr	8hr	10hr
Individual Block	87%	90%	88%	90%	7%	4%
Bailey	92%	93%	92%	94%	6%	5%
3 Bailey	95%	97%	97%	97%	5%	3%
2atatime	89%	91%	90%	91%	7%	5%

Table 20: Result of Tukey-Kramer pairwise comparison for provider Utilization

Least Squares Means for effect Schedule Pr > |t| for H0: LSMean(i)=LSMean(j) Dependent Variable: Time								
i/j	Individual block 8hr	Individual block 10hr	Bailey 8hr	Bailey 10hr	3-Bailey 8hr	3-Bailey 10hr	Two-at-a-time 8hr	Two-at-a-time 10hr
Individual block 8hr		0.0512	<.0001	<.0001	<.0001	<.0001	0.0073	<.0001
Individual block 10hr	0.0512		0.0193	0.0001	<.0001	<.0001	0.9838	0.7581
Bailey 8hr	<.0001	0.0193		0.1494	<.0001	<.0001	<.0001	0.9038
Bailey 10hr	<.0001	0.0001	0.1494		0.0006	<.0001	<.0001	0.0501
3-Bailey 8hr	<.0001	<.0001	<.0001	0.0006		0.2847	<.0001	<.0001
3-Bailey 10hr	<.0001	<.0001	<.0001	<.0001	0.2847		<.0001	<.0001
Two-at-a-time 8hr	0.0073	0.9838	<.0001	<.0001	<.0001	<.0001		0.0614
Two-at-a-time 10hr	<.0001	0.7581	0.9038	0.0501	<.0001	<.0001	0.0614	

Table 21: Tukey Kramer grouping of schedules for provider utilization

Obs	Schedule	Estimate	Standard Error	Letter Group
1	3-Bailey 10hr	1794.97	59.2074	A
2	3-Bailey 8 hr	1643.8	27.4177	A
3	Bailey 10 hr	1370.09	58.6123	B
4	Bailey 8hr	1201.34	26.7527	B
5	Two-at-a-time 10 hr	1118.06	58.9076	BC
6	Individual Block 10 hr	986.16	58.6123	CD
7	Two-at-a-time 8 hr	926.76	26.4783	C
8	Individual Block 8 hr	791.85	26.2385	D

5.3 Kepner-Tregoe (KT) analysis and Test run of Bailey rule

A provider survey was done to establish the weights the providers would give to each of the performance measures on a scale of 100 points. Using those weights, a KT analysis (Kepner et al., 2013) was performed. Table 22 shows the result of the KT analysis. From the values of weights, it is apparent that the patient times were valued more than the provider times by the providers. The Bailey rule had the least score in the KT analysis. To evaluate the effect of weighting on the analysis, a sensitivity analysis was also done by varying the weightage to create four scenarios: (1) with full weightage (100 points) for provider times, (2) 50-50 weightage for the provider and patient times, (2) 44 - 56 weightage for the provider and patient times respectively (as from the survey), and (4) full weightage (100 points) for the patient times. The results of the sensitivity analysis are given in Table 23. It shows that the 3 Bailey rule had the least score when there was more weight for the provider measures, which means that it is more preferable to use 3 Bailey rule when the provider time is considered important. The Individual block rule had least score when there was more weight for the patient measures, which means that it is preferable to use the Individual block rule when the patient time is considered more important than provider time. The Bailey rule worked best for scenarios where the patient times and provider times are considered equally important.

To assess the best rule from KT analysis, a test run of the Bailey rule, was conducted with one provider for a period of 10 days. This evaluation was done to get a sense of the impact of this new rule system if implemented in the SHC. The provider startup idle time, provider overtime, provider utilization and patient throughput time were measured and compared with past values of the same provider. The results of the test run are shown in Figure 29. It shows the comparison of the test run's Bailey rule with the past values from individual block rule. The provider startup idle time and provider overtime for the Bailey rule were lower than the individual block rule, as predicted by the model. The provider utilization and the patient throughput times were higher for the Bailey rule in comparison with the individual block rule. This was in accordance with the results of the model.

Table 22: KT analysis of schedules

Sl.No	Criteria	Weight	Socre							
			Individual Block		Bailey		3Bailey		2 at a time	
			Score	Wt.Score	Score	Wt.Score	Score	Wt.Score	Score	Wt.Score
1	Patient Throughput time - 10 minutes per patient	28	39.6	1109	41.4	1159	48.1	1347	41.2	1154
2	Patient Wait time - 10 minutes per patient	28	15.5	434	17.3	484	24.1	675	17.1	479
3	Provider Idle time - 10 minutes per provider per shift	17	50.5	859	31.8	541	17.0	289	44.8	762
4	Provider Startup Idle time - 10 minutes per provider per shift	14	10.4	146	6.5	91	4.6	64	7.3	102
5	Provider Overtime - 10 minutes per provider per shift	13	16.2	211	6.9	90	5.6	73	9.5	124
	Total	100	2758		2365		2448		2620	

Table 23: Sensitivity analysis for choosing schedules

Weightage distribution	Individual Block	Bailey	3Bailey	2 at a time
100 - 0, PR-PA weight	2572	1508	907	2056
50 - 50, PR- PA weight	2661	2219	2258	2482
44 - 56, PR - PA weight	2758	2365	2448	2620
0 - 100, PR - PA	2755	2935	3610	2915

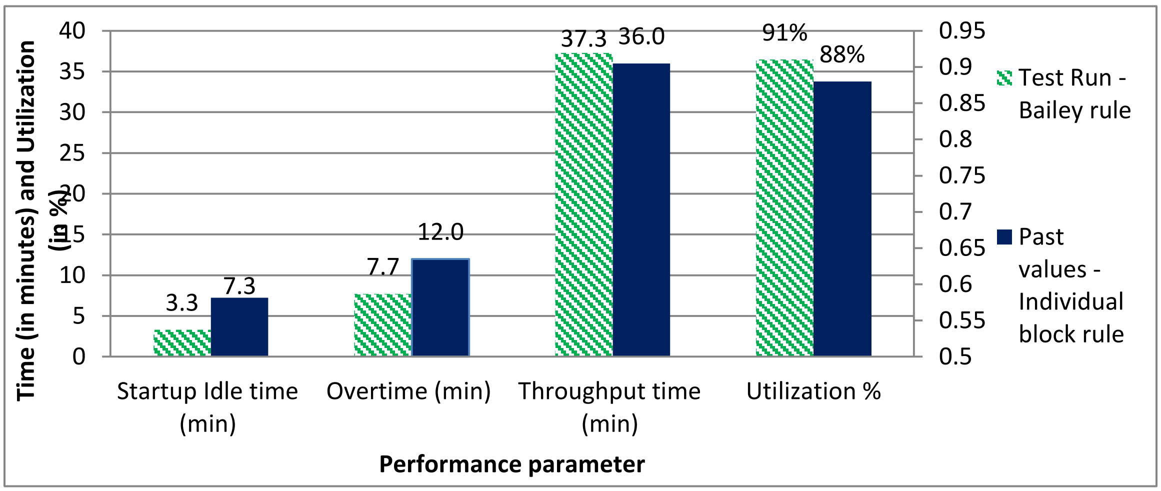

Figure 29: Results from the test run of Bailey rule

CHAPTER 6: DISCUSSION AND CONCLUSION

The objective of this study was to understand the effect of different appointment schedules on the operational performance of an SHC. The Louisiana State University's SHC was used for this study. The four different appointment schedules chosen for this study were: (1) Individual block rule, (2) Bailey rule, (3) 3-Bailey rule and the (4) Two-at-a-time rule. Six performance parameters were measured, namely the patient throughput time, patient wait time, provider idle time, provider startup idle time, provider overtime and provider utilization; whose results are given in Chapter 6. The discussion section is divided into the subcategories of the performance parameters. The recommendations based on the KT analysis, scope for future research and conclusions of the study are also presented in the end.

