Lean Implementation and Pediatric Intensive Care Unit Bed Availability Analysis via Simulation at the Winnipeg Children's Hospital

by

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Abstract

The Winnipeg Children's Hospital encounters delays within the surgical patient flow and cancellations due to a lack of available resources in the Pediatric Intensive Care Unit (PICU). Applying the concepts of lean thinking and the practices of simulation and statistical analysis, these problems were better understood and solutions were developed. Improvement projects were performed centralized on lean concepts and utilizing the tools of value-stream mapping and 7 forms of waste. Building and running a simulation model provided a capacity versus demand measure for the overall performance of the PICU. Simulation allowed for the study of hypothetical situations such as varying department resources and fluctuating patient levels. Statistical calculations were used to create a prediction tool to determine the probability of a PICU bed being available. This would enable a reduction in last-minute cancellations of surgical cases requiring a PICU bed.

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List of Abbreviations

APAC	Anaesthetic Pre-Admit Clinic
ATD	Admission/Transfer/Discharge Data Collection
CH4	Children’s Hospital Ward
CK3	Children’s Hospital Ward
DS	Day Surgery
ER / ED	Emergency Room / Emergency Department
HSC	Health Sciences Centre
JIT	Just-In-Time Supplier Management
MDR	Medical Device Reprocessing
MSW	Multi-Skilled Worker
OR	Operating Room
PAC	Pre-Admit Clinic
PACU	Post-Anaesthetic Care Unit
PDU	Pediatric Day Unit
PICU	Pediatric Intensive Care Unit
PSCU	Pediatric Special Care Unit
RWI	Resource Weight Intensity
SIMS	Shared Information Management Systems (Hospital Data Collection Software)
VSM	Value Stream Mapping

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Chapter 1 Introduction

1.1 Thesis Motivation

As part of the National Wait Times Initiative established by the Canadian Government, a surgical patient flow project was developed at the Winnipeg Children's Hospital at the Health Sciences Centre (HSC) in Winnipeg, Manitoba. This project team was responsible for directing attention towards hindrances along the steps progressed through by pediatric surgical patients and problem-solving to improve the number of completed cases and subsequently reduce wait times. Fortunately, the project managers wanted an outside perspective and thus funding was made available to include engineering students.

The author began working on the Pediatric Surgical Patient Flow Project in January 2008. The author's background in lean thinking in a manufacturing setting contributed nicely to the streamlining efforts within the hospital. The lean philosophy of identifying and removing waste was utilized within the departments affecting surgical patient flow by establishing projects involving necessary stakeholders to solve the system's performance related issues.

The first issue that was presented to the project team was the cancellation of elective surgeries and the resulting negative effect it had on patients. One of the contributing factors to surgical cancellations was the fact that there wasn't always an available bed in the Pediatric Intensive Care Unit (PICU), necessary for the post-operative care of a select group of complex procedures and patients. Stories were told of situations where patients were scheduled for an elective surgical procedure and were cancelled multiple times on the morning of the scheduled surgery date due to unavailability of PICU beds. These beds were occupied by emergency and very complex cases. Many of these patients and their families, whom experience having their cases are cancelled, travel long distances to the hospital and must endure the pre-operative preparation routine such as fasting before surgery. Additionally, the cases requiring a post-operative bed are complex and require significant surgery time. Therefore, when these procedures are cancelled, the operating room remains unused for most of that day. As a result, the major motivation for this thesis became finding a way to use data and engineering-type methods to better understand the patient flow specific to the PICU and reduce the number of last-minute cancellations.

The solution to the unexpected cancellations involving PICU required having earlier knowledge of when the PICU was going to be full and also taking steps to reduce the amount of times the department would reach capacity (or over-capacity). It was realized quickly that the approach to analyzing the PICU would need two paths; one that is more acute, focusing on the day-to-day operations, and one that is more long-term.

One of the delays incurred in the day-to-day operations of the surgical OR was a direct result of the inability to know whether there would be an available bed in the PICU when a procedure would be completed. Given a tool to better understand the demand versus capacity balance of the PICU and a statistical measure of bed availability, the management of the OR and PICU would not be required to overcome as much uncertainty. As well, the flow of the OR, and other tangent, dependent departments would be improved. In the end, this would ideally improve the experience of patients. The author's knowledge of simulation led to the belief that this would be a useful application of the established engineering tool.

1.2 Thesis Objectives

The objective of this thesis is to describe the improvement ideas implemented as a result of the patient flow project. Focusing more closely on one specific area of need, this thesis outlines ways to reduce the number of surgical cancellations by providing decision makers in the PICU admissions process a more pre-emptive understanding of the state of the unit, both short and long term.

A substantial part of the thesis focuses on the implementation of lean concepts in a healthcare setting. Projects performed at the Health Sciences Centre are described and used as examples of how improvements can be made using lean methods.

The thesis provides a long term understanding of the capacity versus demand balance within the PICU. It indicates whether the department has adequate resources by providing statistics on how often the unit is at full capacity, bed utilization, and the average number of patients and time spent in queue waiting for a bed to open. The tools developed for the thesis will provide a means of experimentation to examine the effects of altering department resources and patient statistics without having to disrupt anything in real life. This is a valuable approach in situations such as pandemic planning.

Lastly, the thesis will discuss a solution to short term PICU management and a way to reduce the effect of cancellations on a day-to-day basis. By creating an anticipatory operations management tool, surgeons will have access to more information leading up to a case requiring a monitored bed. This will hopefully result in PICU managers experiencing less perpetual stress from having to react to ever-changing conditions and relaying the status on to those involved. The conceptual idea is that the resource will be able to supply the probability that a monitored bed will be available on the day that it has been requested, providing some sort of progression analysis (red/yellow/green light) on whether to proceed. In an elective surgery situation, this will provide a surgeon with the information in which to base the decision of whether to continue as scheduled or postpone the case and schedule a replacement. Equally, if not more important, if it can be determined at an earlier stage whether a surgery is able to proceed or not, patients and their families will receive sooner notice that the surgery must be cancelled. No one wants to hear that they have to wait longer for their surgery and ideally no cases would get cancelled, but at least with earlier notice it would eliminate some of the difficulties of patient fasting and then traveling into the hospital on the morning of the surgery and finding out it was all for nothing.

1.3 Thesis Outline

Chapter 1 of the thesis is an introductory chapter with the purpose of outlining the background and motivation behind the work performed. It also provides an outline of the thesis and states the targeted objectives. The body of the thesis begins with Chapter 2, a literature review outlining past work performed that is related to the topics of lean thinking and simulation in the healthcare industry. Subsequently, Chapter 3 describes the work performed as part of the pediatric surgical patient flow project and the specific lean improvement projects that were performed. This is followed by Chapter 4, a detailed outline of the preliminary and current-state simulation models constructed to analyze the PICU. Also included are future-state models showing the analytical process involved in preparing for hypothetical situations. Chapter 5 outlines the creation of a tool which provides a statistical probability indicating the state of the PICU leading up to a procedure. A concluding chapter acts as a summation for the thesis and discusses future work that may be performed as an off-shoot from the work performed within.

Chapter 2 Literature Review

2.1 Introduction

The purpose of this chapter is to summarize the recent academic findings in the field of simulation and lean in healthcare via publications and research papers reviewed in journals and conference proceedings. In addition, reporting on the future trends of the field will be included. Specific points to be emphasized in the chapter include highlighting the special need for modeling and simulation in the healthcare field and commenting on previous case studies and related research performed in the healthcare system and, more precisely, the intensive care unit of a hospital. The chapter will conclude with a discussion on areas in the field yet to be explored as well as a look at the developing trends in healthcare simulation.

2.2 Lean Thinking in Healthcare

The concept of lean thinking originated in the manufacturing industry but is applicable to all sectors of work, including healthcare. Many successful examples of implementing lean in a hospital setting have already been documented, resulting in benefits such as reduced costs, increased quality, increased output, increased patient satisfaction, and increased employee job satisfaction.

2.2.1 Introduction to Lean Thinking

Lean production was created in the 1950's by Taiichi Ohna at Toyota (recognized as the Toyota Production System) and is known for its minimal use of resources and the elimination of all forms of waste. The lean philosophy has grown out of this method of production into a mind-set applicable to all areas of work and life. It encourages managers to "understand, stabilize and maximize what you have now, not expand and automate what you already can't control" (Morrissette, 2009).

One of the important themes of the lean philosophy is the definition of waste as anything that does not add value to a product in the mind of the customer. Simply put, it is any activity or outcome that the customer is not willing to pay for. Thus, strong customer relations are central to lean. Another theme is the reduction of variation within a process to accompany the elimination of waste. Organizations often achieve this by merging the Six Sigma concept into their lean philosophy. Six Sigma is a concept developed by Bill Smith, an engineer at Motorola in 1986, and focuses on improved quality through rigorous statistical analysis, customer feedback, data collection, and improving business performance (Meredith & Shafer, 2007). The book "The Six Sigma Way" defines Six Sigma as:

> "a comprehensive and flexible system for achieving, sustaining and maximizing business success. Six Sigma is uniquely driven by close understanding of customer needs, disciplined us of facts, data, and statistical analysis, and diligent attention to managing, improving, and reinventing business processes." (Pande, 2000, p. xi)

The goal of lean is essentially to accomplish more with fewer resources. Examples of waste that could be eliminated in a healthcare system are excessive delays in treating patients, excessive lead times, carrying too much inventory, or workers or patients traveling excessive distances. This is important in order to require fewer resources, such as workers, inventory, space, equipment, time, and still produce a higher quality product.

In the influential book “Lean Thinking” by Jim Womack and Dan Jones, the authors identify five lean principles:

1. Define value from the customer’s point of view
2. Identify the value stream
3. Make the process flow
4. Pull from the customer
5. Pursue perfection

Defining value from the customer’s perspective requires evaluating which steps of a process the customer is willing to pay for or considers necessary to reach the outcome. Customers can be either external, someone who buys a product or service, or internal, the person who accepts the product at the next step within the process. For example, an external customer is a person who purchases a product from a retail store and an internal customer is a charge nurse in the post-operative recovery unit who accepts a patient that has just exited surgery. There are also three categories for defining value: value added, non-value added, and non-value added but necessary. Non-value added steps are waste and should be eliminated. Value added steps are processes that the customer cares about, are performed correct the first time, and alter the item going through the process in some way. Non-value added but necessary steps are activities in which an attempt should be made to reduce them, but cannot be eliminated because they are essential to the overall system. A common example of a non-value added but necessary activity is an accounting or payroll department; the department in no way alters the product being made yet is still necessary in order to ensure workers get paid and remain able to perform their job functions.

To help with identifying waste within a department or specific activity, there are seven identified forms or waste: Overproduction, Waiting, Transportation, Inappropriate Processing, Unnecessary Inventory, Unnecessary Motion, and Defects.

Overproduction refers to producing more product and/or finished product sooner than the internal or external customer needs. Excess amounts of inventory are a visual indicator that overproduction is prevalent in a system. The costs associated with carrying inventory are excessive and include the cost of purchasing material earlier than required, insurance, obsolescence, theft, damage, and storage. Most often, the excuse for carrying excess inventory is so that a company can react quicker to a change in the product or demand. While a certain small amount of buffer supply is necessary, lean suggests carrying less inventory and responding to customer demand in a timely fashion by creating close relationships with suppliers. This is the basis for the just-in-time (JIT) concept. By demanding that smaller amounts of raw materials be delivered with a shorter lead time, production can adapt quicker to changes and the cost of receiving and storing huge shipments is avoided.

The waste of waiting is defined by long periods of inactivity for people, information, machinery or materials. If either a customer or a worker is forced to wait for something, they are unable to perform the value-added activity. Instead of a worker having to wait for a machine to be repaired after a breakdown, scheduled preventative maintenance checks can eliminate long delays.

The third type of waste is transportation, relating to any amount of excessive movement of people, information, or materials. Resource travel is a physical measure which can be communicated to others and analyzed using tools such as a spaghetti diagram, a continuous line on a map or floor layout that tracks the movement of a person or object. Ways of decreasing the amount of transportation include efficient building layout, ensuring departments with a lot of inter-process movement are located in close proximity, and point-of-use equipment placement, designing a work space so an employee has all the needed equipment within reach.

The waste of inappropriate processing are the steps of a process which are the wrong procedures for the system and are non value-added. When a seemingly simple task ends up taking days or even weeks to be completed, it is usually because there are a series of needless steps along the way. Unnecessary steps in a process often become hidden to the people performing them because they have been completed that way for so long that they become ingrained and a comfort zone develops. When new employees are hired into the process they provide a fresh perspective and can see things more objectively.

The waste of unnecessary inventory is the excessive storage and delay of products or information. In order to avoid the costs associated with inventory storage, strategic levels of supplies need to be established and the urge to stockpile and exceed these levels must be avoided.

Unnecessary motion is a waste defined by any motion performed by a worker that does not add value to the product or process. This type of waste tends to be on a smaller time scale but one that adds up significantly over time. Examples of unnecessary motion are when a worker has to repeatedly bend over to pick up a piece of equipment off the floor, reaching up to get supplies off of a shelf, and moving materials unnecessarily around a department. The emphasis that many companies place on ergonomics aids in eliminating unnecessary motion by improving tasks which are physically strenuous for workers. Improvements are also achieved by moving materials so that they are more easily accessible. 5S is also a valuable tool for encouraging the maintaining of a clean work environment and exact placement of tools so that a worker knows exactly where everything is and can easily recognize when something is missing.

Lastly, the waste of defects is any error identified within the unfinished product at any point in time within the process or within the finished product by the customer. Defects require rework and anytime a process must be performed twice, it is a waste of resources. When things are not performed right the first time, it is a sign that there is a flaw in the process. Using root cause analysis is an important practice in identifying the true source of the defect and altering the process so that the mistake is avoided in the future.

Identifying the value stream requires creating a value stream map to visually indicate the series of processes necessary to fulfill the customer's demands. The value stream map can then be used in the next step, making the process flow, by charting a timed, paced product flow with right-sized tools to eliminate any work in process and excess inventory. Takt time is an important measure in synchronizing the flow of work with the customer's demands. Takt time, often called cycle time, defines the pace that work must be completed at and is equal to the total available work time divided by the customer required volume. This paced production can then be calibrated to the customer demand numbers so that a pull system is created which only makes products for which a specific need exists. Finally, continuously monitoring the production steps, the quality of the output, and any alterations and improvements made constitutes an effort to strive towards perfection. This step is where Six Sigma as well as 5S can be implemented. 5S is an approach to increasing the efficiency of individual work activities and workspace by progressing through the 5 "S" terms: separate, sort, shine, standardize, and sustain.

2.2.2 Lean Thinking in Healthcare

While the notion that lean thinking is only applicable to manufacturing situations is prevalent, even from the beginning of the lean concept development experts expressed that the healthcare sector could gain from it. Womack and Jones (2003) advocate the application of lean in medical systems and argue that the first step involves making the patient the primary focus and including time and comfort as key performance measures. Healthcare is an industry where an estimated 98,000 deaths a year are caused by error, indicating a definite need for lean practices (Connolly, 2005).

The 7 forms of waste outlined in the previous section can be customized to the healthcare industry. Overproduction could include requesting unnecessary/precautionary medical tests, testing ahead of time to suit lab schedule, surplus medications, or receiving paperwork too far in advance. Examples of waiting are bed assignment delay, delays in admissions, testing, treatment, or discharge, or traveling to pick-up a transfer patient and finding that they're not ready. In hospitals, transportation waste can occur in any unnecessary transport of patients or supplies/tests. Inappropriate Processing refers to multiple bed transfers, retesting, excessive paperwork, and unnecessary procedures. Unnecessary Inventory is any excess pharmacy stock or department supplies. Examples of unnecessary motion are searching for patients, medication, charts, etc., gathering equipment or supplies, and handling paperwork. Types of defects include missing information, redraws, medication error, or wrong patient or procedure.

An article entitled "Time-release fix" written by Matt Morrissette (2009) describes how 5S can be used to improve healthcare practices. Morrissette emphasizes developing a better understanding of current resources before pouring more resources into the process. The article describes how the 5S concepts can be applied to healthcare and examples of hospital implementation.

Morrissette (2009) states that decision makers so often use automating to update a process but then fail to recognize the data and its use towards realizing related process changes and improvements. Based on the author's experience, this situation is entirely accurate. Data systems are purchased and set in place because they are deemed necessary and then a lot of work is invested in installing and filling the database. The problem seems to be, however, that numbers go in but rarely come out. The statistical data is so rarely used to drive any process changes and process performance measures remain unknown. "Employees in healthcare juggle so much that throwing tons of money at them … is merely adding one more extension of the burden" (Morrissette, 2009).

5S is a tool of lean healthcare and is often the first step when starting a lean transformation. This is because of its popularity, people are most likely to be familiar with it, and because it is the easiest to implement, producing relatively immediate results. There are limitless interpretations of how to use 5S making it applicable to any department. Morrissette describes the 5S's in current state hospital conditions as being scrounge, steal, stash, scramble, and search. The actual 5S acronym (separate, sort, shine, standardize, and sustain) defines a method for creating and maintaining a clean and organized workspace to ensure safety and promote high performance.

Exeter Hospital in New Hampshire (Morrissette, 2009) has been using lean healthcare since 2005 and has explored 5S solutions in several kaizen events. One such kaizen was performed on the inpatient discharge process. The team separated out waste in preparing for discharges, defined exactly what was of value for the patients, managers, and extended care facilities, and standardized checklists, urgency labels, and clinical roles. Case management daily meetings, hospital timing, and priorities were established and a monthly audit by the nurse manager was used to provide data feedback to maintain the changes and evaluate new modifications. The result of the kaizen was that discharges before 11 a.m. doubled even though admissions increased over the timeframe by 10 percent.

In 2005, The Washington Post reported on the lean efforts being performed at Virginia Mason Medical Center in downtown Seattle (Connolly, 2005). The 350-bed hospital had an overarching goal to improve the patient experience while increasing the overall efficiency of the process using lean concepts. "Whether making a car or a healthier patient, the approach fundamentally is about eliminating waste – from paperwork and inventory to waiting-room delays and extraneous surgical tools." Implementing such a radical new management style required the full support of top executives and still was met with resistance. A few top executives left the hospital and many physicians ridiculed the philosophy because of a sense of threat to their autonomy.

According to Connolly (2005), the chief executive of Virginia Mason Medical Center, Gary S. Kaplan, estimates that the lean initiatives have resulted in savings of $6 million in planned capital spending, freed up 13,000 square feet of floor space, cut inventory costs by $360,000, reduced the amount of staff walking distance by 34 miles per day, shortened bill collection times, reduced infection rates, created new business opportunities, and, most importantly, improved patient satisfaction. Being able to increase interaction time while seeing more patients and reducing wait lists makes everyone happier; patients appreciate the doctor spending more time with them and doctors enjoy being able to "walk out the door at 5:15 p.m. instead of 7:30".