6.1 Comparison of Schedules

The comparison of the four schedules will be discussed based on the results of 8 hour shift providers. The 8 hour shift cases are chosen as the SHC has six providers in the 8 hour shift and just one provider in the 10 hour shift. Moreover, it is observed that all the performance parameters of 8 hour and 10 hour shift providers behave in the same manner for all cases. After analyzing the difference between the schedules using the 8 hour provider, a comparison between the 8 hour and 10 hour provider shifts is also be done for every schedule. The individual block rule is considered as reference in all comparisons as it is the rule that is currently used in the SHC.

6.1.1 Patient throughput time

Past studies like Cayirli et al. (2006), Wijewickrama et al. (2008), Kaandorp et al. (2007), Cayirli et al. (2008) mainly investigated the effect of schedules on patient wait time and not on patient throughout time. However the throughput time is considered as a key parameter in this study as it is an important factor for the students visiting the SHC. Students tend to schedule appointments between class hours and so it is desirable to have low patient throughput times to ensure that they are discharged quickly from the clinic and they can get back to classes quickly. From Table 4 and Figure 23, it is seen that the mean patient throughput time is the lowest for Individual block rule with 39.6 minutes. The highest throughput time is noted for the 3-Bailey rule with 48.1 minutes, which is higher than the individual block rule by 21%. The Bailey and Two-at-a-time rules also have a higher means, 4.8% and 4% higher than the individual block rule respectively. The Kruskal-Wallis test shows that the schedules have a significant effect on the throughput times. The Tukey-Kramer comparisons in Table 5 and Table 6 show that the Individual block rule and the 3-Bailey rule are significantly different from all the rules. The Bailey and Two-at-a-time rules do not show significant difference from each other with a *p*-value of 0.069. They have patient throughput times of 41.4 and 41.2 minutes respectively.

The throughput times of patients for the 10 hour shift providers for Bailey and 3-Bailey rules are longer than that of the 8 hour shift providers by 4% and 3% respectively. No difference was seen between the two providers for the two-at-a-time schedule from Table 5. The throughput time for the 10 hour provider in the individual block rule was shorter than that of the 8 hour provider by 2%. Only the Bailey rule showed a statistically significant difference for the throughput times between the 8 hour and 10 hour shift providers. However the difference was only 1.8 minutes.

6.1.2 Patient wait time

Patient wait time is also an important performance criterion for the SHC as it can lead to crowding and patient dissatisfaction. A high Pearson correlation, 0.98 was observed between the patient throughput times and patient wait times. This means that the increase in patient throughput time is caused by an increase in patient wait time. The individual block rule had the lowest patient wait time with a mean of 15.5 minutes and the 3-Bailey has the highest patient wait time with a mean of 24.1 minutes, as seen in Table 7 and Figure 24. The Bailey rule and the Two-at-a-time rules also showed significantly high patient wait times when compared to individual block rule, by 11.5% and 10.1% respectively. The higher wait time for the Bailey and 3-Bailey rules can be attributed to the extra patients at the beginning of the shift. This result is similar to that found by Cayirli et al. (2006), who studied the effect of individual block rule, Bailey and Two-at-a-time rules along with other rules on patient wait time in an ambulatory clinic. The study also showed that the Bailey and Two-at-a-time rules had higher patient wait times compared to the individual block rule. Wijewickrama et al. (2008) also showed similar results in a study on outpatient ward in a university hospital. The increase in the wait time of the Bailey rule compared to the Individual block rule in their study was 15%, which is higher than the 11.5% increase found in this study.

From Figure 24, it is seen that patients seeing the 10 hour shift provider had higher wait times than the 8 hour shift providers in all cases other than the two-at-a-time schedule.

The difference was 6%, 10%, 5% and 0% for the Individual block, Bailey, 3-Bailey and two-at-a-time rules respectively. The Tukey-Kramer results from Table 8 and Table 9 shows that the difference between the shift schedules is not significant for 3-Bailey and Two-at-a-time rules, but is significant for the Individual block and Bailey rule.

6.1.3 Provider Idle time

The provider idle time is an important criterion for the SHC as it disrupts the work flow for the providers and causes provider annoyance. The comparison of the provider idle time is shown in Table 10 and Figure 25. The individual block rule has the highest value with 50.5 minutes of idle time per provider per shift. The 3-Bailey rule had the least provider idle time with a value of 17 minutes per provider per shift, 66.3% less than the individual block rule. The Bailey rule at 31.8 minutes per provider per shift is 37% less than the individual block rule. The Two-at-a-time rule had a provider idle time of 44.8 minutes per provider per shift, which is less than the individual block rule by 11.2%. The Tukey-Kramer in Table 11 and Table 12 test showed that there are significant differences among the schedules. The study by Cayirli et al. (2006) shows similar results with high idle time for the Individual block rule and lower idle times for the Two-at-a-time and Bailey rules. The results also matched the findings by Rohleder et al. (2000), Wijewickrama et al. (2008) and Klassen et al. (1996).

The 10 hour shift provider experienced a higher idle time in all cases when compared to the 8 hour shift provider. However, there was no significant difference seen between them in all of the cases from the Tukey-Kramer pairwise comparison shown in Table 11.

6.1.4 Provider Startup idle time

The startup idle time is the idle time experienced by the provider at the start of a session. This is considered as one of the performance parameters as the time lost at the beginning of the shift cannot be substituted by filler work or extra patient from walk-ins. Real time observations also showed that an average of 9.5 minutes is lost as startup idle time per provider. This startup idle time may be attributed to the fact that the patients who schedule early morning appointments tend to arrive late when compared to the patients with appointments during other times of the day. The punctuality study of patients shows that the mean arrival time of patient before 9:30 AM is -2.8 minutes and the mean arrival time of patients after 9:30 AM is -9.3 minutes. Hence it is important to have a schedule that can minimize the startup idle time of the clinic.

From the Arena model, it is seen that the individual block rule had the highest average startup idle time of 10.4 minutes as seen in Figure 26 and Table 13. The 3-Bailey rule had the lowest startup idle time with a mean of 4.6 minutes, 55% lower than the individual block rule. The Bailey rule had an average startup idle time of 6.5 minutes that is 37% lower than the individual block rule. The Two-at-a-time also had a lower startup idle time than the individual block rule, with a mean of 7.3 minutes. The Bailey rule and two-at-a-time rule did not show significant difference in this case from Table 14 and Table 15, whereas there was a significant difference in all other pairwise comparisons between the schedules. This can be attributed to the fact that both the Bailey and Two-at-a-time rules have two patients scheduled to arrive at the beginning of every session.

The startup idle time of the 10 hour shift provider was lower than the 8 hour shift provider in all cases as seen in the Figure 26. However the difference between shifts was not significantly different for all cases from the Tukey-Kramer analysis in Table 14.

6.1.5 Provider Overtime

Provider overtime is the positive difference between the actual completion of the session and the scheduled completion of the session for a provider (Cayirli et al., 2003). The largest provider overtime was observed for the individual block rule with 16.2 minutes per provider per shift, as seen in Figure 27 and Table 16. The lowest value was observed for 3-Bailey rule with a mean provider overtime of 5.6 minutes, 65% less than that of the individual block rule. The second lowest provider overtime was observed for the Bailey rule with 6.9 minutes, 57% less than the individual block rule. The Two-at-a-time rule also had lower provider overtime with respect to the individual block rule at 9.5 minutes per provider per shift. These results are similar to the observations by Cayirli et al. (2006). From Table 17 and Table 18, it is observed that the provider overtimes of Bailey and 3-Bailey rule are not significantly different from each other. However, they are significantly different from the rest of the schedules. The Individual block rule and Two-at-a-time rules are significantly different from all the schedules.

The differences between the overtime of the 10 hour shift providers and the 8 hour shift providers were less than 3% for the Individual block, 3-Bailey and two-at-a-time rules. The 10 hour shift provider of the Bailey rule had an overtime of 5.3 minutes, 23% less than its 8 hour shift provider. The Tukey-Kramer analysis shown in Table 17 did not show any statistically significant difference for all cases.

6.1.6 Provider Utilization

Provider utilization is calculated as the ratio of sum of busy times of provider divided by total scheduled time of the provider. The provider utilization is high when there is low idle time and vice versa. Figure 28 shows the means of the provider utilization for all the schedules. The Tukey-Kramer analysis from Table 20 and Table 21 shows that all the schedules are significantly different from each other. The Individual block rule had the lowest provider utilization at 87%. The 3-Bailey rule had the highest utilization at 95%, while the Bailey and Two-at-a-time rules had utilizations of 92% and 89% respectively. The Kruskal-Wallis test shows that the schedules have significant effect on the provider utilization.

Even though the utilizations of the 10-hour shift providers were higher than the 8-hour shift providers in all cases, no statistically significant difference was observed from the Tukey-Kramer analysis in Table 20. The difference was only 2% to 3% in all cases.

6.2 Kepner-Tregoe (KT) analysis and Test run

From all these comparisons, it is evident that the schedules which have high patient wait times have low provider idle times, which is in line with other similar research. Wijewickrama et al. (2008), who performed a simulation study on a large university hospital in Japan found that the 3-Bailey rule had the highest patient wait times and the individual block rule had the least patient wait time among the four rules. Past studies by Norman (1952), Klassen et al. (1996), Cayirli et al. (2006) and Walter (1973) have shown that the patient wait time is inversely related to the provider idle time. It is well known that no appointment system will perform well in all conditions and every situation should be considered individually before an appointment system can be recommended (Cayirli et al., 2003). It is clear that the individual block rule is the most patient friendly rule with the least patient-throughput times and patient-wait times, but has high provider times. The 3-Bailey rule with the least provider idle time, startup idle time, and overtime is the most provider friendly rule. However, it has the longest patient throughput times and patient wait times. The Bailey rule, even though it doesn't have the best provider and patient parameters, has a good trade-off compared to the other schedules.

To aid the decision making of the schedule selection process for the SHC, a KT analysis was performed by weighing the performance parameters, shown in Table 22. The schedule with the lowest score from the KT analysis was the Bailey rule, so it was considered the most suitable rule for SHC. The Bailey rule has a better trade-off between the patient times and the provider times when compared to the other rules. It has significant reduction in provider times (Idle time: -37%, Startup idle time: -37%, Overtime: -57%) and only a small increase in patient times (Throughput time: +4.8%, Wait time: +11.5%) with respect to the individual block rule. It also has a better provider utilization rate at 92%, 5% higher than the individual block rule. The sensitivity analysis in Table 23 shows how the decision would change if the weights change. The first scenario shows that the 3-Bailey rule is more effective when the provider times are considered important. The Bailey rule has the least score for the second scenario which weighs the patient and provider times equally. The Bailey rule also had the least score for the third scenario with the weightage 44 – 56 for provider and patient times as distributed in the KT analysis. The fourth scenario considers full weightage for the patient times and none for the provider times. The individual block rule had the least score for this scenario and so is the most patient friendly rule among the four.

The results of the test run of the Bailey rule are analogous with that of the model. The average startup idle time in the test run was observed to be 3.3 minutes. This is 54% less than the past values observed from the individual block rule. The model also predicted a decrease in startup idle time, but by 37%. The average provider overtime at 7.7 minutes was also less than the past values by 36%. The model had also predicted a decrease in overtime, but by 57%. The average throughput time of the test run was 37.3 minutes which was higher than the past value by 3.6%. The model also predicted an increase in throughput time, by 4.8%. Finally an increase in utilization was also observed as predicted by the model. The utilization of the provider increased from 88% to 91.5%. This was also analogous to the results from the Arena model, which predicted an increase by 5%. Even though the values are not exactly the same as the model, the trends are in line with the results from Arena model. The differences may be due to the fact that the test run was executed for only 10 days, which is a very short span of time. There may also be other compounding factors like time of the year, different patient population, effect of single provider and changes in the EMR system which could have affected the results of the test run. However, the test run was able to show that the Bailey rule has better provider times and utilization than the Individual block rule. It also shows that there would be an increase in throughput time for the patient.

6.3 Limitations

- This study assumes the same attendance rates for the additional appointments in the Bailey and 3-Bailey rule at the beginning of the shift. Only implementations in the real setting will show whether students prefer to schedule appointments for the extra slots during the beginning of the shift for all days.

- The providers were considered to be punctual at the beginning of the sessions, since direct observation of providers shows that all of them were punctual. Punctuality of the providers can be considered as a factor for future studies to understand its effect on the performance characteristics.
- The average values were considered for all input parameters. The input parameters like service time, punctuality and no show rates might change according to different times of the semester.
- The test run of the Bailey rule was done with only with one provider for ten days. The test run was performed only to compare how the Bailey rule performed with the individual block rule. More observations with more providers for a longer duration would provide more accurate results for the Bailey rule.
- The examination and charting time were considered together as service time. This might have overestimated the throughput time of the patient in the model. However, this does not affect the provider times or the patient times.
- The SHC has different appointment reasons for the 15 minute and 30 minute appointment time periods (like fever, headache, stomach pain, etc). They were not considered individually in this study in order to reduce complexity.