One of the most drastic areas of improvement was the care for cancer patients. Chemotherapy patients in the past endured long distances of travel through the hospital from doctors' offices to schedulers to the lab to examination and treatments rooms, a tiring experience which typically lasted 11 hours. After the improvements were made, the distance from lab to exam room to treatment is less than 12 feet. Patients no longer wait in a noisy reception area but receive their IV in a cheerful private room equipped with a television, a computer, nursing supplies, and a bathroom. A separate pharmacy was built within the cancer centre, eliminating delays of up to two hours. In the first five months following the changes, the preparation time for chemotherapy patients was slashed from three hours to less than one. This equated to additional capacity of 50 patients a week, supplying additional revenue available to recruit another doctor and expand research.

Other improvements within the hospital include standardization of equipment and procedures and better space management. By devising one standard instrument tray for all 12 doctors performing laparoscopic gallbladder surgery, the hospital reduced the cost of the procedure by $950. Construction of a new hyperbaric chamber inside the hospital reduced the amount spent on transporting patients via ambulance outside of the facility by $55,000 each year. In the sleep disorders unit, three physicians now share one office and conduct 90 percent of their work in the exam room. This freed up space for the hospital to open a business delivering sleep assistance devices and reduced the appointment wait time from six months to two weeks. To ensure that heart attack patients receive the full, universally accepted treatment regimen, a bracelet was designed using symbols to track the steps involved and ensure quality practice. Patients are not discharged until each item on the “wristband medical record” is checked off.

A case study performed at the Valley Baptist Hospital in Harlingen, Texas (DeBusk, 2005) addressed the inefficiencies of the hospital’s patient discharge process. The discharge process at a hospital can be lengthy and can create problems in other units which must wait to transfer a patient until the room is vacated. The study evaluates Lean, Six Sigma, and change management techniques as tools to reduce the time from when a discharge order was entered into the computer until the time the patient left the room to a goal of 45 minutes.

The patient discharge process improvement was centred on mapping the current steps taken in the process. Beyond the steps involved in the discharge, the process map included rework loops, communication flows among staff, and key performance metrics. Also each activity was classified as either value-added, non value-added, or non value-added but necessary. The improvement team was able to identify the steps that did not help discharge patients any faster, thus were non value-added, and uncovered the fact that there was little consistency in the nurses’ approach to discharging patients.

It was discovered that in 21% of the cases, nurses required clarification from a doctor before the discharge could be entered into the computer, adding an average of 33 minutes to the overall process. In some cases the primary nurse took the patient’s vital signs, in other cases a second nurse took the patient's vital signs and then reported them to the primary nurse. Standardizing the process and having only the primary nurse be responsible for the vital signs reduced the overall time by an average of 64 minutes. Based on these discoveries and other insights, a standard operating procedure consisting of six steps for the patient discharge was developed. The result was that the mean patient discharge time was reduced by 74%. In regards to the goal of decreasing the time elapsed from when the discharge order was entered into the computer until the patient is transported from the room to 45 minutes or less; 61.7% of patients achieved this target, up from 6.9% before the study.

2.3 Simulation in Healthcare

The use of simulation in healthcare has still not been adopted as frequently or as emphatically as in other industries, such as manufacturing and business. By establishing the use of simulation in their core operations, these other sectors have subsequently reaped much more significant benefits. They have noted that while creating a simulation model can require more time at the beginning of a project, the resulting quicker installations and product optimizations can reduce overall project time. There is an abundance of academic publications related to the application of simulation in the healthcare field yet a relatively few number of documented successful implementations compared to other industries.

Speculation as to the reasons why implementing simulation activity in healthcare has been lagging behind other industries has led to theories such as the human intricacies of healthcare and the ingrained cultures of a hospital. The entities which flow through a hospital are emotional human beings with feelings, often in life-threatening situations, and not inanimate objects on an assembly line. Thus additional attention must be given to safety and trialing the results of a simulation model become less feasible. Nevertheless, complex models of an airport are centred on human entities which take into account feelings, reactions, and the corresponding uncertainty. Similarly, the “clinical hierarchy” involving professional boundaries and the silo effect between departments are equally prevalent in other settings, notably military models (Brailsford, 2007). Internal clashes between staff occur in all organizations.

In 1977, Kenneth F. Watt wrote a paper entitled “Why won’t anyone believe us?” which deals with the issue of the modeling community’s failure to influence social policy. Model issues and the nature of the output, a lack of motivation from those who influence policy, and the method by which modeling projects are run are all mentioned as contributing factors. In another study, eight percent (16 out of 200) of healthcare simulation projects surveyed reported successful implementation (Wilson, 1981). Common factors which were believed to contribute to the successful implementations included at least one author who worked at the healthcare institution, a model used to analyze a problem of high priority, external funding, and a detailed description of data collection. More recently, Fone et al (2003) performed a systematic review of healthcare simulations documented between 1980 and 1999 and found very few examples of implementation. The author writes “we were unable to reach any conclusion on the value of modelling in health care because the evidence of implementation was so scant" (Fone et al, 2003, p. 333).

The healthcare sector faces continuous growth and unprecedented levels of change which would benefit immensely from the application of simulation. This puts care providers and managers and their decision-making system under increasing scrutiny. "Metrics of performance" (Kuljis et al., 2007) have been introduced to ease the process but there seems to be a state of give-and-take where progress in one area is often at the expense of another. One reason suggested why the widespread numerical and simulation techniques applied to health care have been criticized is that the approach taken focuses on the tool (simulation). Because the techniques originated in other industries, there is a feeling that the approach starts with a solution and tries to find a problem within healthcare that it can be applied to. A more effective methodology would be to start with a real problem and create a unique model and simulation to target the exact requirements.

Another key point made in the article by Kuljis et al. (2007) is the fact that patients are not typical customers and are certainly not widgets moving down a conveyor belt. Healthcare patients are often in life-threatening situations and thus they are vulnerable human beings with feelings and emotions and much more responsive and free to exercise their right to make choices. This often adds an element of unpredictable pressures and often irrationality to the system. Nevertheless, although patients are obviously not inanimate objects in a production process, humans are represented in models of airport terminals and military complexes so human safety factors and emotions are taken into account in many other settings.

As new diseases lead to an increase in model developments and tighter budgets lead to data-driven efficiency measures, the advancement of simulation software occurs with the combination of other techniques, such as optimization. Improvements in the user-friendliness of simulation software equates to an increased number of healthcare professionals who can use the product without a vast background in computer programming. This results in simulation being not just a tool for Operations Research modellers but something anyone could use. Combining simulation techniques (such as discrete-event and system dynamics) to utilize the strengths of each is another progression. The development of more generic models and a forum for sharing them is an area of future focus. A model developed for one hospital is seen as being specific to that hospital with limited usefulness elsewhere. This has resulted in thousands of models being created for different emergency departments, many of which probably have very similar qualities.

The journal articles that were reviewed contained a number of examples where simulation was used in a healthcare setting, as well as more specifically, and more relevant to the scope of this study, departments which provide intensive care to patients. The simulation methods used were done so with specific purposes and dealt with the uncertainty involved within the system. They were applied to a variety of departments, were based on the different methods listed, and used different levels and types of simulation programs and technology.

One of the most common measurements monitored by hospitals is bed utilization, strongly affected by the factors bed allocation and admission policies. Bed allocation simply refers to the assignment of beds to a category of patients in accordance with medical specialty, physical layout, and equipment type. For example ICU beds are allocated for patients with intensive care needs who require specialized monitoring equipment in a close proximity to the operating room. Bed allocation must take into account both patient needs and hospital needs, such as economic and educational requirements. Admissions policies involve the control that a hospital has over the patient mix and hospital demand through the efficient handling of scheduled elective cases, wait list priority, accepting emergency admissions from outside centres, and inpatient transfers. Dumas (1984) warns that reallocations need to be approached with caution and carefully analyzed before implementing; they are not just a matter of adding beds to units where demand is high and reducing them where demand is low. Dumas stresses that "attention must be paid to the character of the hospital, its physician and patient mix, service interactions, and the nature of anticipated demand".

The computer model described in the article by Dumas was developed to simulate the complex interactions which occur throughout a patient's travel through the hospital and the processes which lead to a patient being assigned to a specific bed. The simulation became a means for evaluating bed allocation. It was able to do so by incorporating pertinent distinctions used by the hospital in order to differentiate between patient groups; distinctions such as medical specialty and diagnosis type, the location that the patient is admitted from, and the time of demand. From the author's experience, these distinctions are very difficult to determine, let alone document. There are so many different attributes for each patient compiled with the seemingly limitless options for some of the attributes, grouping patients into subgroups becomes a rough estimate. For example, to categorize patients by diagnosis would result in thousands (if not hundreds of thousands) of groupings. Alternatively, categorizing patients by specialty (ie. plastics, ENT, etc.) would drastically reduce the number of groupings but would lead to very dissimilar patients within a group, rendering generalizations inaccurate. A balance must be found using the most accurate patient classification criteria available.

The article by Dumas on hospital resource planning and bed allocation is supported by a number of other studies performed in the area. A substantial amount of the work in this field has focused on higher level problems, such as regional resource assessments in order to meet the demand of a city or region. Many of the older studies were encouraged due to a sense that there were too many beds in most regions supported by low overall occupancy rates. The simulations were then used to identify where bed reductions should occur. Examples of this include an article which analyzes a large city hospital entitled "Harlem Hospital Bed-Reallocation Plan" by Corrigan (1978) and a study by MacStravic (1978) which addresses regional occupancy levels. Most likely due to a long-term emphasis on reducing costs, the number of hospital beds has been reduced. Include the fact that patient populations are steadily increasing and most hospitals now face the opposite challenge, proving more resources are required to adequately fulfil the demand.

Work in the field of resource allocation has also been performed at a hospital level. Webb et al. (1977) discussed the issue of demand management, more so than bed allocation, in Kings College Hospital, a major teaching hospital in London, England. They examined controlling bed utilization and occupancy by reviewing the errors of forecasting admissions and discharges. In the article “Swing beds: rural hospitals seek solution to old problem of bed distribution”, Rusting (1978) weighs the value of utilizing flexible “swing” beds in handling fluctuations in demand in a small rural hospital. The size of the hospital made the option more feasible than in a large, multi-building hospital. However, it is certainly possible that it would be useful on a smaller scale (ie. within two units in close proximity).

Hancock et al. (1978) performed a hospital management systems study with a focus on admissions scheduling and control. They were successful in creating a simulation model that assessed the impact that a variety of control policies had on bed utilization and could indirectly analyze bed allocation changes. The study resulted in recommendations for occupancy levels and a manual scheduling system.

The most heavily studied department in the healthcare system seems to be the operating room (OR). This is most likely because the OR consumes a large portion of the hospital’s monetary resources and surgeons are such a valuable and limited resource that every effort is made to maximize their utilization. The journal article entitled "Simulation of a Multiple Operating Room Surgical Suite" by Denton et al. (2006) looks at the uncertainty surrounding the activities related to the intake process, surgical procedure, and recovery process as part of the outpatient surgery scheduling. Uncertainty combined with the need to trade-off criteria such as patient waiting times, OR team waiting, OR idling, and overtime makes scheduling a difficult challenge. The article focuses on creating a simulation model for a multiple OR suite, unique from the typical single OR study, and discusses how the simulation model can be used to aid in scheduling changes and the strategic decision making relating to the surgical services. The study applies a Monte-Carlo simulation model and is based on data collected at the Mayo Clinic in Rochester, MN. The analysis indicates that "even a simple scheduling heuristic based on scheduling of the bottleneck (surgery) activity can lead to simultaneous improvements in expected patient waiting time and overtime."

Another article focusing on the OR is by Ballard and Kuhl (2006) entitled "The Use of Simulation to Determine Maximum Capacity in the Surgical Suite Operating Room". This article points out the importance of recognizing the variability in hospitals resulting from unique procedures and patients and the difficulty this causes in performing capacity analyses without making drastic simplifying assumptions. The researchers present a "general methodology" for determining the maximum capacity of a single OR suite through the use of a discrete-event simulation model created with Arena software. The aim of the project is to aid in doctor/resource acquisition decisions, patient satisfaction improvements, and increased productivity. The study devises a useful new method of calculating OR utilization statistics under maximum capacity.

Another heavily studied area of healthcare is the emergency department (ED, or commonly the ER) because of its strictly random nature, the large emergent population which flows through the unit, and the public visibility and social focus on it. A paper by Ruohonen et al. (2006) entitled "Simulation Model for Improving the Operation of the Emergency Department of Special Health Care" presents a simulation model created based on the operations of the Emergency Department of Special Health Care at the Central Hospital in Jyvaskyla, Finland. The idea behind creating the simulation model is to demonstrate a new operational method which increases effectiveness and can be used as a decision support tool. The study uses patient waiting times and throughput times as the main target variables and attempts to identify optimal amounts of staffing for every phase of the process. The researchers determined that the average throughput time of all patients was the best target variable and calculated the difference between the output values of the simulation results and the real system was a mere 3%, validating the model and rendering the results suitable to base decisions on.

The Intensive Care Unit is a unique department within a hospital which provides simulation challenges unlike other departments. Most difficult to account for is the mixture of emergency and elective patient streams and the resulting effect on bed capacity and dedicated resources. The random arrival of emergency patients and the need to have space to accommodate them leads to a difficult task in scheduling the elective surgical patients and the possibility of cases being cancelled due to insufficient resources. Other challenging ICU aspects are its varying patient care complexity (and therefore varying patient length of stay) and its relatively undefined different levels of care, where patients can be discharged early (or bumped) to alternative wards.

A simulation model created for the general intensive care unit at the Southampton General Hospital is described in the article “Capacity planning for intensive care units” by Ridge et al. (1998). The simulation investigates the relationships between the number of ICU beds, bed occupancy levels, and the number of cancellations (or transfers) due to lack of resources.

The intensive care unit being studied in this project is subject to many constraints that would be experienced within all hospitals, such as accurately determining demand and deciding on the needed capacity and how to allocate the resources. An “uneven spread” of ICU beds between hospitals indicates little standardization while case cancellations are strongly related to overall capacity and bed allocation between elective and emergency cases. The article by Ridge et al. points out that basing the number of beds needed on mean monthly arrival patterns and a selected confidence interval is inaccurate because of the randomness of emergency patient arrivals, often in quick succession, and the need to admit these patients with as little delay as possible. As well elective patients skew the data due to constraints imposed by other hospital services. These services include surgeon availability, admission profiles which vary based on time and day of the week, as well as patient length of stay which is consistently short and based on patient type. The length of stay is also a difficult metric because it is subject to outliers, such as patients which require an ICU bed for a very long time and cause a “blocking” effect.

Ridge et al. warn that a major challenge in building a model is the initial data collection and analysis. The data collection must ensure accuracy and is made easier by an ICU database system. The data analysis becomes difficult when attempting to classify patients into similar entities. For a model to produce the most accurate results, grouping patients in order to minimize the variability in the length of stay within any patient group is necessary. Properly distinguishing between different levels of the severity of a diagnosis between otherwise similar patients is a strenuous task but useful in identifying expected length of stay and cost of care. Thus, most ICU’s have their own classification system, based on procedure, severity, etc. This, however, makes it difficult to compare data across multiple hospitals. The article mentions the INFORM initiative (Leaning et al., 1991) as a source for a standardized data system.

The author emphasizes the fact that the length of stay value is an important variable to get correct and how it is a useful step in developing an ICU patient scheduling system. What often happens in an ICU is managers are pressured to create space for incoming patients which results in current, less intensive inpatients being discharged or bumped to an alternative ward, something like a step-down unit. This leads to a shortened length of stay value being recorded even though under different circumstances the patient would have remained in the unit. Very few ICU’s, if any, track which patients are released early and estimate by how much. Ridge et al. gives recognition to a few articles which deal with the issue of predicting length of stay: Tu and Guerriere (1993), Tu et al. (1994), and Rawlings et al. (1993).

The simulation model created by Ridge et al. was done using PASCAL with data collected over a five year time span, representing 2000 patients. Like previous simulations (Shahani et al., 1994), this one used a negative exponential curve or a Weibull curve-fitting routine to represent the length of stay of the emergency and elective patients. There is also a bed allocation priority rule favouring emergency patients and patient inter-arrival times follow a negative exponential distribution. The creators also included features in the simulation such as planned patients being deferred or placed in a queue for a certain time period if the ICU is full upon arrival and elective patients taking on emergency status after a user-defined maximum number of deferrals. The author is not in complete agreement with elective patients becoming emergent cases in a simulation. From a macro perspective, if an elective case is unfortunately cancelled and rescheduled enough times it should be given a higher priority and possibly require emergency status. However, in a simulation model focused on data, these can be treated as individual cancellations and instances of demand not being fulfilled.

Based on the work of Cohen (1956), Ridge et al. provide an analytical solution, f(x), which calculates the probability of a state in which x beds out of a maximum S beds ($0 \leq x \leq S$) are occupied (as seen below). As well there is a formula for D, the probability that a patient is delayed.

$$f(x) = \frac{S - \lambda_{\mathrm{e}} - \lambda_{\mathrm{p}} \qquad (.)}{S - \lambda_{\mathrm{e}} - \lambda_{\mathrm{p}} + (\lambda_{\mathrm{e}} + \lambda_{\mathrm{p}})\, E(S, \lambda_{\mathrm{e}} + \lambda_{\mathrm{p}})}$$

$$\text{where } (.) = \frac{(\lambda_{\mathrm{e}} - \lambda_{\mathrm{p}})^{x}}{x!\, N(S, \lambda_{\mathrm{e}} + \lambda_{\mathrm{p}})}$$

$$\text{where } N(a, b) = \sum_{i=0}^{a} b^{i}/i!$$

$$\text{and } E(a, b) = \frac{b^{a}}{a!\, N(a, b)}$$

$$D = \frac{SE(S, \lambda_{\mathrm{e}} + \lambda_{\mathrm{p}})}{S - \lambda_{\mathrm{e}} - \lambda_{\mathrm{p}} + (\lambda_{\mathrm{e}} + \lambda_{\mathrm{p}})E(S, \lambda_{\mathrm{e}} + \lambda_{\mathrm{p}})}.$$

In these formulas, S represents the number of beds, λ_e the emergency arrival rate which has high priority, λ_p the planned arrival rate which has low priority.