6.4 Future studies

- The Arena model can be further modified to add different appointment reason codes and their corresponding service time to study their effect on the performance.

- Only four scheduling rules were tested in this study. More schedules with multiple block and variable interval rules can also be tested using simulation.
- Studies by Welch et al. (1952), Ahmed et al. (2011), and Williams et al. (2014) have shown that the unpunctuality and no-shows of patients can significantly affect the operational performance of a clinic. More studies may be conducted to test the effect of these variables on the performance of the SHC. Different combinations of no-shows, punctuality and schedules may be tested to see which schedules work best for a specific condition.
- Interventions to improve the no-show rate and the punctuality of patients may also be implemented in the SHC.
- This study concentrated only on the utilization of provider resources. Staffing optimization for nurses and lab technicians can be studied by analyzing their utilization rates in SHC.

6.5 Conclusion

This study provides an insight into how different appointment schedules perform in a Student Health Center type setting. A simulation model of the LSU SHC using Arena simulation software was created. Four schedules were tested using the Arena model, namely the Individual block rule, Bailey rule, 3-Bailey rule and Two-at-a-time rule. The schedules were compared based on the patient throughput times, patient wait times, provider idle times, provider startup idle times, provider overtimes and provider utilization rates. From the analysis, the following observations are made.

- Individual block rule was the most patient friendly rule with the shortest patient throughput time (39.6 min) and patient wait time (15.5 min), but had the longest provider times (Idle time – 50.5 min, Startup idle time – 10.4 min, Overtime – 16.2 min). It also had the lowest provider utilization rate (87%).

- The 3-Bailey rule was the most provider friendly rule with the shortest provider times (Idle time – 17 min, Startup idle time – 4.6 min, Overtime – 5.6 min) and the best provider utilization rate (95%) but had the longest patient times (throughput time – 48.1 min and wait time – 24.1 minute).
- The Bailey rule had marginally higher patient throughput time (41.4 min) and patient wait time (17.3 min) compared to the individual block rule but had better provider times (Idle time – 31.8 min, Startup idle time – 6.5 min, Overtime – 6.9 min) and better utilization rates (92%).
- The Two-at-a-time rule also had higher patient wait times (17.1 min) and throughput time (41.2 min) when compared to the individual block rule but had lower provider times (Idle time – 44.8 min, Startup idle time – 7.3 min, Overtime – 9.5 min) and better provider utilization (89%).

It was seen that there is no single rule that performs best for all measures. The KT analysis showed that the Bailey rule was the most preferable rule for this SHC, as it had a good tradeoff between the patient and provider times. The test run also confirmed the performance of the Bailey rule from Arena model.

This research studied the effect of four appointment schedules on the performance of a University Health Center. Even though similar studies have been conducted on general outpatient clinics in the past; from the literature review, it was seen that there were no such studies performed a University Health Center type setup. The simulation model created in this study was a detailed replication of the process at SHC involving the provider, nurse, self-check-in and the lab processes. This research also studies the patient throughput times of the schedules as it is an important factor for the student population coming to the SHC. This was not seen in most of the other studies as they considered only the patient wait times for assessing the performance of schedules. This study also compares the provider startup idle time of the schedules, which is an important measure for the providers at an SHC. Analysis on the startup idle time of providers was also not seen in the past studies. Another new contribution of this study is the introduction of the KT analysis tool to help in the decision making process of schedule selection. Even though a lot of studies have been conducted to compare different schedules in the past, a good selection method for choosing the best schedule was missing. The KT analysis tool can help the management to easily weigh different criteria and chose the best schedule. Finally the scope for future studies was also discussed based on the findings in this research.

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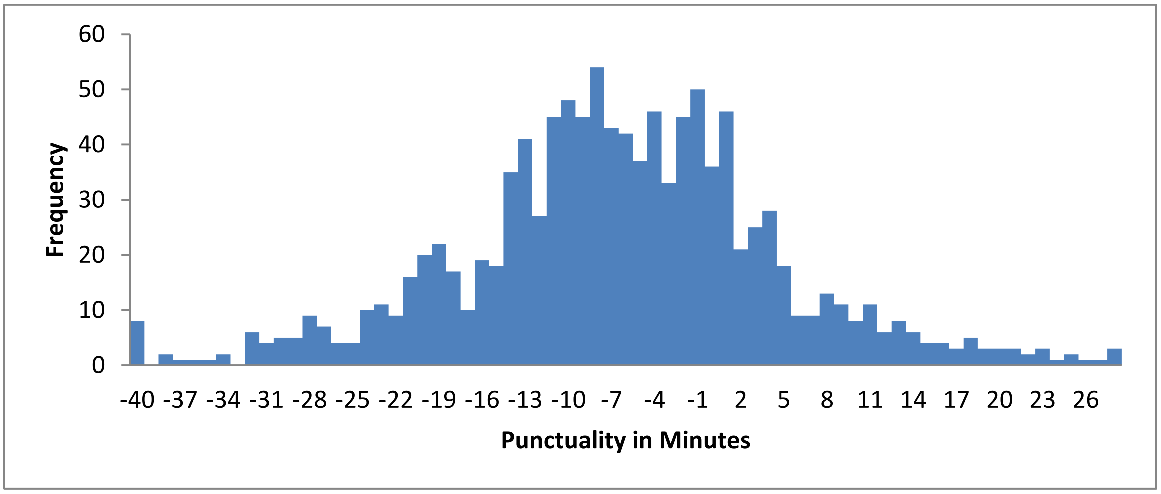
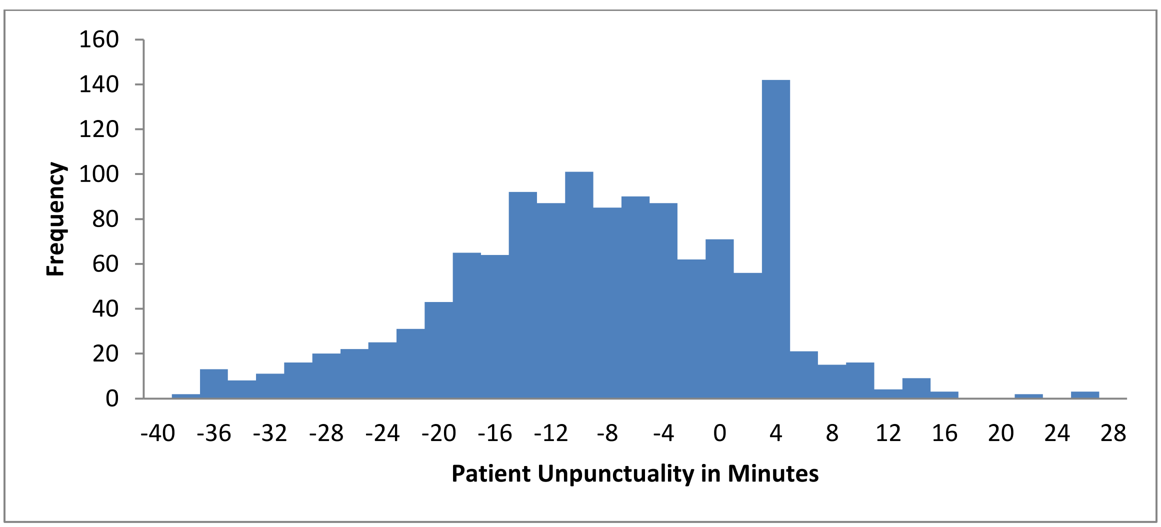
APPENDIX – INPUT PARAMETERS