The simulation model utilized by Ridge et al. is set up to produce five sets of data which enable the user to observe the effects of varying the number of ICU beds, varying the time between an elective case being cancelled and the resulting rescheduled procedure performed, changing the number of beds reserved for emergency admissions, and the typical number of free beds at the end of the day (midnight) and the typical available bed probability distribution. The stated results show that increasing the number of ICU beds produces an initial steep drop in cancellations (or “transfers”) which levels out as further beds are added. Thus the percentage of case cancellations is non-linear with respect to the number of beds and the mean occupancy rate suffers increasingly as more beds are added (ie. the bed usage becomes less efficient). The second set of data showed suggested that the elective case deferral time did not influence the number of cancellations. In regards to the notion of reserving ICU beds strictly for potential emergency cases, the results showed that this would only slightly decrease the number of emergency patient rejections while raising the number of elective patient cancellations considerably. "Overall transfers are minimised when no beds are reserved at all". There was no mention in the article of dedicating a certain number of beds to the elective patients, a patient flow which is much more predictable (scheduled) and thus could be regulated and make better use of dedicated resources.

This article contains a description of how the model users were able to determine a probability distribution of the number of available beds at any particular time of day, something the author can see as being a useful planning tool. The results showed that with six beds the ICU being studied, the unit had most often zero, one, or two beds unoccupied. With eleven beds used in the unit, the distribution shifts so that there are between four and eight beds free the largest percentage of time. Graphical representations of the results can be seen below in Figure 2.1.

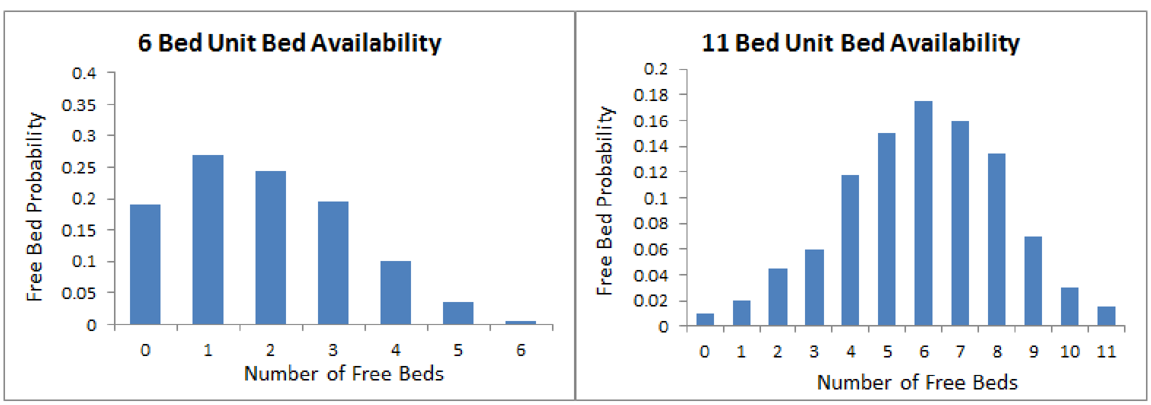

Figure 2.1 Ridge et al. Probability Results

This article, like many others, touches on the vast amount of effort that has been dedicated to the area of simulation in healthcare with a disappointingly small percentage of application. The authors' proposed solution is to bring together disconnected past work to form a "single, flexible and sufficiently detailed model". This is a novel plan, however seemingly impossible. If by "single" it is meant one encompassing ICU than that is no different than past simulations. If by "single" they mean an ICU and all departments that affect it (essentially an entire hospital) then not only would this be an extremely large effort, achieving the other objective of being flexible would be exponentially more difficult. Further work to be performed listed by the article includes an elective patient scheduling system, a range of different levels of care, and a semi-automated historical data analysis including a statistical method for defining patient groups.

An article by Seung-Chul Kim et al. (1999) uses a queuing and computer simulation model to analyze the capacity management and bed utilization in an intensive care unit (ICU) in a public hospital in Hong Kong. The data collected includes the number of admitted patients and the number of rejected or cancelled cases as a result of no available beds. A queuing analysis was performed, along with a statistical Chi-Square test of the hypothesis, to determine that the cancellation of surgeries was due to the "timing of bed supply and demand, rather than to a shortage of overall capacity." The computer simulation, performed on XCELL simulation software, was used to confirm the findings and determine the exact bed utilization and time in queue. The report was able to conclude that the cancellations that occur in elective surgeries are not a result of a lack of resources but from managerial aspects and the scheduling of the cases. A suggestion is made that the problem might be alleviated through better coordination between the ICU and the referring surgeons during the scheduling process.

2.4 Summary

It is very apparent that simulation modeling is a feasible approach for dealing with healthcare issues however the lack of successful implementation resulting from its use indicates that it is still underutilized and lagging behind other industries. The flexibility of simulation and its ability to produce (optimal) results for hypothetical situations without ever affecting the actual system is a key attribute in using it within the healthcare decision making forum. The healthcare system is characterized by uncertainty and variability and thus the stochastic approach of simulation modeling is a great fit. As well, simulation modeling is only growing in strength and speed proportionally to computers and the number of available simulation software packages. This renders simulation even more capable of handling the complexities of the healthcare system.

So what does the future of simulation modeling in healthcare systems look like? The largest roadblock is successful implementation. Past research discovered that while surveying over 200 simulation projects in health care, only 16 were found to have been implemented. This indicates that while academic researchers are embracing the method and publishing journal articles in support of their work, the application is not being achieved within the hospital setting. The projects that succeeded all the way to implementation had common elements such as at least one author who worked at the institution, external funding, and a detailed description of the data collection. Another issue is one of generalization. Brailsford (2007) points out that there are over 1000 published simulation models of emergency departments and yet the core characteristics of the departments can't be too different. Therefore, a progressive step in the simulation movement would be to come up with more generic models that are not geared towards a single location or situation but implementable by any healthcare system.

Lean practices in healthcare face many of the same challenges that simulation does. While reports exist showing the benefits of implementation, both are still generally seen as academic and remain untrustworthy methods in the minds of most healthcare professionals. Given upper management support and presented to people who are willing to embrace change, the toolset encompassed by lean and the practice of simulation can improve a process and make it more efficient.

Chapter 3 Incorporating Lean at Health Sciences Centre

3.1 Introduction

It has been shown that the concepts of lean thinking have been applied to healthcare systems across the world. A tool like simulation often takes on a broader perspective and deals with theoretical ideas which cannot be tested in a healthcare setting. Lean utilizes simpler techniques which can improve efficiency using simple and more implementable steps. Lean concepts, however, are for the most part new to the Children's Hospital at the Health Sciences Centre in Winnipeg, Manitoba. Introducing the concepts and utilizing the tools and improvement techniques were one aspect of the surgical patient flow project. The objective of this chapter is to outline the projects that were performed and describe how lean was used to make a difference in the patient flow.

This chapter starts by providing a description of the pediatric elective surgical process at the Winnipeg Children's Hospital and its patient flow system. Section 3.2.2 is dedicated to summarizing the seven forms of waste as identified by lean thinking. The seven forms of waste theory was vital to recognizing wasteful processes within the individual departments of the hospital, as outlined in subsequent sections of this chapter. Lastly, this chapter includes a section (Section 3.3) devoted to observations made from a lean perspective at a private clinic outside of the hospital setting.

3.2 Pediatric Surgical Patient Flow Project at Health Sciences Centre

The pediatric surgical patient flow project at the Health Sciences Centre began in January 2008 and ran until April 2010. The overall objective of the project was to improve the flow of patients through the pediatric elective surgical system. This included streamlining and standardizing certain procedures identified to cause delays, reducing the number of cancellations which lowered operating room utilization, and using lean to better the overall experience of the patients and their families.

3.2.1 Elective Surgery Process at Children's Hospital

The pediatric elective surgical process at Health Sciences Centre starts when the surgeon's office receives a referral letter from a family doctor who has determined that a patient requires the diagnosis of a specialist and possibly surgery. The referral letter is used by the surgeon's office to determine the severity of the case. If the patient requires immediate attention, the case is processed quickly and the child receives emergency surgery. However, if more information is needed or the case is not an emergency but rather elective, then the patient is scheduled into the surgeon's allotted clinic time and the surgeon's secretary contacts the patient, or in most cases their family, to inform them of the scheduled appointment and any further details.

At this point, the patient physically enters the system. The patient, and their family or guardian, comes to the clinic for their scheduled appointment and checks in at the front desk. Once all the paperwork is complete, the patient enters one of the clinic rooms and is seen by the surgeon. The patient assessment is very brief, about four minutes, because four patients are booked to be assessed in 15 minute time slots. Once the surgeon is finished with the assessment and has decided whether surgery is necessary or not, a clinic nurse enters the room. The clinic nurse cleans up or applies any dressings necessary and teaches the patient anything required related to their medical condition, after which the patient is free to leave. The clinic nurse then fills out an operating room (OR) requisition form and forwards it to the surgeon's office and the pre-admit clinic (PAC).

The flow of paperwork returns to the surgeon's office where the secretary receives the OR requisition form and fills out a wait list code form. This form is then filed in the wait list binder which contains all of the cases waiting for a surgical procedure. Once it is established that the patient is in line on the wait list, the corresponding next available surgery time is determined, often this date is months into the future. The secretary then contacts the patient to inform them of their scheduled OR date and confirms with them if the date is suitable. Once a final date has been decided on, the surgeon's secretary sends the case information to the Health Science Centre's central slating office where the OR slate is booked.

While a patient sits on the waiting list they have the option of preparing for the surgery by coming into the hospital and attending the pre-admit clinic (PAC). The PAC staff contacts the patient to see if they would like to attend and book an appointment. If a patient does not want to attend a PAC session or are unable to, they are given the necessary surgery preparation information over the phone. This would include requirements such as not to eat any food on the day of the surgery. If a patient does want to attend a PAC session, they come in on the day of their appointment and meet with a PAC nurse. The patient undergoes somewhat of a screening process where patient information (such as allergies and medication history) is collected and recorded. To prepare for the actual surgery, the patients are taken on a tour of the area of the hospital where they will have to travel during the day of their surgery. The patients are taken to the Day Surgery area where they have a mock OR set up, filled with stuffed animals, and the whole anaesthetic and surgical procedure is described to them. The PAC is also integrated with the anaesthetic pre-admit clinic (APAC). If a patient requires anaesthetics for their surgery or are on other medications which could add to the complexity of the surgical procedure, they undergo an additional step where they consult with an anaesthetist during their PAC visit to make arrangements for the day of the surgery. Lastly, the PAC is responsible for reviewing patient charts and medical records one week prior to the date of surgery to ensure that everything was accounted for and no further tests or preparation is needed.

On the day of surgery, patients arrive at the hospital at their scheduled time and pass through admitting where they check in and receive their identification tag. From there the patient is directed to Day Surgery where they meet with a Day Surgery nurse who gives them pajamas or an OR gown to wear. The nurse also takes measurements of height and weight and checks over chart information, such as any allergies. After that, the patient waits in the Day Surgery unit until the porter takes them down a floor to the OR waiting room. They wait until their surgeon is ready to meet with them to go over the surgical procedure and, if necessary, receive final consent from the patient's legal guardian.

Once an operating room has become available and has been cleaned and prepped by the multi-skilled workers (MSW), the anaesthetist takes the patient into the OR or a pre-op room and begins to administer the anaesthesia. When the patient is adequately sedated, the surgeon performs the procedure.

The post-operation process begins when the patient is transported from the operating room to the post-anaesthetic care unit (PACU). In this unit the patients are closely monitored by the nursing staff while they regain consciousness. When the anaesthesia wears off it is safe to relocate the patient to the corresponding recovery department. There are three main paths that a patient can follow depending on their needs. The first is returning to day surgery where the patient will rest for an average of six hours and require minimal attention before leaving the hospital that same day. The second path is for the patient to be taken to the children's ward for a long-term stay. In the ward patients will require more attention and are therefore monitored at a higher level than in day surgery. Lastly, patients undergoing the most serious and complex procedures are taken to the post-intensive care unit (PICU) where they will have access to specialized equipment and one-to-one continuous monitoring by a PICU nurse. Due to its high consumption of resources and an uncertainty of the number of required monitored beds for emergency cases, the PICU department is the most obvious source of cancelled surgeries.

3.2.2 Seven Forms of Waste

A project was initiated to implement the lean concept of identifying the 7 forms of waste in the system or series of processes. The 7 forms of waste and typical health care examples are explained in Section 2.2.1 and 2.2.2. Meetings were held with different departments and staff groups within the pediatric elective surgical patient flow. The 7 forms of waste and how they might apply to hospital functions were explained and then staff members came up with various aspects of their jobs which they felt hindered their performance, disrupting the patient flow, and were able to develop a list of improvement ideas. The meetings were performed with the multi-skilled workers, the OR nursing staff, Day Surgery, PACU, and the ward (CK3). The resulting lists of these meetings can be seen in Appendix A. After completing this process and developing the lists of improvement ideas, we selected the work group of multi-skilled workers (MSWs) as the area that would most benefit and experience the quickest improvements from focused efforts.

3.2.3 Multi-Skilled Worker (MSW) Analysis Project

The MSW's are primarily responsible for performing the clean-up duties between surgical procedures. There was a notion that the MSW's were overworked at times, especially when multiple surgeries end concurrently. Therefore, it was agreed upon that the project would develop an understanding of the standard tasks involved in the MSW role and collect data to determine where any problems might be occurring and if the clean-up process was responsible. As well there was a goal to obtain feedback from the staff and attempt to make any necessary improvements to the job or the working conditions.

The MSW staff performs the clean-up duties once an operation has finished in order to prepare for the next one. The crew consists of one designated anaesthetic MSW who looks after cleaning the anaesthetic machine and restocking its supplies. As well, there are usually three other MSW's who perform the rest of the clean-up and assist in the anaesthetic duties when needed. The MSW's also fill the role of the porter (who transports patients from Day Surgery to the OR Waiting Room) when the porter goes for break and they interact with MDR (Medical Device Reprocessing), the department responsible for supplying clean equipment and accepting used equipment. The MSW's have two cellular phones, one for the anaesthetic MSW and the other for one of the others. The OR nurses call the MSW's when an operation ends and notifies the staff that the theatre requires cleaning. The basic OR theatre cleaning guidelines are listed in Appendix A.

Data was needed in order to develop a sense of how long the clean-up process took. The OR nurse recorded the time that the MSW's were contacted via cell phone and notified that the patient had exited the operating theatre and then the MSW's recorded the time they entered the room, the number of staff performing the clean-up, and the time they exited the room. The data collected indicates that the average cycle time for the clean-up procedure is 10 minutes (Figure 3.1). As well, the average amount of time it takes for the MSW staff to arrive at the OR after the patient has been taken out is only 2 minutes.

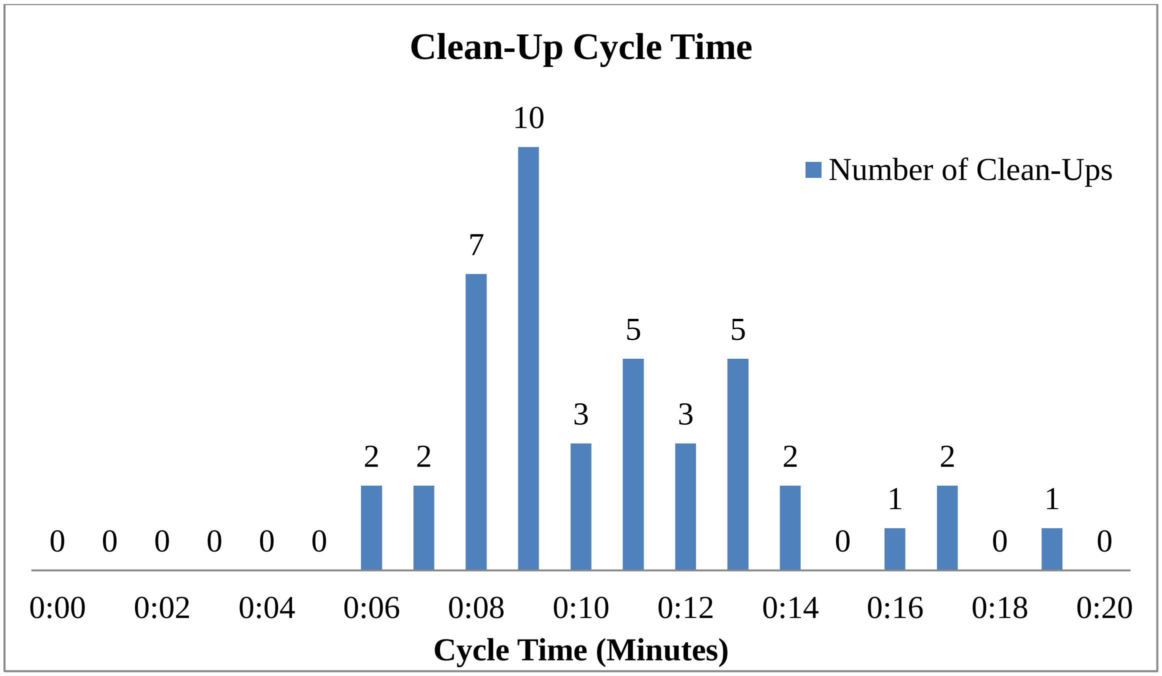

Figure 3.1 MSW Clean-Up Cycle Time Histogram

The number of MSW staff that are available to clean a theatre post-operatively fluctuates depending on the number of surgeries that end at the same time or close to each other as well as all of the additional tasks which are required of the MSW's. Therefore, the speed at which an OR is cleaned is dependent on the number of MSW's performing the tasks. Table 3.1 and Figure 3.2 indicate that the average clean-up cycle time decreases from 14 to 10 minutes when the number of MSW staff increases from 2 to 3. There is no change in time when a fourth MSW is added and an increase in cycle time on the rare occurrence that 5 MSW staff are available to clean the room. While the situation involving 5 MSW staff is limited to one instance, the trend makes sense; increasing staff up to a certain point is beneficial, having more workers to divide the tasks among, having too many staff present prolongs the process because the room becomes crowded and people are in each other's way.

Table 3.1 Average Clean-Up Time based on Number of MSW Staff

# of MSW's	Average Clean-Up Cycle Time
2	0:14
3	0:10
4	0:10
5	0:17

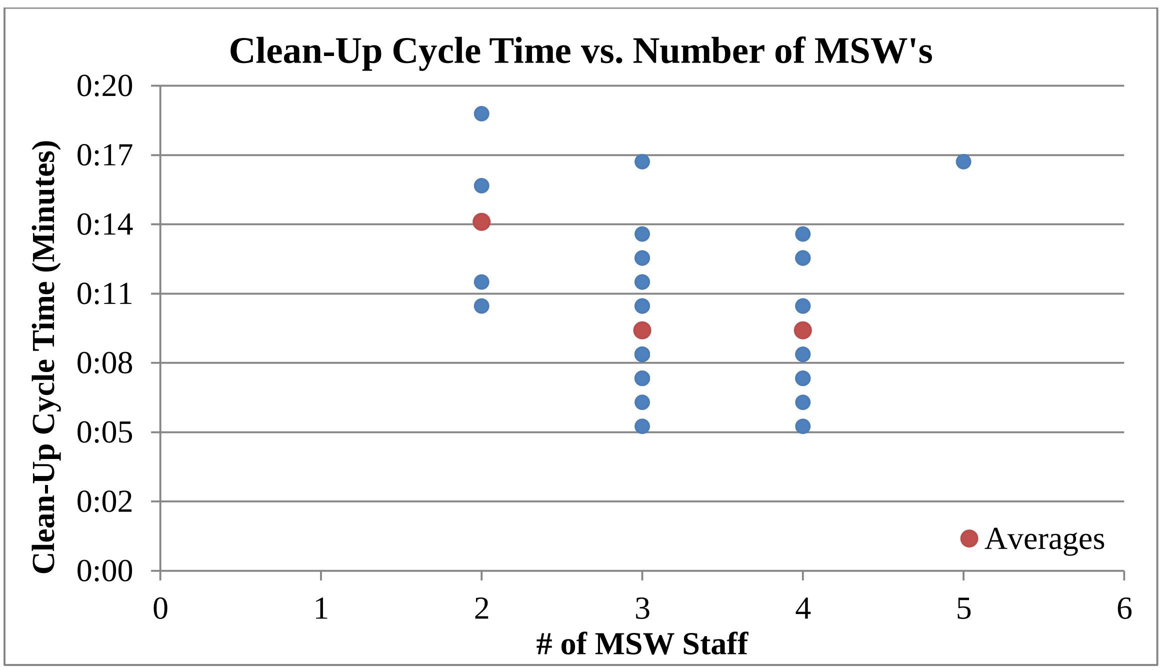

Figure 3.2 Clean-Up Time versus Number of MSW Staff

In reference to the notion that the MSW responsibilities and the clean-up process was slowing down the OR, looking at the amount of time between cases which is attributed strictly to the clean-up process was deemed a useful study. Thus if the clean-up was the limiting constraint by being the longest procedure, it would be close to 100 percent of the turnover time requiring others to wait. The turnover (or changeover) time is the overall time from when one patient exits the OR theatre to the time when the next patient enters and was determined using the recorded MSW data. The changeover time with delay metric compares the changeover time to the average cycle time of the MSW clean-up including the time from when the OR nurse calls the MSW staff until they arrive. This measure is more useful for observing the total amount of time needed for the MSW's to perform the task however is dependent on their availability and the number of additional tasks they are performing and does not reflect the clean-up performance or standard routine. For example, the overall clean-up time associated with the MSW's may be 25 minutes, 15 minutes of delay for them to arrive after being called due to another room requiring cleaning or various other tasks, and 10 minutes to physically clean the room.

Comparing the average clean-up cycle times to the overall changeover time of 20 minutes, it was calculated that approximately 62.6% of the changeover time between cases is attributed to the clean-up and arrival delay. Displayed in Table 3.2 and Figure 3.3, this value decreases to 52.2% when the delay is taken out of the calculation and only the average clean-up cycle time is used. This indicates that the MSW clean-up is not the rate-determining step and not consistently responsible for OR delays. In fact, basically two rooms could be cleaned in this changeover window. Therefore, as long as no more than two operating rooms completed surgeries at the same time, the MSW clean-up process does not slow down the flow.

Table 3.2 Percent of Changeover Time Associated with Clean-Up

Total Delay Between Surgeries	% of Changeover (w/o Delay)	% of Changeover (w/ Delay)
0:20	0.522	0.626

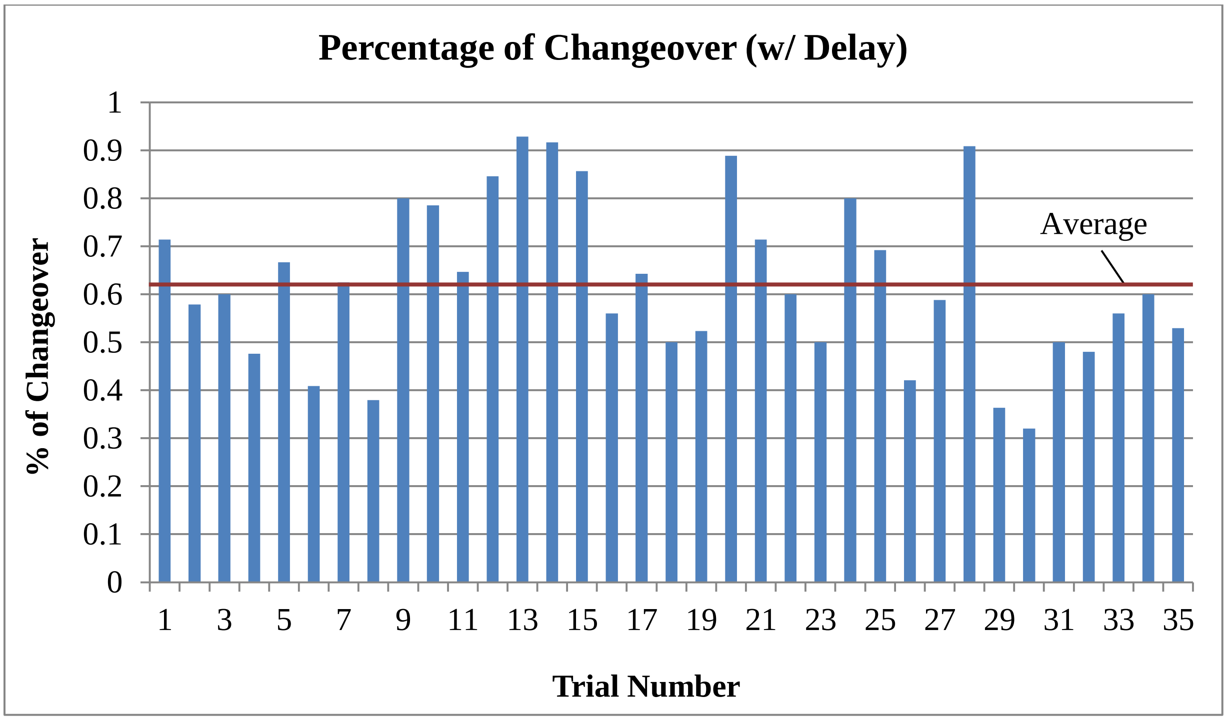

Figure 3.3 Percent of Changeover Time Associated with Clean-Up

Cleaning the anaesthetic machine is the longest task within the clean-up procedure and thus it must be ensured that an MSW is available to perform this task promptly. Therefore, specifically designating a second MSW to perform this task when the anaesthetic MSW is busy or on break might help to clarify the responsibilities.

Lastly, the method by which the MSW's are notified that an operating room requires cleaning is far from efficient. Because the MSW crew is often split up doing various tasks in different areas, only the two people with cell phones are directly contacted and notified that a room needs cleaning. This results in the two MSW's with cell phones arriving quickly to the room while the other MSW's don't get there until they find out that they're needed.

A way to efficiently divide up the tasks involved in OR cleaning in order to increase worker utilization and decrease cycle time is a Gang Chart. This involves creating standardized groups of tasks which are categorized based on task similarity and the possibility of being naturally performed together by one person and assigning the groups to workers based on availability and the order in which they must be performed.

Figure 3.4 and Figure 3.5 are examples of Gang Charts that were created to analyze the MSW OR cleaning process. The first chart (Figure 3.4) represents how the work is commonly divided up and performed by the MSW's present with task group 1 (TG1) being the anaesthetic assistant (P1) tasks. The overall process takes 12 minutes with the utilization being relatively low. If the task of refilling the anaesthetic cart supplies (TG1-SB) were separated off from TG1 and could be performed by another MSW, then Figure 3.5 could be achieved. In this scenario, the entire cleaning process could be performed in under 8 minutes by only 3 MSW's with much higher utilization.

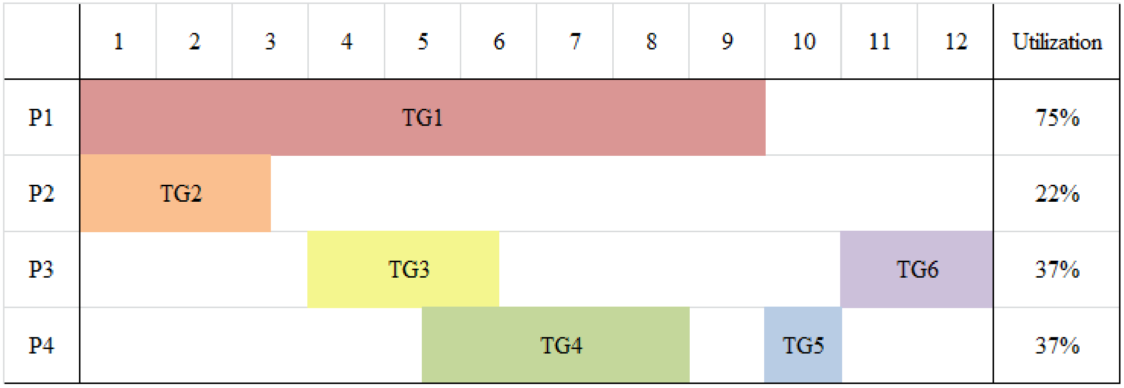

Figure 3.4 Gang Chart of Initial Task Allocation

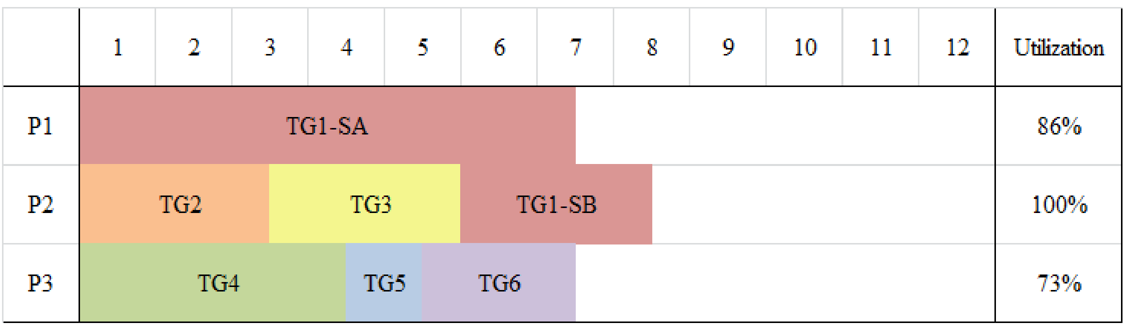

Figure 3.5 Gang Chart of Modified Task Allocation

From the list of MSW improvement ideas (Appendix A) developed using the process described in Section 3.2.2, specific needs were prioritized as being contributing factors to the longest delays in the MSW responsibilities. Sub-projects were performed using teams of stakeholders from all areas affected by these delaying factors.

The first of these working groups targeted improving the communication within the OR between the MSW staff and the OR nursing staff within the theatres and at the front desk. More specifically, the communication involved in contacting MSW staff in order to notify them of a room that requires cleaning or a patient ready for transport. Through a series of meetings and weeks of trial and adapting the procedure, a standardized communication method was developed in order to increase the efficiency of the the process of contacting the MSW staff when they are needed once an operating room has been vacated. After weighing a variety of possible device solutions, implementing additional cell phones was settled on so that more of the MSW staff could be directly contacted. This reduced the problem mentioned earlier where the two MSW staff with cell phones received all of the requests to perform tasks while other staff members were unaware of what was going on. The use of the Vocera hands-free system was considered as well and is still regarded as a viable option in the future. The standardized procedure flow chart (Appendix A) was used to aid in the implementation phase and ensure the new cell phones were efficiently utilized. Speed-dial was installed on the phones within the operating theatres so that it is no longer necessary to memorize the full phone numbers.

The second, and more lengthy, of the sub-projects focused on the OR department's external communication and the delays that the MSW staff experienced in retrieving patients from other departments and transporting them back to the OR for surgery. The MSW staff were frustrated that other departments within the hospital (wards, ER, etc.) would call and say that a patient was ready to be picked-up and transported to the OR for surgery but when the MSW arrived the patient was not ready and they would have to wait for an extended period of time. In order to decrease the amount of non-value added waiting time, a standardized communication plan was developed (as shown in Appendix A). Use of this standardized practice was introduced on June 5, 2009 and data was collected by the MSW staff to compare to data collected previously from October 1, 2008.

The results of the practice change and analysis of the collected data can be seen in Figure 3.6 and Figure 3.7 with a sample data collection template in Table 3.3. The trending of the data (Figure 3.6) indicates that the wait time from the time that the MSW staff person arrives on the unit until they leave the unit with a patient decreased. The original average MSW wait time was 5.9 minutes but decreased to 4.4 minutes over the period of June 2009 to June 2010 and is currently at 3.7 minutes, a 63% improvement. The reasons for the delays are helpful for the MSW staff to record because they continue to identify the most common sources of disruption in the patient flow and further areas of potential improvement. Frequently the longest delays are a result of the confusion regarding the required method of transportation for the patient. The importance of clarifying the mode of transportation prior to the MSW staff person coming to the ward will be reinforced with the OR and MSW staff.

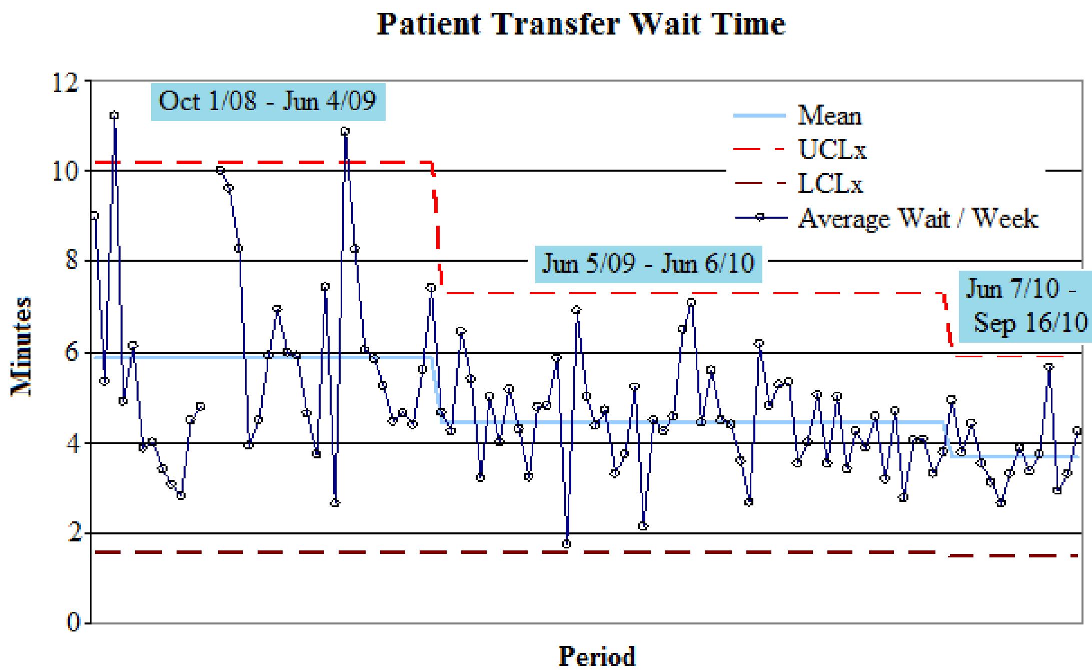

Figure 3.6 MSW Patient Transfer Wait Time X-Chart

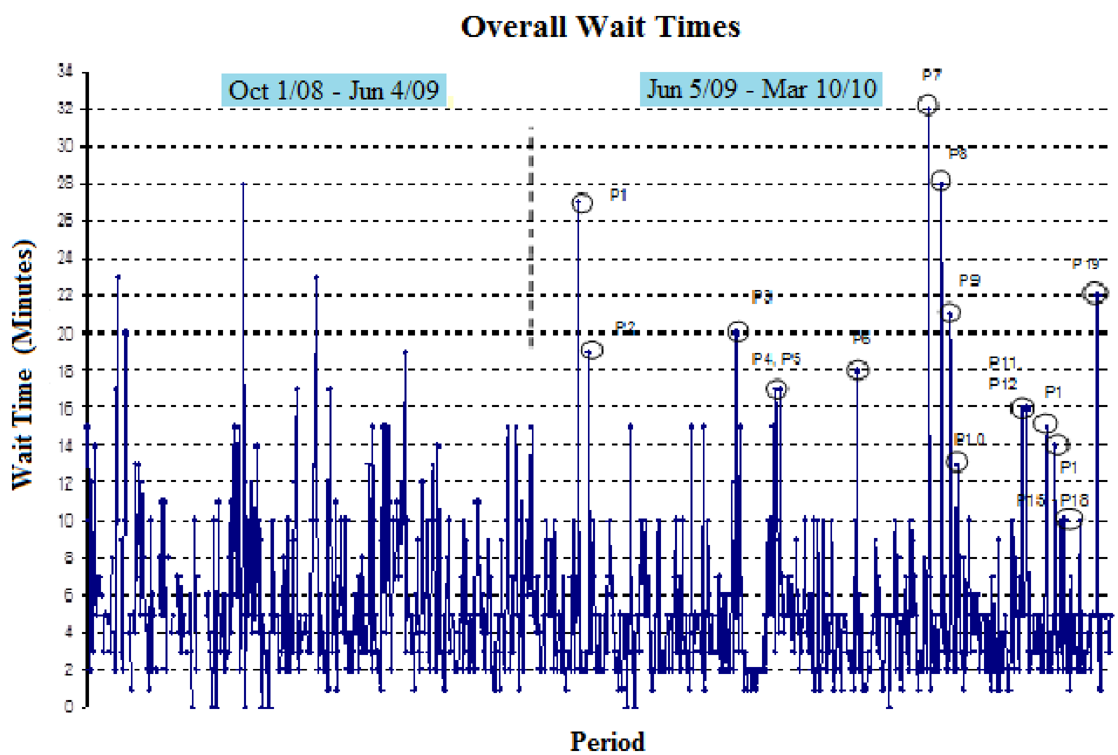

Figure 3.7 MSW Patient Transfer Individual Wait Times

Table 3.3 MSW Wait Time Data Collection Sheet

Points	Date	DOW	Unit	Time In	Time Out	Wait	Reason
P1	June 22/09	Mon	ED	20:08	20:35	27	Patient using washroom
P2	June 29/09	Mon	CK5	11:46	12:05	19	Patient in washroom
P3	Aug 31/09	Mon	CK5	16:15	16:35	20	Child Life was visiting
P4	Sept 13/09	Sun	CK3	16:30	16:47	17	Needed stretcher
P5	Sept 14/09	Mon	DS	15:27	15:44	17	Needed stretcher, pt had morphine

3.2.4 Operating Room (OR) Analysis Project

In progressing through the lean process the OR nursing staff developed a list of improvement ideas (Appendix A) that included streamlining the communication with Day Surgery and the efficiency of MDRs delivery of instrumentation. Another issue was identifying and decreasing the impact of pre-operative delays such as waiting for history and physical, consent, and blood work, surgeon delays, and waiting to hear if a monitored/PICU bed is available.