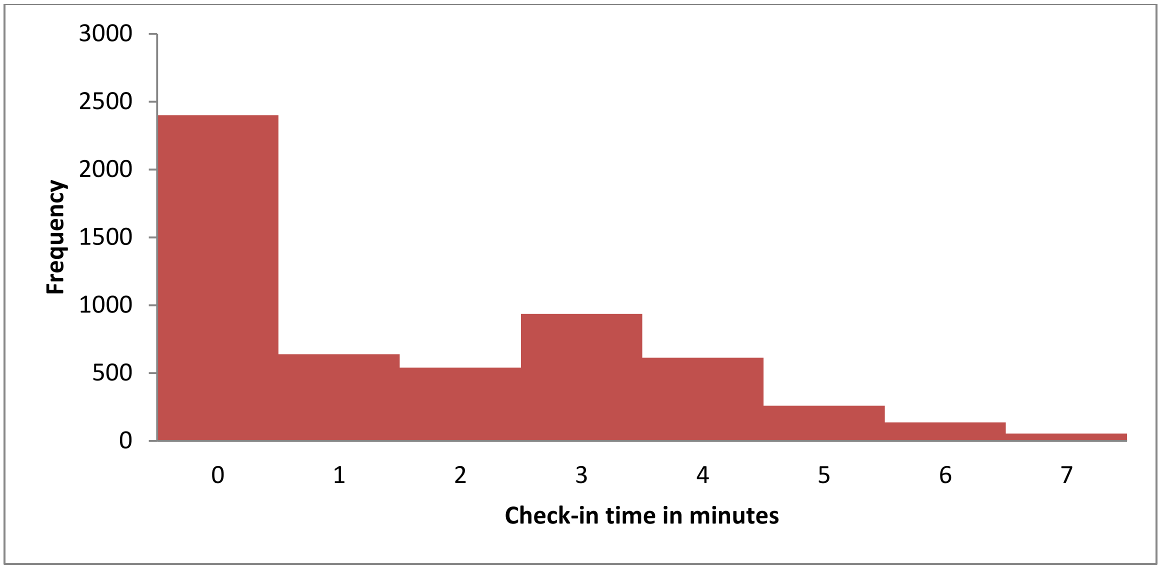
1. Frequency distribution of patient punctuality (before 9:30 AM)



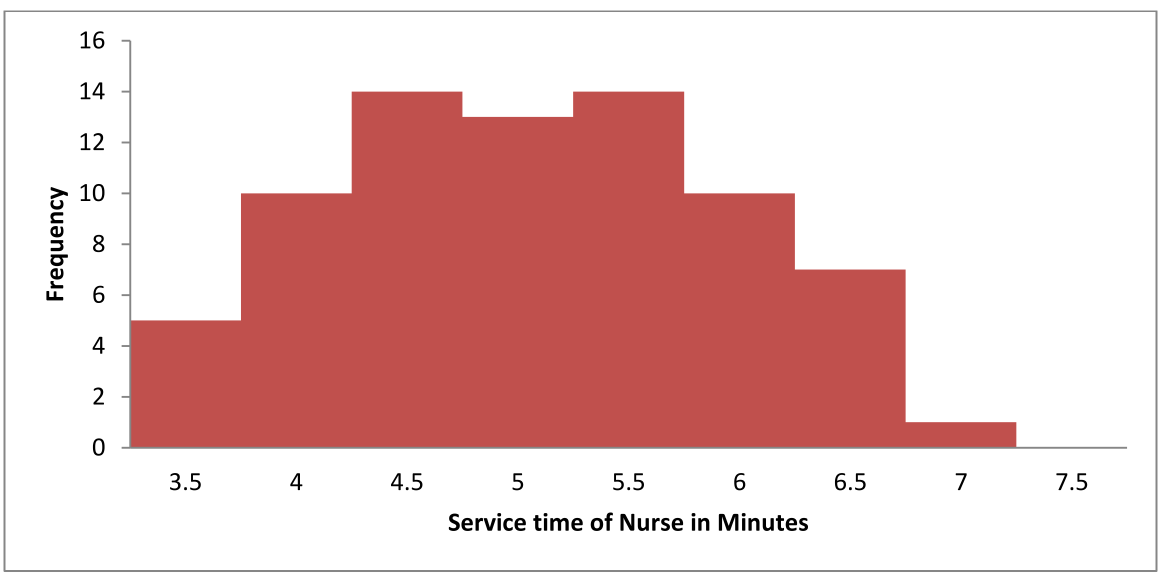
2. Frequency distribution of patient punctuality (after 9:30 AM)



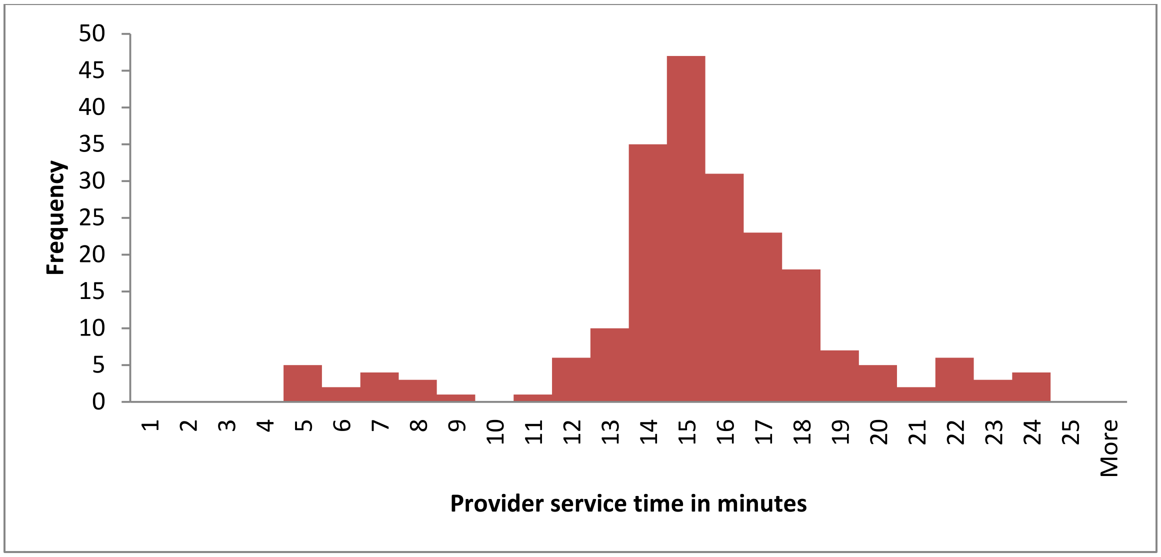
3. Frequency distribution of self-check-in time of patients



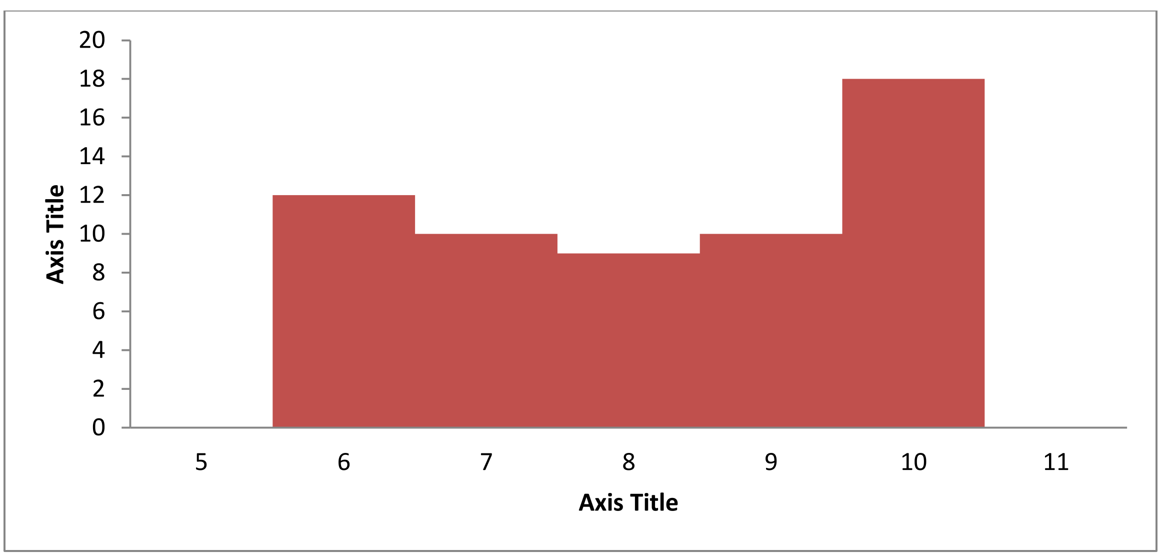
4. Frequency distribution of the service time of nurse



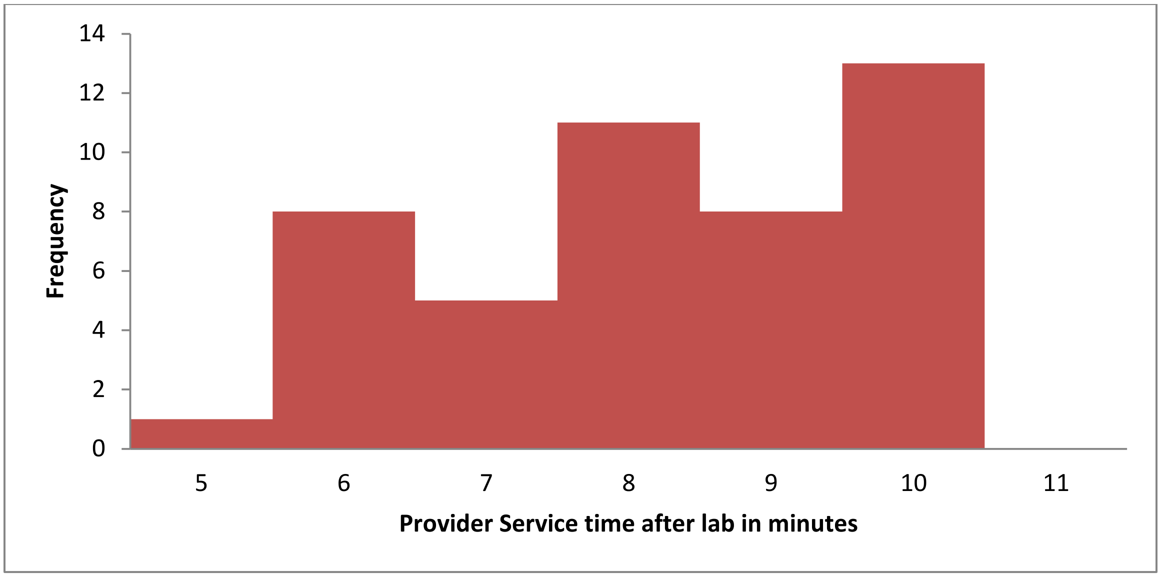
5. Frequency distribution of provider service time for 15 min appointments



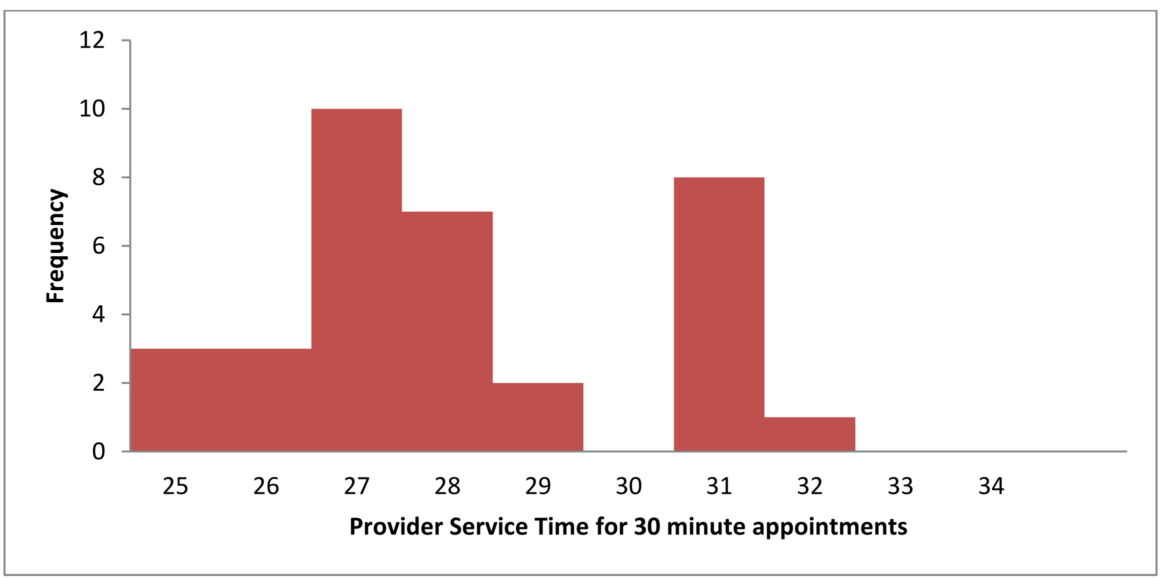
6. Frequency distribution of provider service time before lab