The communication issues mentioned by the OR nursing staff were in large part a reinforcement of the problems outlined by the MSW staff and the difficulties faced during external communication with other departments. Thus the OR nurses were represented in the working groups mentioned earlier and their side of the communication issues were addressed at the same time. One of the specific implementations which was targeted directly at the communication between the OR front desk and Day Surgery was the addition of the OR white board in Day Surgery. It was expressed that a large number of phone calls were made between the OR and Day Surgery to determine if patients in Day Surgery were ready for surgery and conversely to check if the OR was ready for a patient or how long the schedule had been delayed. The white board is a computer visualization of the OR slate and updates to show when cases have been started, the surgical progression, and when the case is finished. This allows the staff in Day Surgery to have a good sense of the state of the OR and send patients early if the surgeon is ahead of schedule or inform patients if their case is delayed.

One of the procedures that the OR staff requested to look at was the delivery of instrumentation from MDR. Data was collected by the Children's OR nurses from September 8 to October 5, 2009 and the following presents a summary of the analysis concerning instrumentation requests made to MDR. The process for the request equipment was established as shown in the following figure (Figure 3.8):

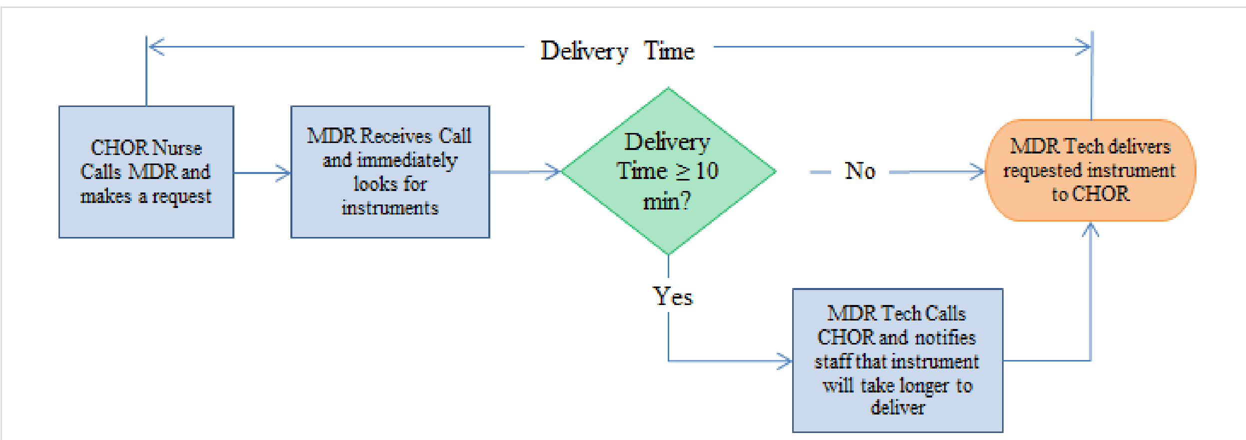

Figure 3.8 MDR Instrument Delivery Process

It was established that a delivery target of 10 minutes would be used as the time from initial request to instrument acquisition. Based on the data collected, 77.8% of requests met the target. Figure 3.9 shows the distribution of wait times while Figure 3.10 shows the percentage of specific wait times and their relation to the target.

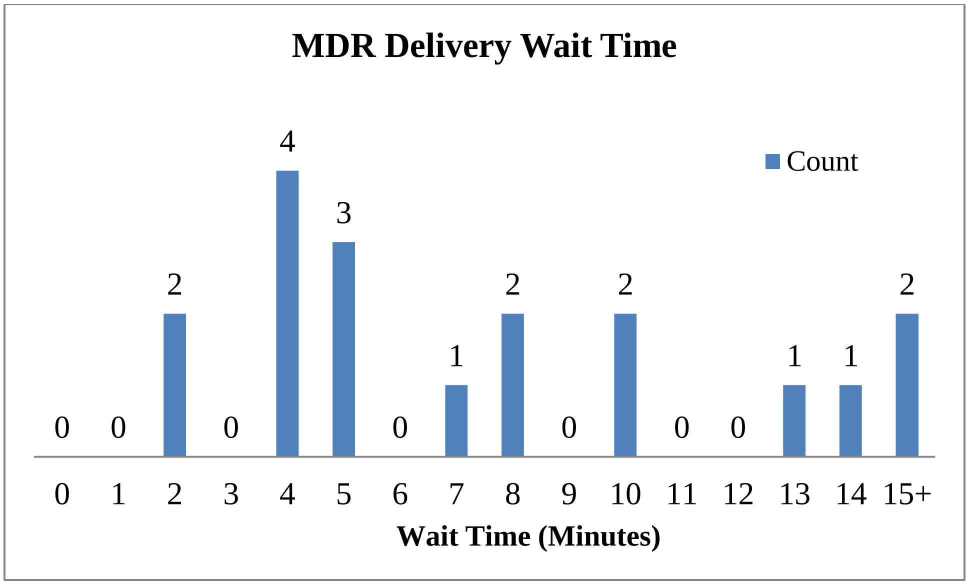

Figure 3.9 MDR Delivery Wait Time Histogram

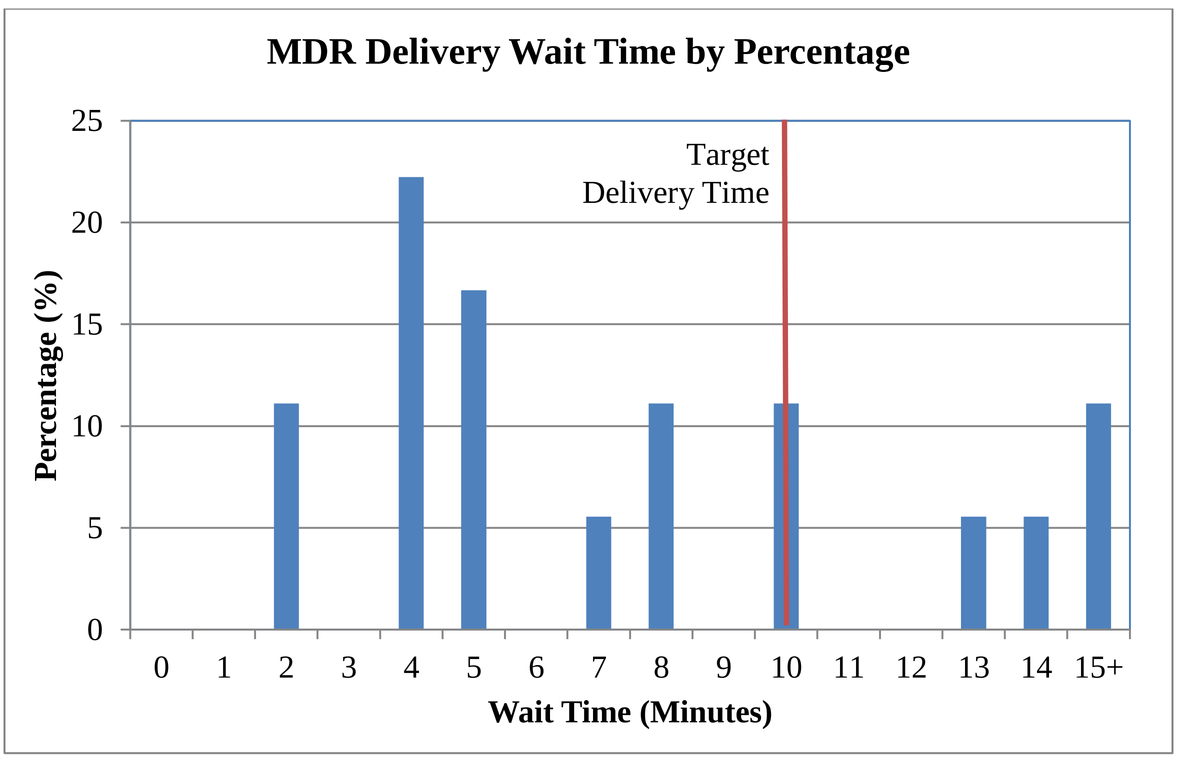

Figure 3.10 MDR Delivery Wait Time by Percentage

The following is a breakdown of the requests that either met the standardized criteria (delivery arrived within 10 minutes or OR staff was notified process would take longer), failed to meet the criteria, or were not documented properly.

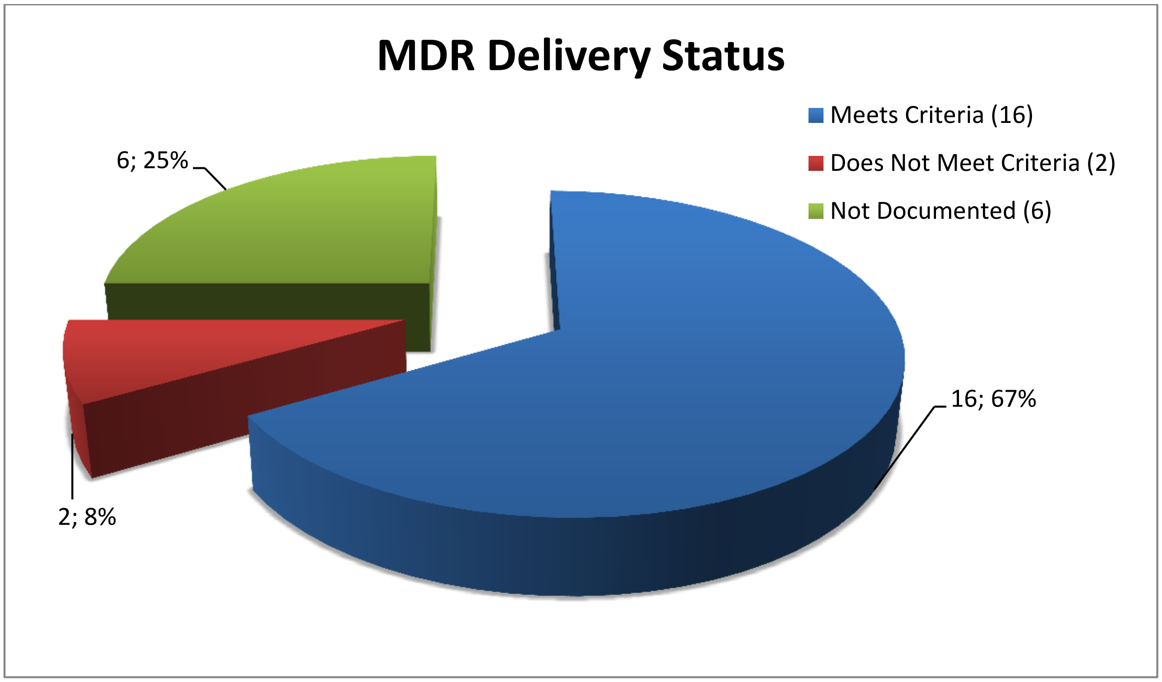

Figure 3.11 MDR Percentage of Acceptable Deliveries

3.2.5 Day Surgery (DS) Analysis Project

The patient flow project targeted a few areas of Day Surgery practice and was able to create some positive change and make improvements. From a lean perspective, cross-training staff to provide external support and eliminating over-processing by streamlining patient discharge criteria were priority objectives. Also based on feedback from the OR staff, the project wanted to improve the first case start time accuracy by ensuring that patients were processed and ready for surgery well before the scheduled start time, dependent on the Day Surgery and Admitting functions.

As part of the patient flow project and with the intention of incorporating lean concepts, cross training and extra-departmental support was hypothesized. One of the candidate areas for this was Day Surgery. With Day Surgery staff already supporting aspects of the Pre-Admit Clinic, it was thought that further break and extended hours support could be achieved if the location of Day Surgery was in a closer proximity to the wards. The arrival of the H1N1 outbreak expedited, if not forced, this relocation. Thus a study was performed on the demand and capacity of Day Surgery and the implications of an incorporation with the Pediatric Day Unit (PDU).

To start with, a demand and capacity analysis was performed on the existing Day Surgery unit to determine if additional capacity was available to provide support to other surgical flow functions. Data collected by staff from November 2008 to February 2009 provided information about patient cycle time pre- and post-operatively and gave a perspective on the number of patients being cared for in Day Surgery throughout the day. Below are three graphs displaying the average daily patient volume in Day Surgery. Figure 3.12 shows the total patient volume, with the first surgical cases of the day arriving at 0630, and initial surge of opening cases ending just after 0700, and then an overall peak of overlapping pre and post-op patients just after 1200 before the patients volume tapers off by the end of the day. Figure 3.13 and Figure 3.14 divide the total patient volume into pre-operative and post-operative patient groups.