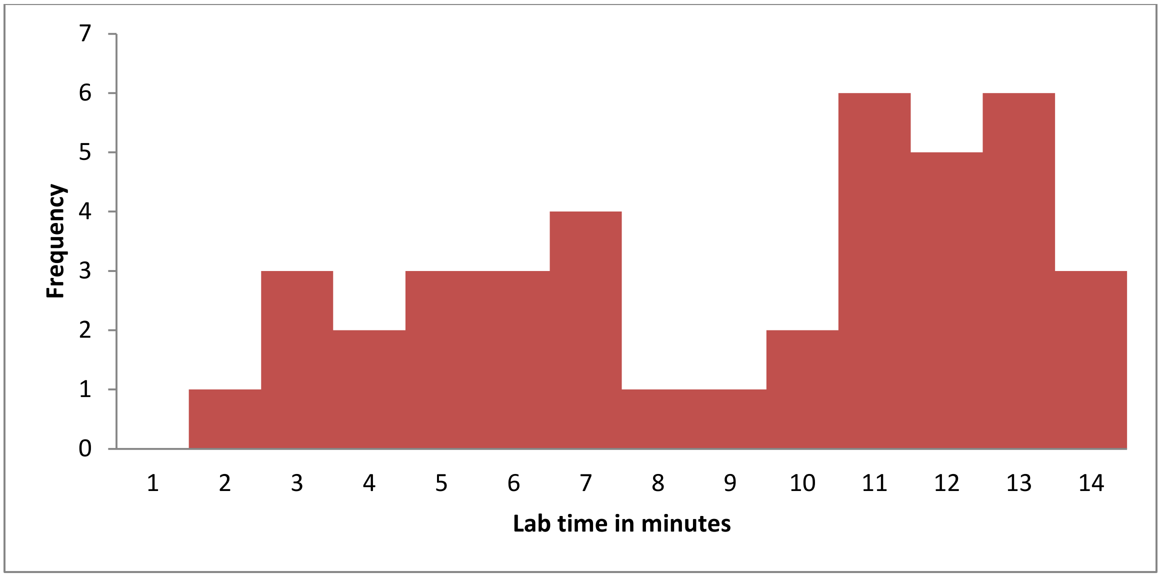
7. Frequency distribution of provider service time after lab



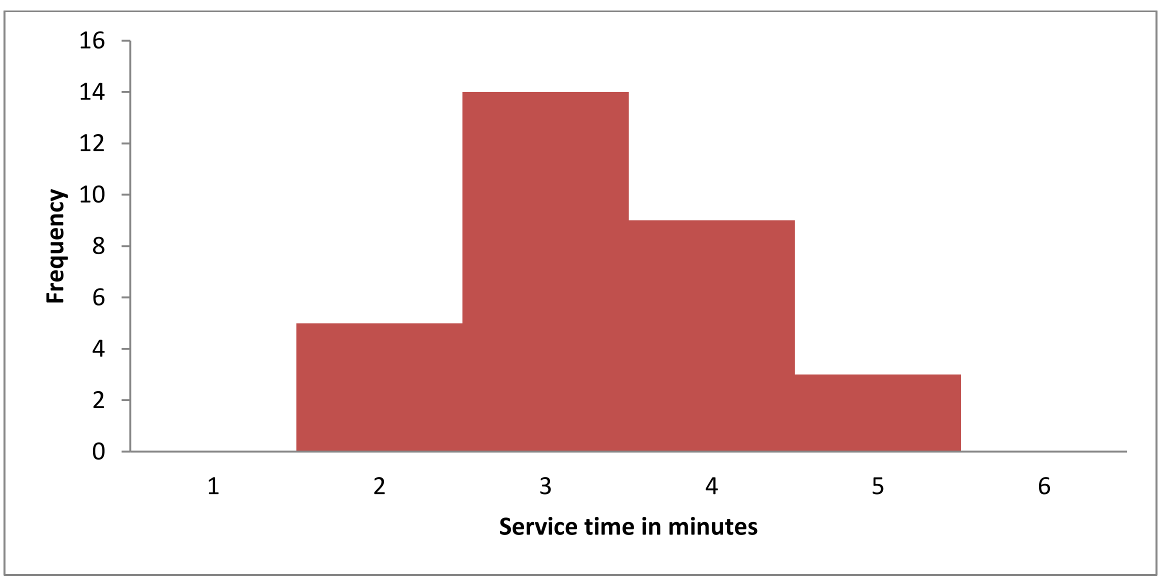
8. Frequency distribution of provider service time for 30 minute appointments



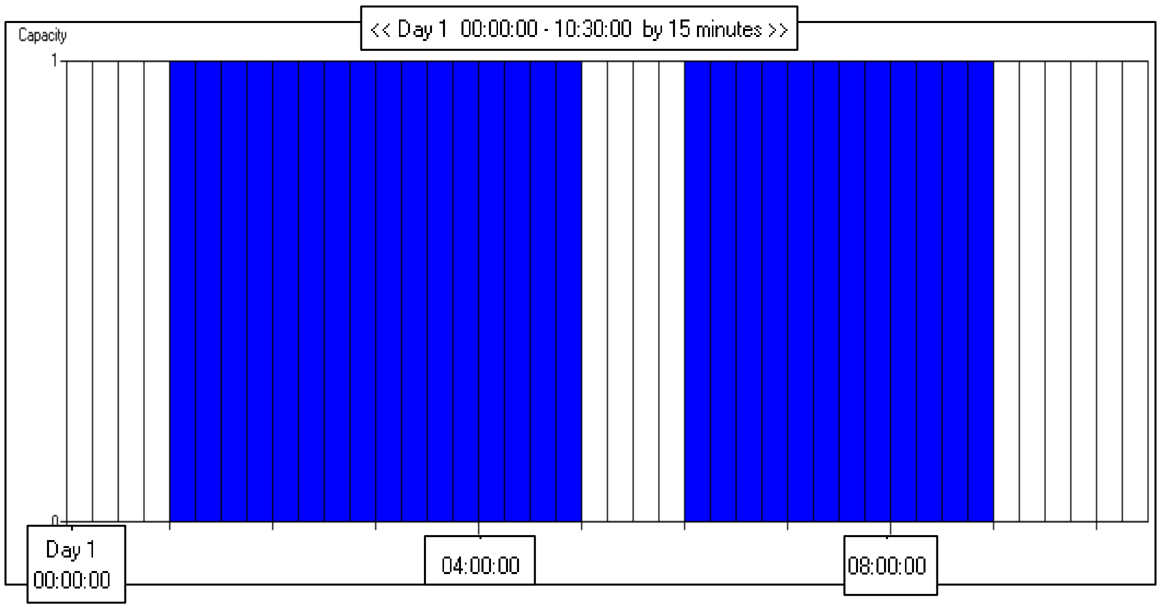
9. Frequency distribution of lab service time