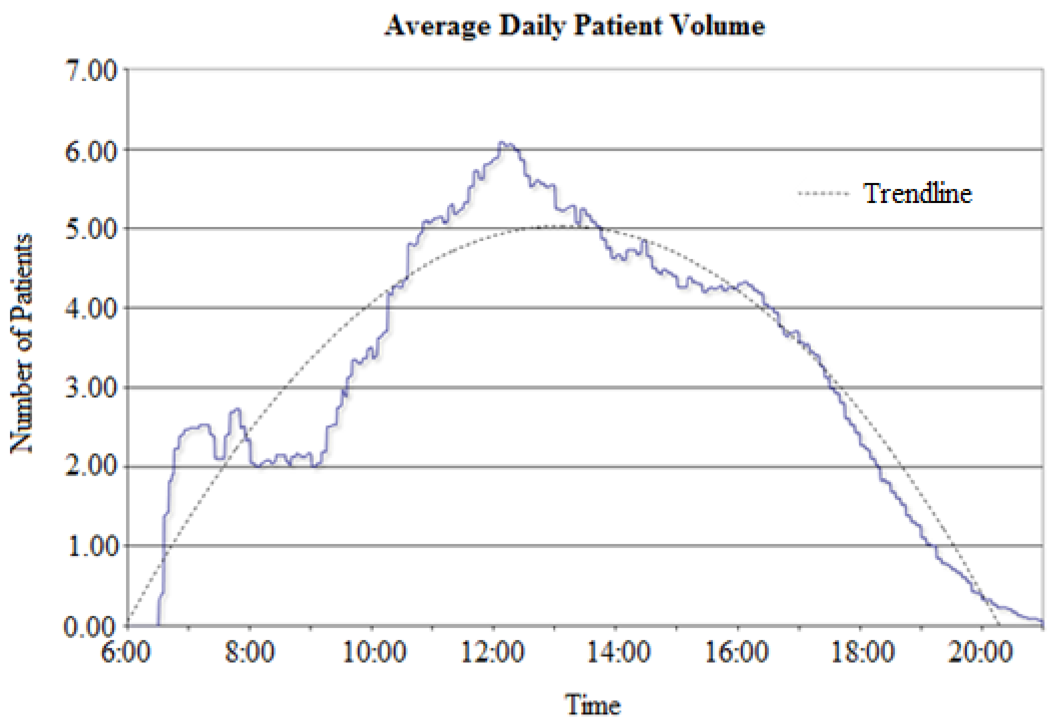

Figure 3.12 Day Surgery Average Total Daily Patient Volume

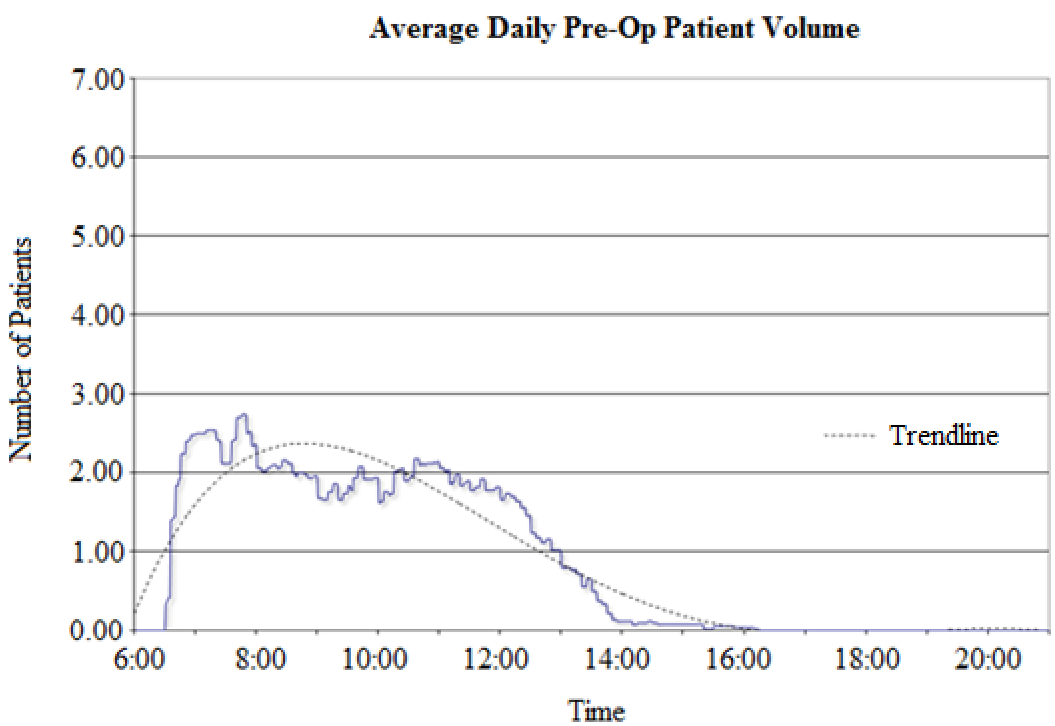

Figure 3.13 Day Surgery Average Pre-Op Patient Volume

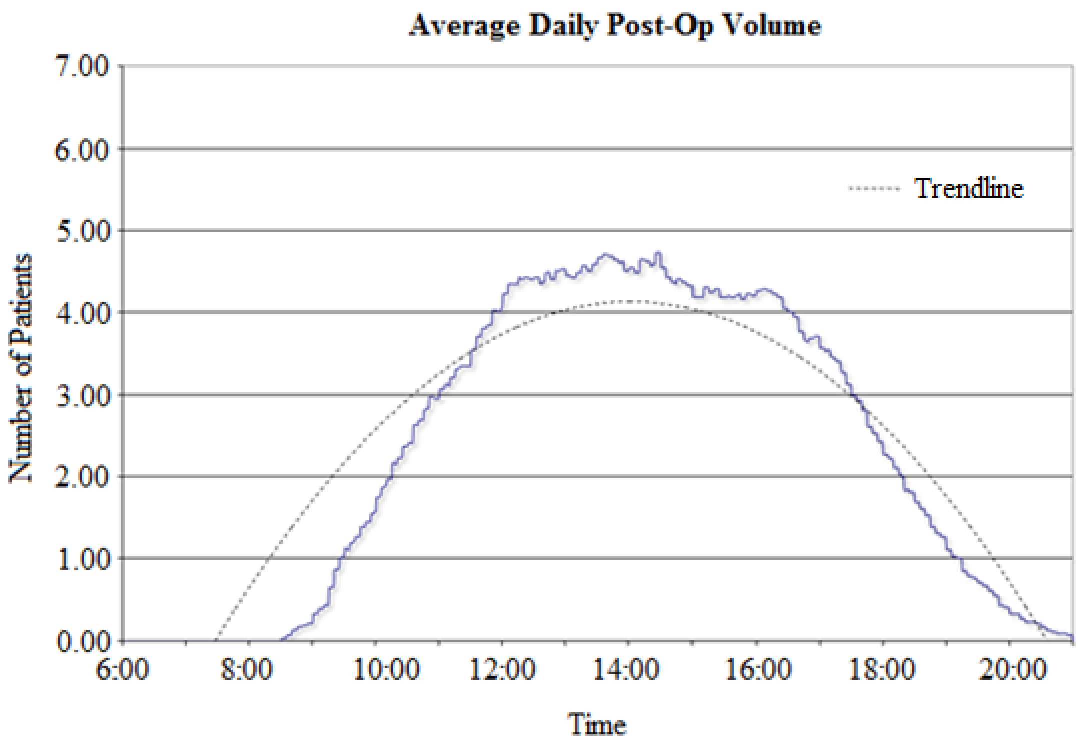

Figure 3.14 Day Surgery Average Post-Op Patient Volume

Adding staffing statistics to the analysis it can be observed how the staff volume compares to the patient volume. Based on the trendlines in Figure 3.16 it can be seen that the staff volume is higher than the patient volume throughout the day at a 1:1 level. Figure 3.15 shows the exact levels with a few noticeable offsets. The staffing numbers do not increase as quick as the patient numbers do at the beginning of the day, leading to a overwhelming start to the day. Also the peak staffing period, occuring from 1300 to 1430, is later than the peak patient volume at about 1200 and the decline of staff volume at the end of the day is not as uniform as the patient volume. Determing the average number of patient hours required each day, as shown in Table 3.4, can provide an estimate for how many staff are required. The pre-operative tasks are much more predictable then the post-operative ones and the resource weight intensity is much easier to set because of the variability in patient needs after surgery.

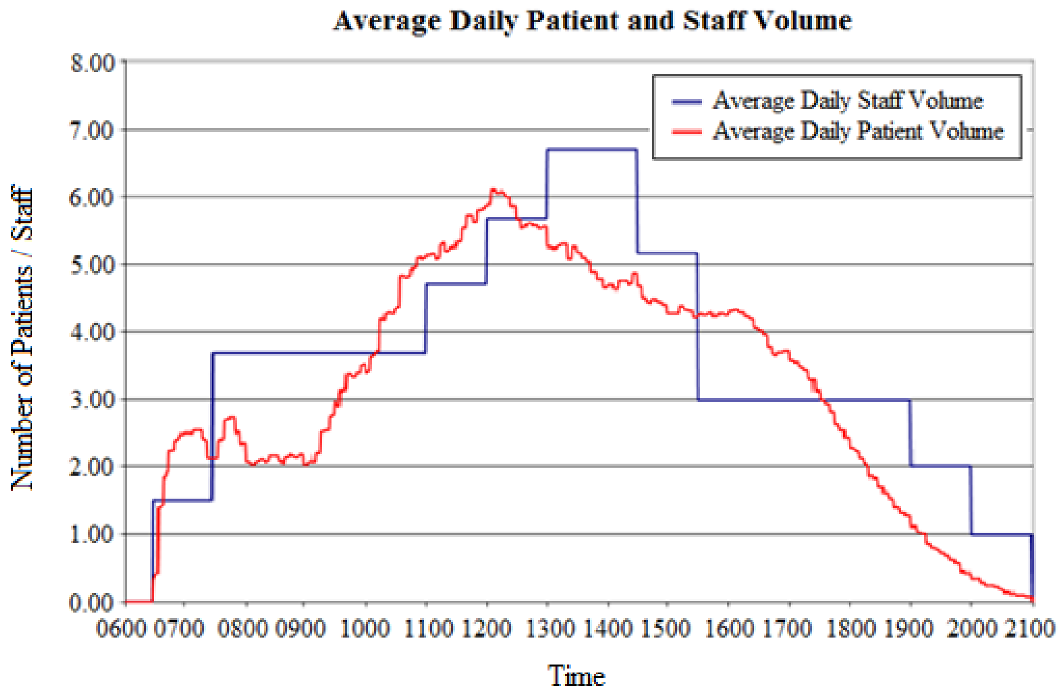

Figure 3.15 Day Surgery Average Daily Patient and Staff Volume

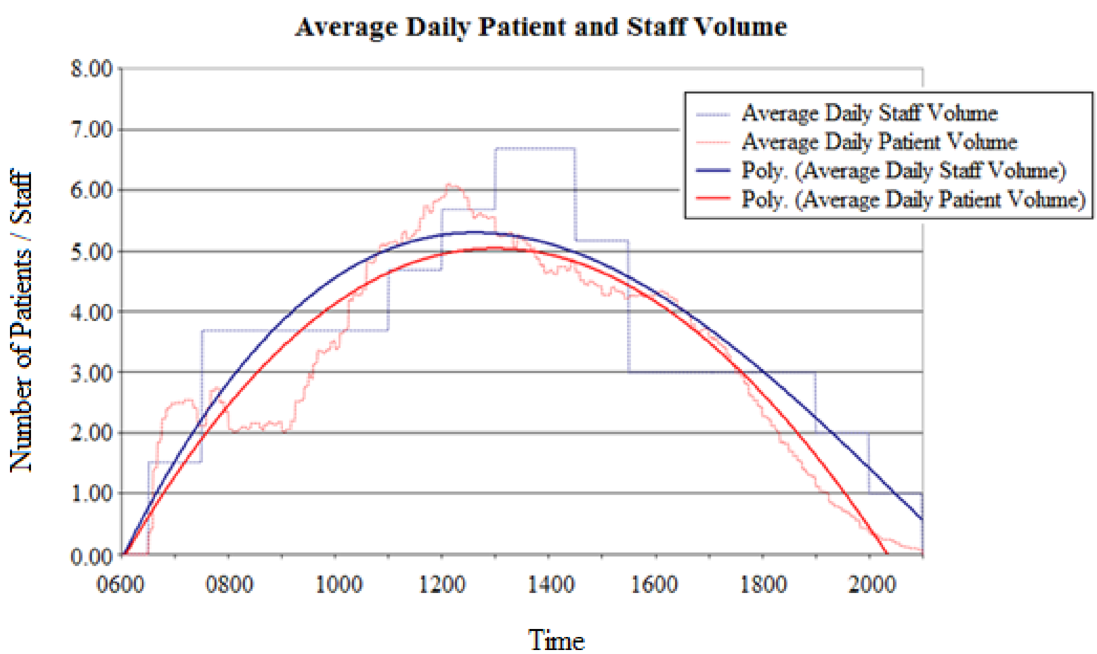

Figure 3.16 Day Surgery Average Daily Patient and Staff Volume Trendlines

Table 3.4 Day Surgery Patient Hours Pre and Post-Op

1088	Total # of Pre-Op Patients
50	Total # of Days
21.76	Average Patients per Day
35	Average Cycle Time per Patient
761.6	Average Total Minutes per Day for Pre-Op
12.69333	Average Total Hours per Day for Pre-Op
890	Total # of Post-Op Patients
50	Total # of Days
17.8	Average Patients per Day
116	Average Cycle Time per Patient
2064.8	Average Total Minutes per Day for Post-Op
34.41333	Average Total Hours per Day for Post-Op

As a result of the need for space caused by H1N1 and supported by the analysis performed, the Day Surgery unit was integrated into the Pediatric Day Unit (PDU). Physical layout was looked at to ensure there would be enough space for the Day Surgery resources and a proposal was developed for how the rooms could be allocated to reduce the amount of travel and improve the process from the patient's point-of-view, as displayed in Figure 3.17.

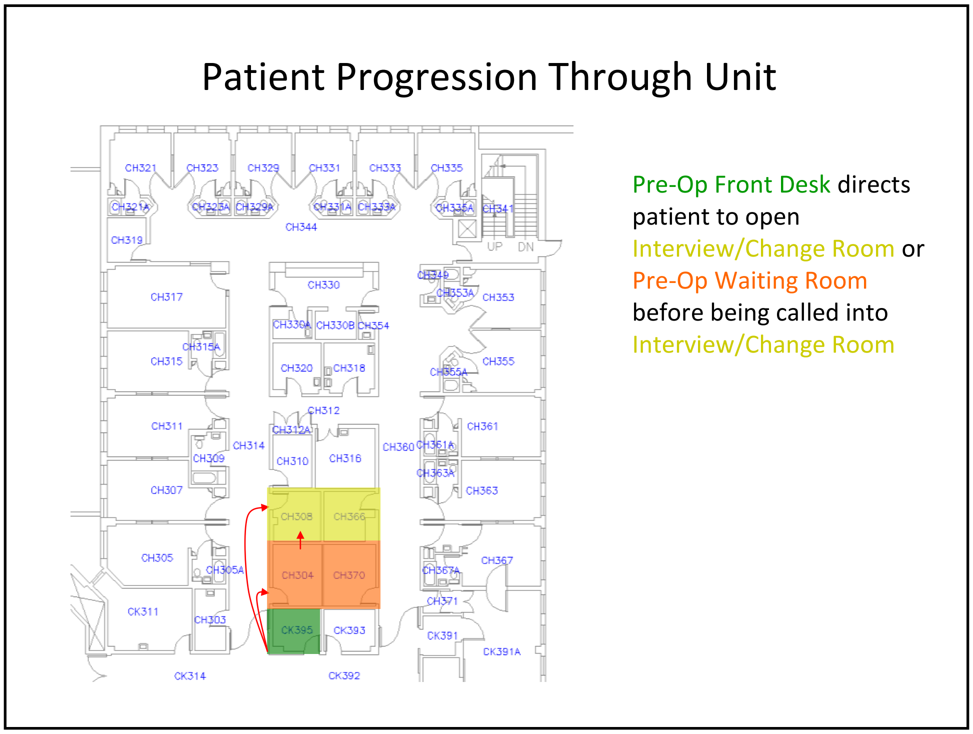

Figure 3.17 Day Surgery/PDU Integration Process

A capacity/demand analysis was performed on the Pediatric Day Unit and combined with the Day Surgery analysis to determine if the staffing levels would be sufficient and to develop a sense of how many patients would be in the space at one time. Figure 3.18 shows the average daily patient volume in PDU with a maximum of 3 patients occurring from between 1000 and 1100. The graph also shows the current staffing from 0730 to 1515 and a possible staggered start time which would compensate for the cases later in the day. The average daily patient volumes in Day Surgery and the PDU and the combined level are shown in Figure 3.19. The peak of just under 9 patients (8.8) occurs at 1209. Looking at the maximum levels that occurred in each department over the time frame, an absolute combined maximum that possibly could have happened at one time was 22 patients.

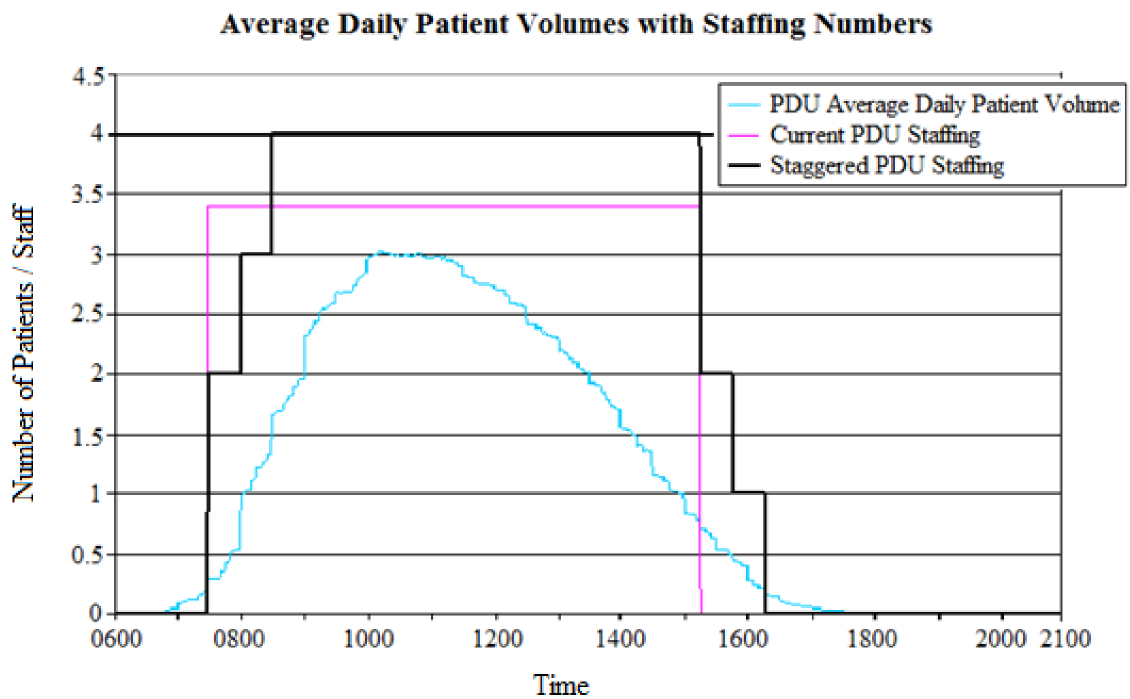

Figure 3.18 PDU Patient and Staffing Levels

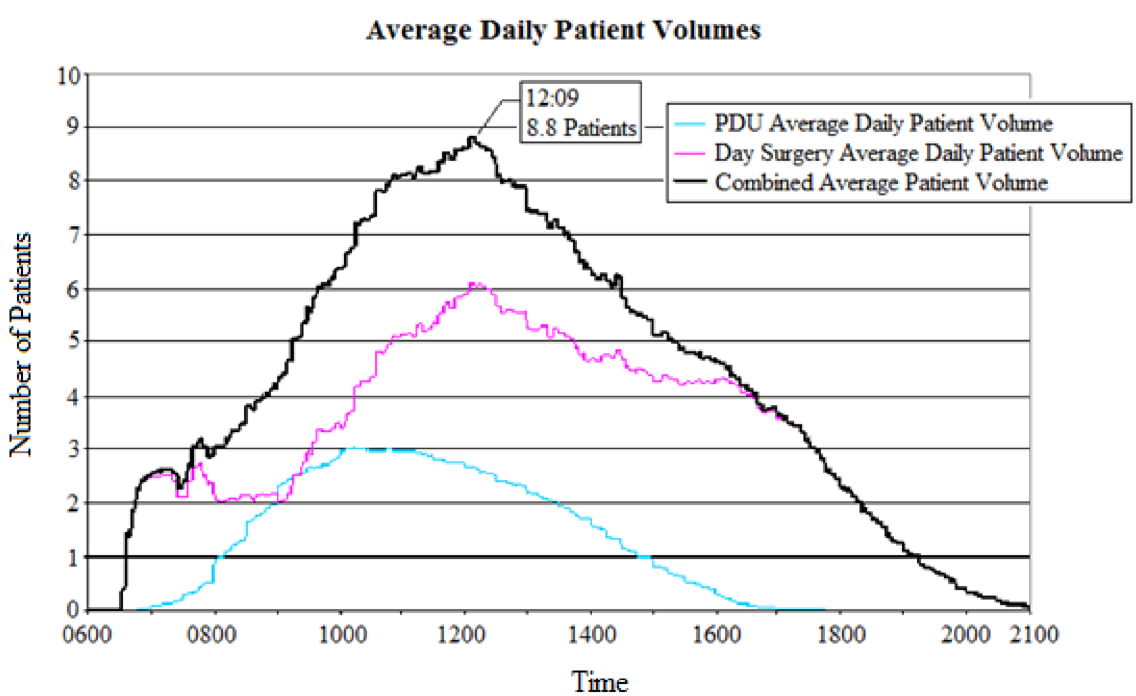

Figure 3.19 DS and PDU Combined Patient Volumes

One of the major contributing factors to delays in the Day Surgery discharge of patients was the fluid management criteria. Perioperative fluid policy dictated that drinking and/or voiding was necessary before discharge could occur. Dr. Heinz Reimer looked into the issue and discovered that the literature does not support either drinking or voiding as important criteria for discharge of day surgery patients, unless there have been special circumstances such as neuroaxial anesthesia or surgical reasons. Surveying other children's hospitals across Canada it became apparent that Winnipeg Children's Hospital was behind the times as all but one other hospital had abandoned this requirement. A "safety net" is still very necessary to prevent sending a potentially dehydrated child home in circumstances such as a small child who arrives after a prolonged fast for a brief procedure. Thus linking the volume of perioperative intravenous fluids administered to the need for drinking and voiding as a discharge criterion is required. A target volume of 30ml/kg was selected as this approximates the maintenance requirement for an average duration of perioperative fasting (preoperative fast + surgery + time until drinking post op). If a patient has been administered this much, they do not need to drink or void; if they have not, they do. This concept can also be applied to PACU practices. Orders will include an addition to make it easier to order the target volume to be given and fluids would also be removed from the PACU discharge criteria.

With all the unexpected events that occur within the Children's OR, the first cases of the day are the only ones that are mostly controllable. Frustrations also arise and time is wasted when staff are forced to wait for the opening case of the day to begin. Thus, the preparation and transport of the first patients on the slate was looked at with a goal of increasing the number of patients that arrived in the OR in the ideal time frame (15 minutes prior to the first case start of the day at 0745).

The first initiative that was taken was to encourage patients and their families to arrive earlier and within a time range to reduce the congestion that occurred when all the patients arrived at the same time. Instead of requesting that patients arrive in Admitting at 0630, families were advised by the Pre-Admit Clinic Program that they should register between 0600 and 0630. As a result, apprehensive families might show up at 0600 to have more time to find their way while more relaxed families might wait until 0630 to arrive, evening out the workload of Admitting and the subsequent flow of patients arriving in Day Surgery. Figure 3.20 shows the results of this practice change, with the peak arrival time shifting earlier to about 0620 instead of 0630.

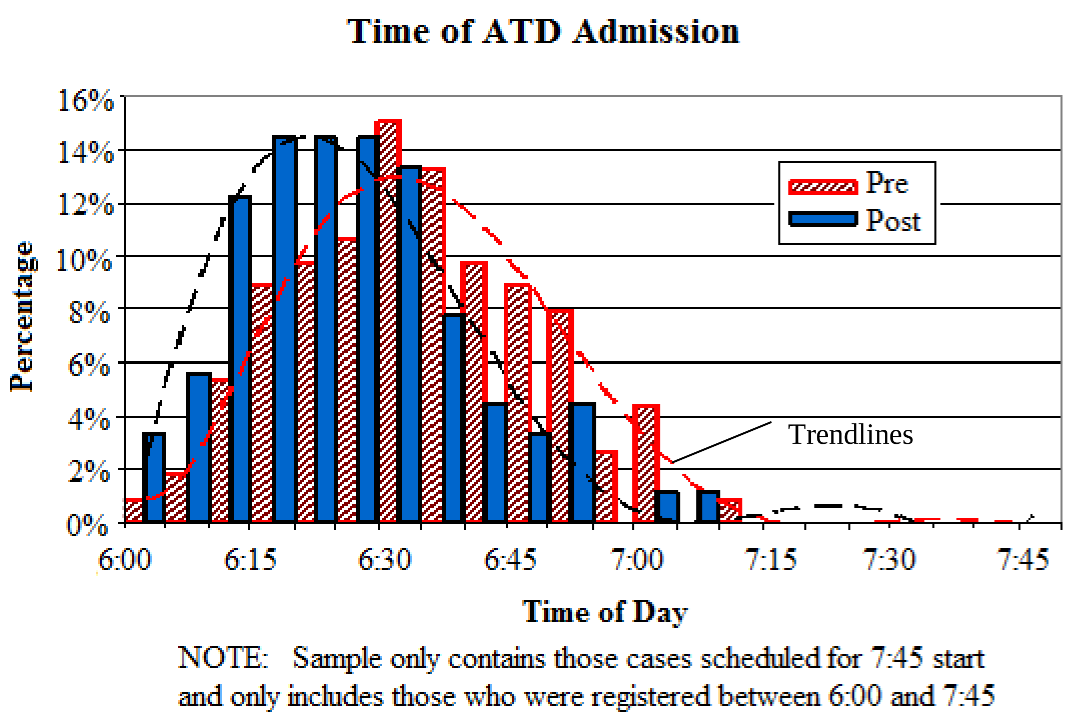

Figure 3.20 ATD Registration Distribution (Pre- and Post-Practice Change)

Another alteration implemented was the practice of not batching patients when transporting from Day Surgery to the OR. In order for a greater percentage of patients to be in the OR waiting room by the target time of 0730, the porter was asked to bring patients as soon as they were ready, even if it was one at a time. It was determined that increasing the number of 5 minute trips between Day Surgery and the OR was more advantageous than waiting until multiple patients were ready for transport and possibly delaying more surgery start times than necessary.

From raw data collected over the time period of December 1 to 11, a baseline of 41.0% of patients arriving by the target time was established. This percentage, as displayed in Figure 3.21, was increased to 61.65% from December 14, 2009 to May 14, 2010 when the aforementioned practice changes were made, and further decreased to 73.9% over the period of May 17 to September 3, 2010. These measures are shown in more detail with weekly variation using smaller time intervals in Figure 3.22 and individual case time difference between actual and ideal in Figure 3.23.

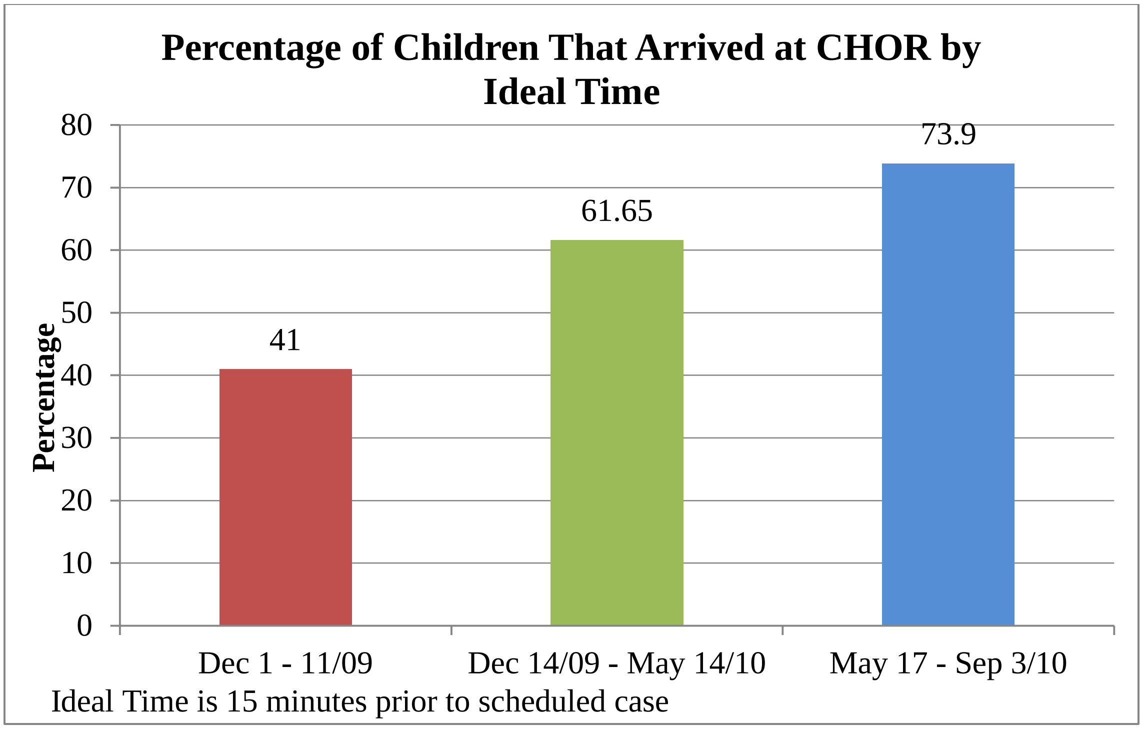

Figure 3.21 Percentage of Patients That Arrive In OR by Ideal Time

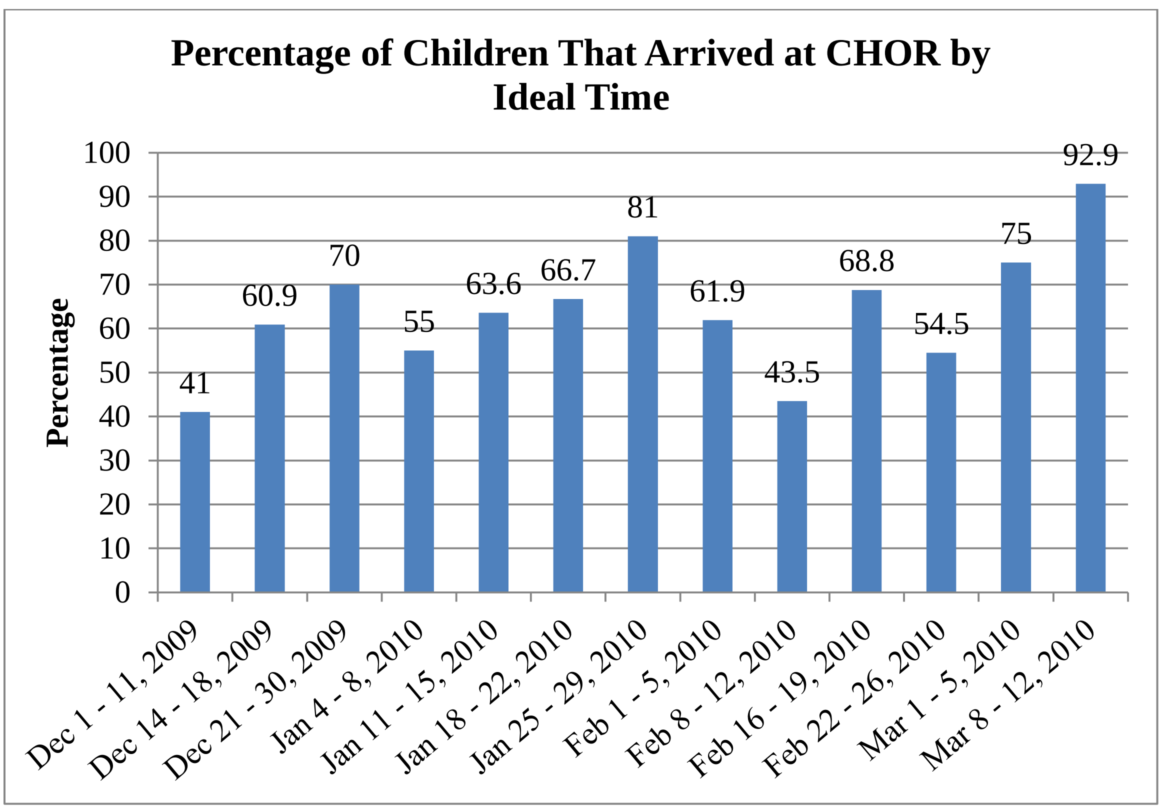

Figure 3.22 Weekly Variation of Percentage of Patients That Arrive In OR by Ideal Time

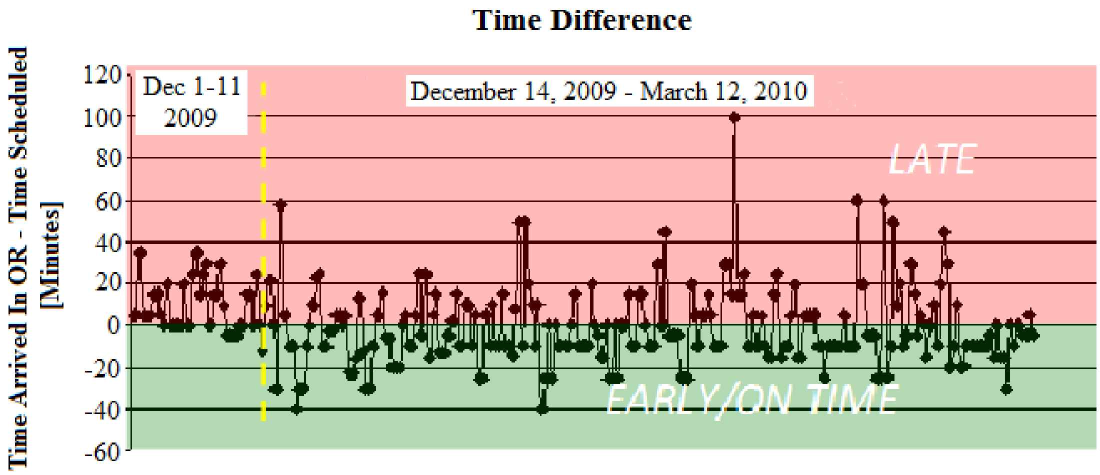

Figure 3.23 Time Difference Between Actual Arrival and Ideal Arrival in OR

Day Surgery staff recorded the reason for any delay that occurred which led to a patient being late to arrive in the OR. From these reasons a cause-and-effect (or Fishbone) diagram was created, as seen in Figure 3.24. Of the reasons for delay, the most prevalent were NPO (the patient ate before surgery) and staff was awaiting confirmation that a post-op bed would be available before sending the patient to the OR waiting room.

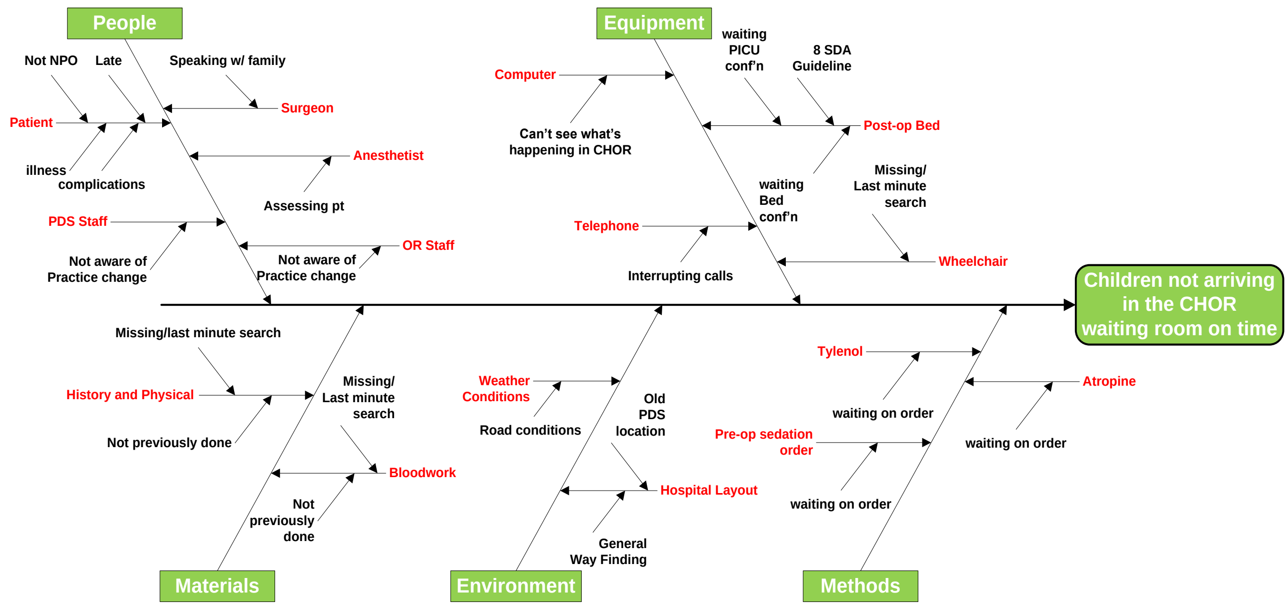

Figure 3.24 Day Surgery Delay Cause-and-Effect Diagram

3.2.6 Post-Anaesthetic Care Unit (PACU) Analysis Project

A similar patient flow analysis was performed on the Post-Anaesthetic Care Unit (PACU) as was done for Day Surgery to compare the patient demand and the staffing capacity. A basic cycle time analysis was completed (Figure 3.25) to determine most patients stay in the unit for a time length between 45 minutes and an hour with an overall average patient length-of-stay to be 1 hour and 2 minutes.

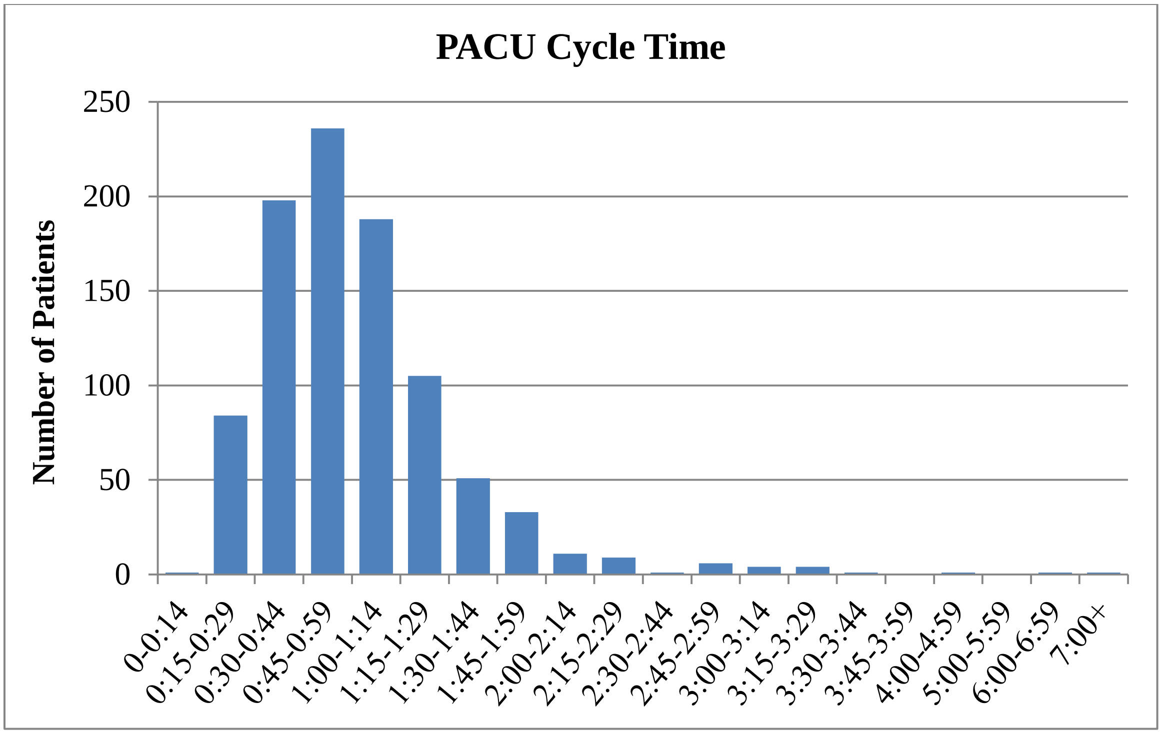

Figure 3.25 PACU Cycle Time

Next the data was used to find the patient volume within the Post-Anaesthetic Care Unit at any given time throughout the day. The average daily volume is displayed in Figure 3.26 and shows that the unit typically hits its peak volume at just after 1100 with between 3 and 4 patients (3.25). The maximum patient volume numbers are shown graphically in Figure 3.27. During the 4 month period over which the data was collected, the maximum number of patient in the unit at one time was 6. Lastly, Figure 3.28 shows a comparison of the average PACU staffing volume to the average patient volume. Based on the graph, the PACU staff level appears to be at a pretty consistent 2:1 staff to patient ratio.