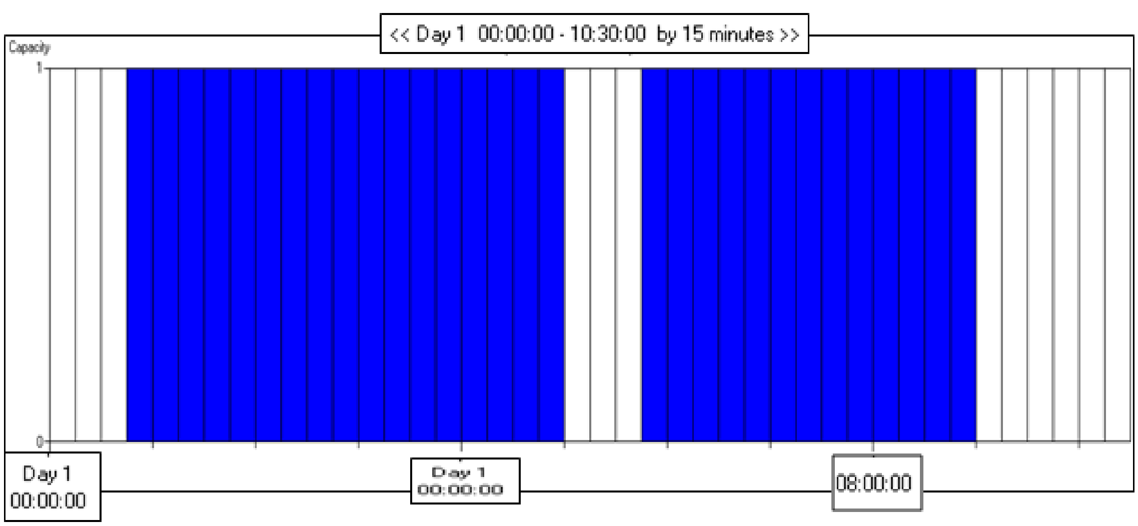
10. Frequency distribution of discharge service time of nurse



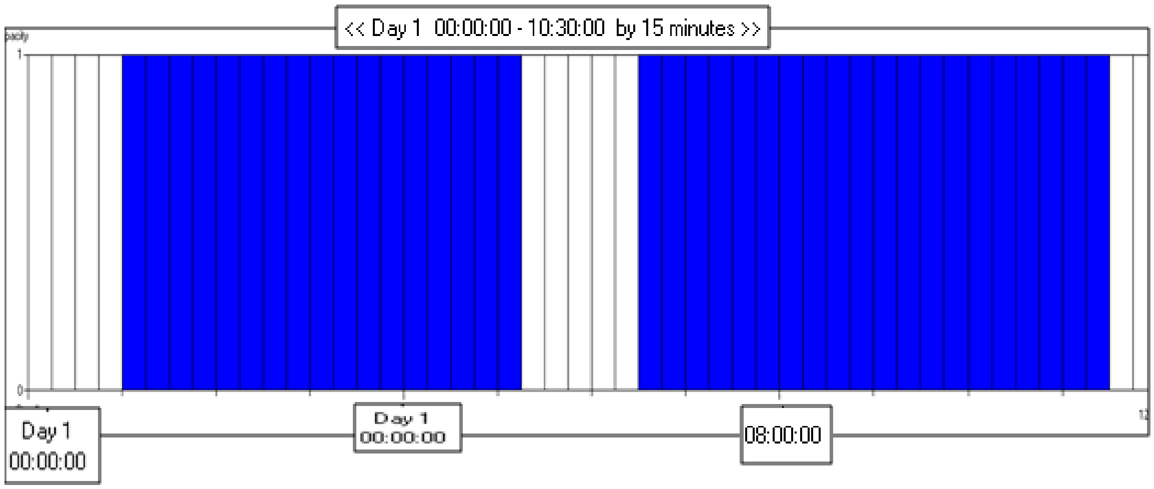
11. Schedule for provider in 8hour shift



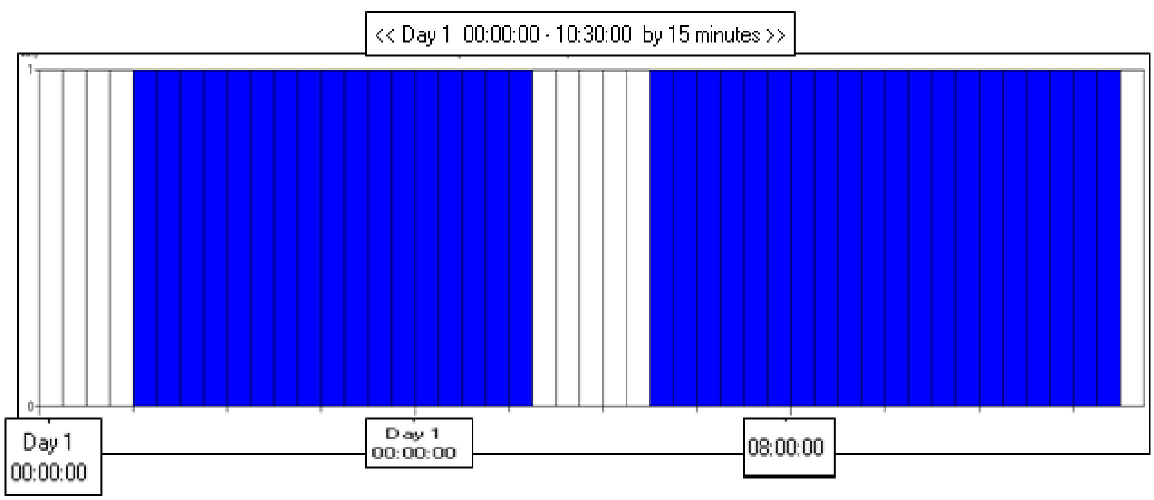
12. Schedule for nurse in 8hour shift



13. Schedule for provider in 10hour shift



14. Schedule for nurse in 10hour shift



VITA

Arunn Pisharody Vijayan was born in Thrissur district of Kerala, India on March 1989. He spent his childhood and did his middle and high school in the city of Coimbatore, Tamil Nadu. His interest in cars and bikes inspired him to pursue a degree in Mechanical Engineering after high school. He earned his bachelors in Mechanical Engineering from Amrita School of Engineering, Coimbatore in May 2010. After graduation, he started working for Tata Advanced Materials Ltd in Bangalore, India; as a Methods Engineer, designing manufacturing processes for making composite parts for airplanes. In December 2010, he joined Bosch Ltd in Bangalore, realizing his desire to work in an automotive company. He worked as a Projects and Process planner at Bosch to establish a manufacturing process to make pressure sensors for cars. Inspired by the Industrial Engineering projects, he did at Bosch; he decided to pursue his Masters in Industrial Engineering at LSU. He joined LSU in fall 2013 as a graduate student in the MSIE program. During his time at LSU, he conducted safety workshops for undergraduate students and worked on various lean improvement projects at the LSU student health center. He expects to receive his master’s degree in Industrial Engineering in May 2015.