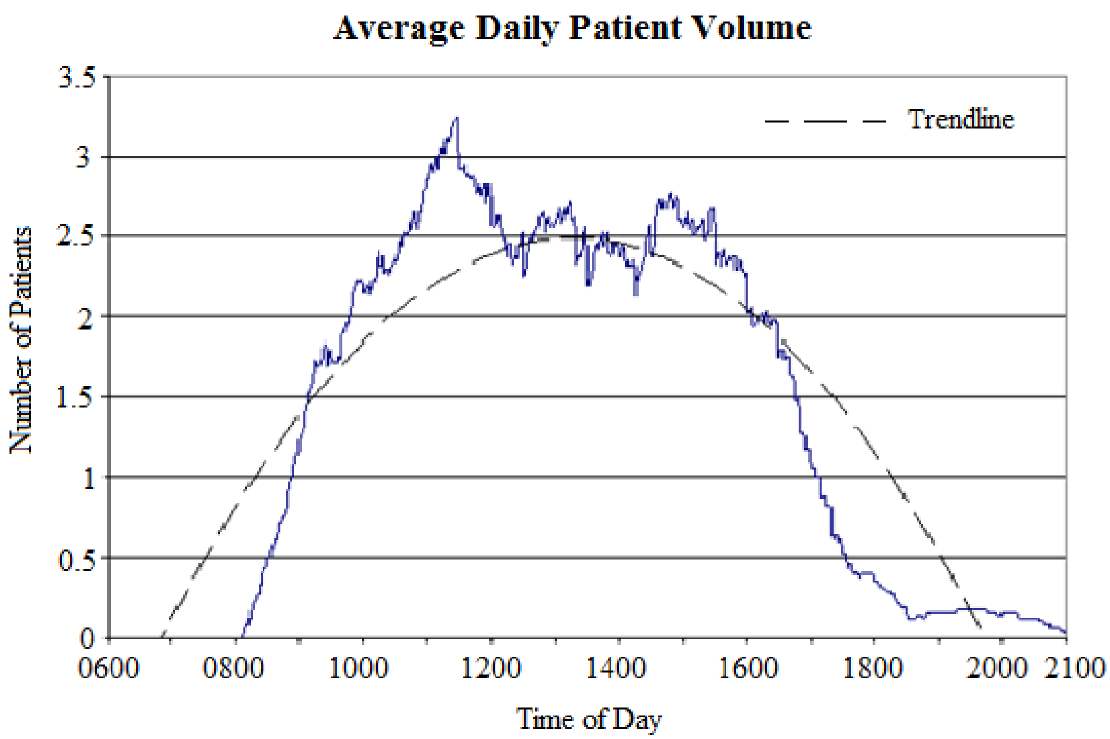

Figure 3.26 Average PACU Daily Patient Volume

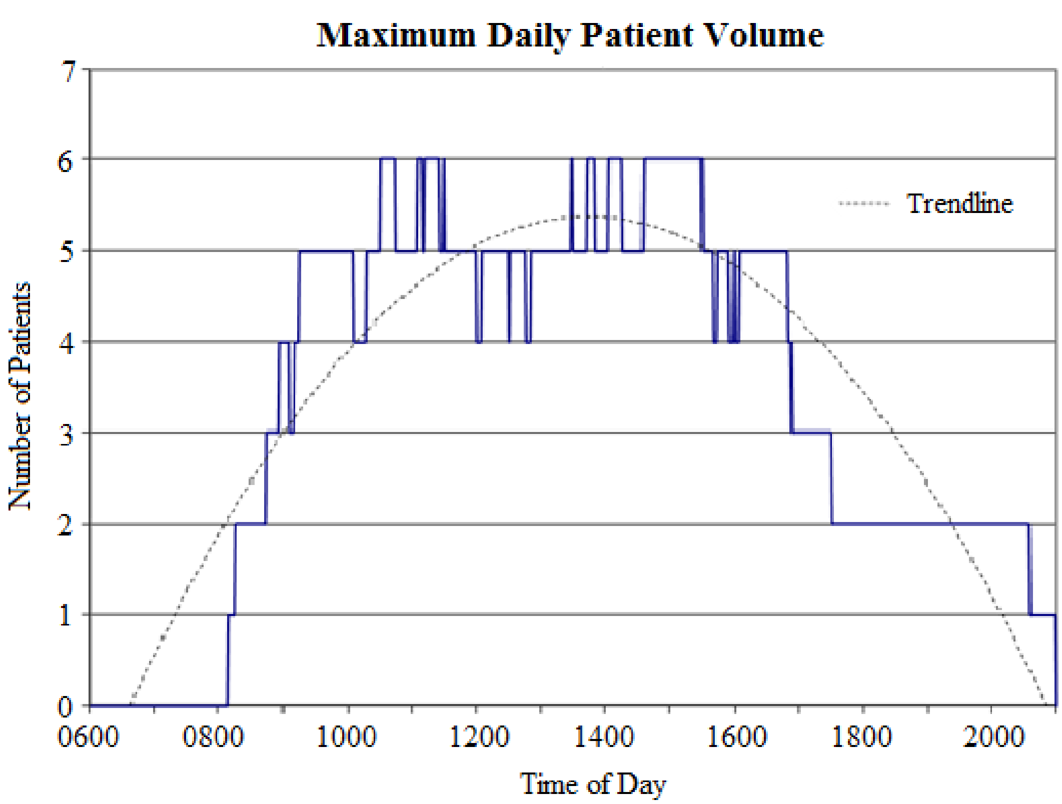

Figure 3.27 Maximum PACU Patient Volume

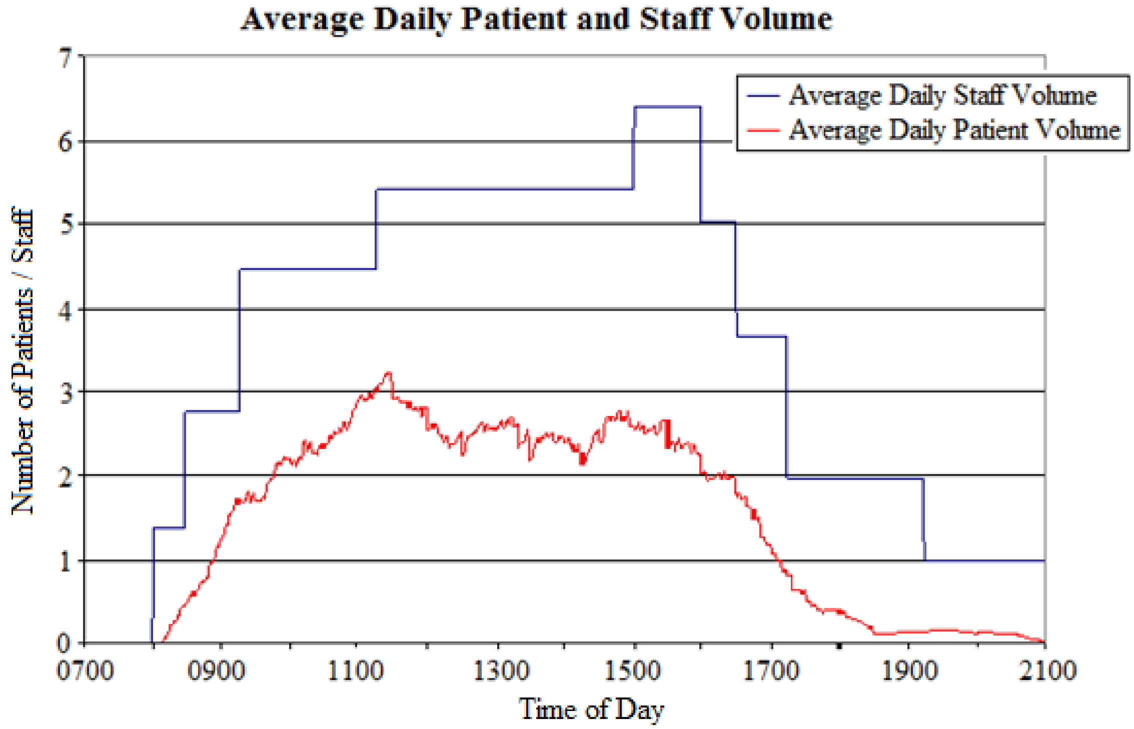

Figure 3.28 PACU Staff Volume versus Patient Volume

One of the issues that arose from the lean thinking process in the PACU was the patient discharge procedure. Long delays occurred when the nursing staff was forced to wait for or try and locate the Anesthesiologist in charge of the patient, being dependent on them to discharge the patient. Once present, the nurse would discuss the details of the child's stay in the PACU with the Anaesthesiologist. A decision on discharge was made by the Anaesthesiologist who then signed the chart. Collected data by the PACU staff indicated that this process prolonged patient flow and caused back logs in the OR. In addition, it was recognized that when the unit was busy patient safety could be compromised due to decreased nurses in PACU. Out of this came the idea for a 2-nurse sign-out process. Through collaboration with other children's PACU's across Canada, it was discovered that a 2-nurse sign-out process was being utilized in many pediatric centers across

Canada. Anaesthesiology was included in the development process and with their input a new scoring system and discharge criteria were developed. For a specific group of patients and complex cases who would still require Anaesthesiology sign out a suggested list of criteria was also prepared. A 3-month trial period began on January 19th, 2009. The PACU staff found there to be an improvement in patient flow since the start of the pilot and patient care and safety have improved now that they aren't left alone while a nurse looks for a discharge signature from the Anaesthesiologist.

3.2.7 Pediatric Intensive Care Unit (PICU) Analysis Project

The project's main concern with the Pediatric Intensive Care Unit (PICU) was finding the right amount of capacity to meet the demand and looking at the fluctuations in patient flow to determine when and why variation was occurring and subsequently causing surgical cancellations due to no bed availability.

Analyzing the patient flow patterns in the PICU, it was found that the unit experiences changes in patient flow at numerous distinct times throughout the day. Due to the limitations in the unit's capacity to admit children, patients flowing into the department from direct admissions and transfers from other units are sometimes influenced by patients leaving the department through discharges, transfers and death. Using the data from the Admission, Discharge, Transfer (ATD) system for the period of January 2008 to July 2009, the following graphs were created. Based on the flow patterns in and out of the PICU (Figure 3.29, Figure 3.30, and Figure 3.31), it can be seen that patients typically were not discharged from the PICU until the afternoon where the peak time occurred around 1600. The peak period for patients entering the department, while not as drastic, also occurred at this time. These particular surges are most likely the result of patients needing a PICU bed and continuously flowing into the system throughout the day even at the times when there are no patients flowing out of the department. As a result, a build-up occurs and any further patients requiring entrance into the PICU are blocked. Decisions about transferring patients and freeing beds not made until blocking occurs closer to the end of the day, when other units might have newly acquired capacity to accept transfers.

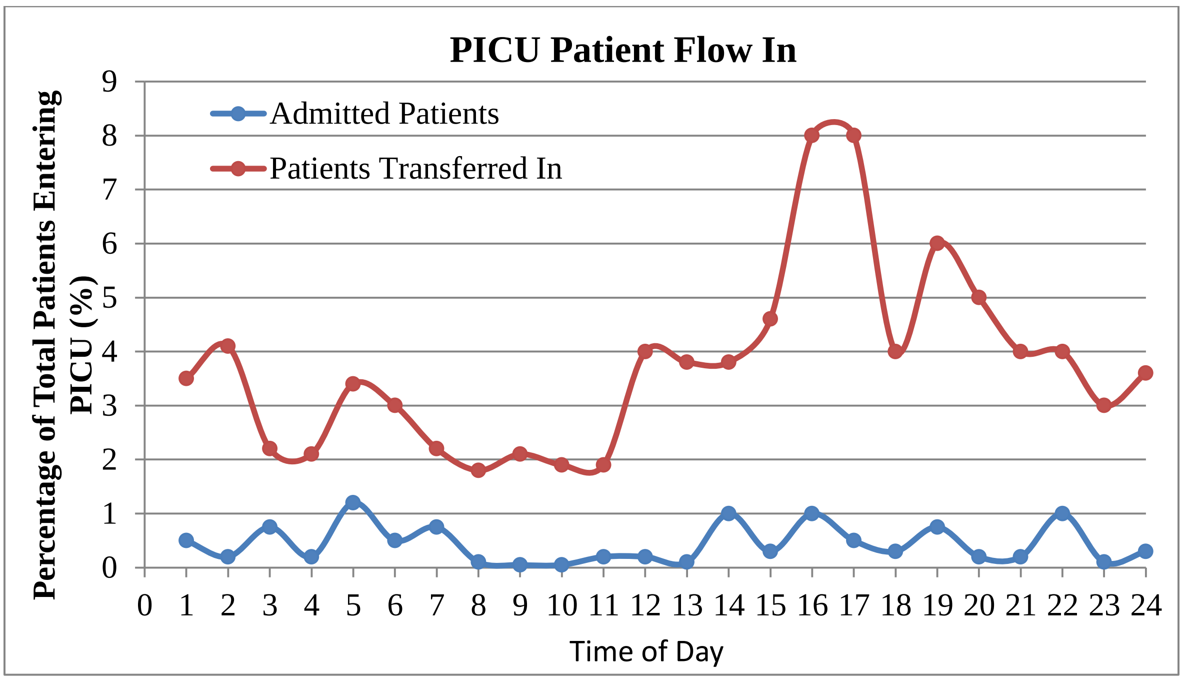

Figure 3.29 PICU Patient Flow In (by Percentage)

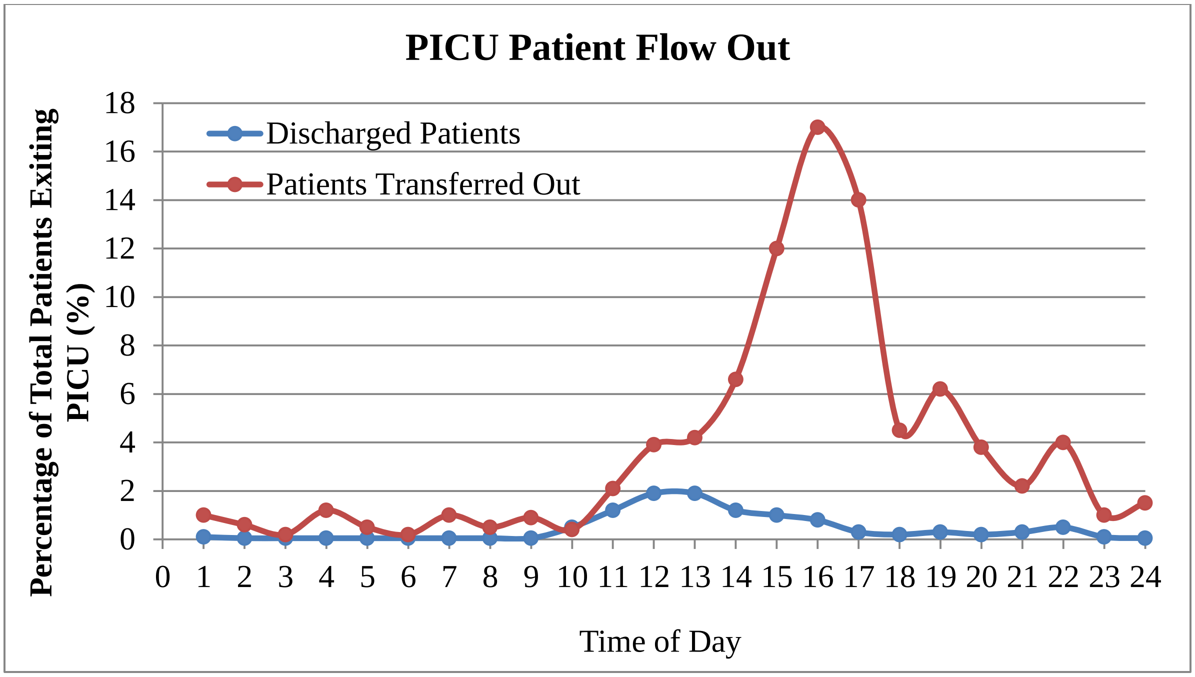

Figure 3.30 PICU Patient Flow Out (by Percentage)

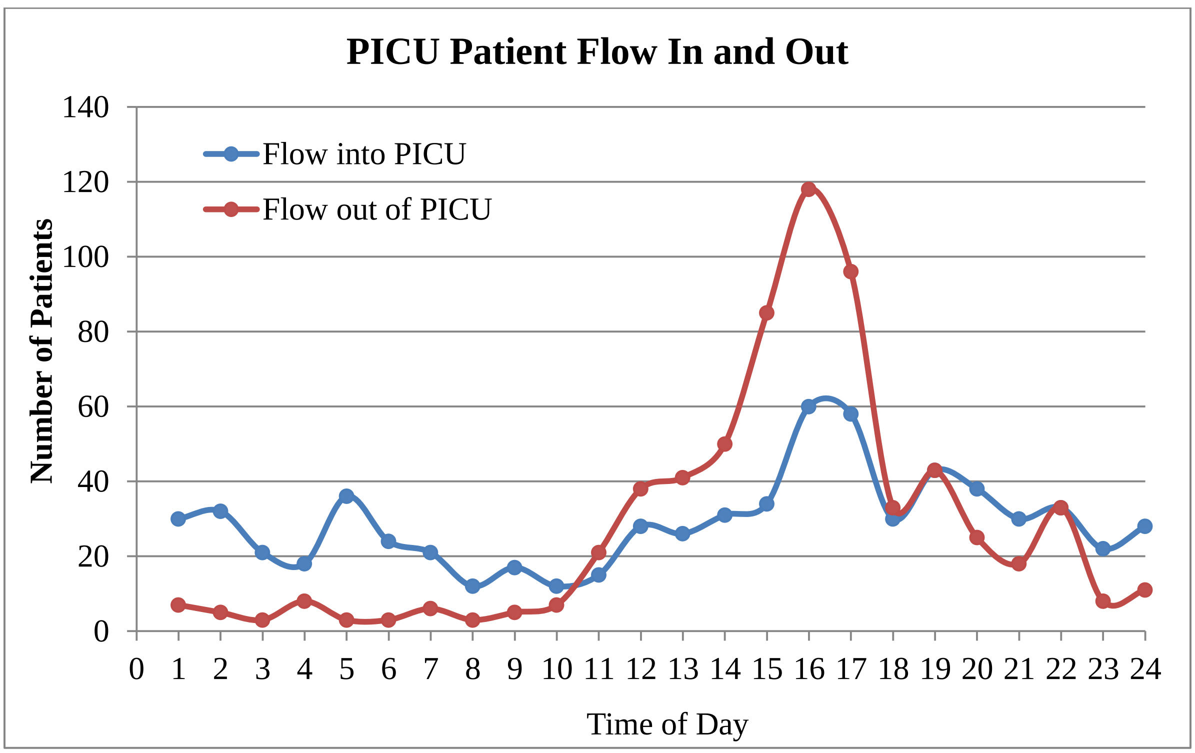

Figure 3.31 PICU Patient Flow In and Out (by Count)

It is also useful to observe where patients are located before entering the PICU and where they are transferred to when they are discharged. The following graphs depict the units that patients belonged to prior to being transferred to the PICU (Figure 3.32) and the units that patients were transferred to after being in PICU (Figure 3.33). The Emergency Department (ED) accounted for about 50% of all transfers into the PICU, emphasizing the randomness which affects the PICU and the variability in bed availability. CH4 is responsible for accepting about 40% of all transfers out of PICU, the largest amongst the wards, with CK3 just under 25%.

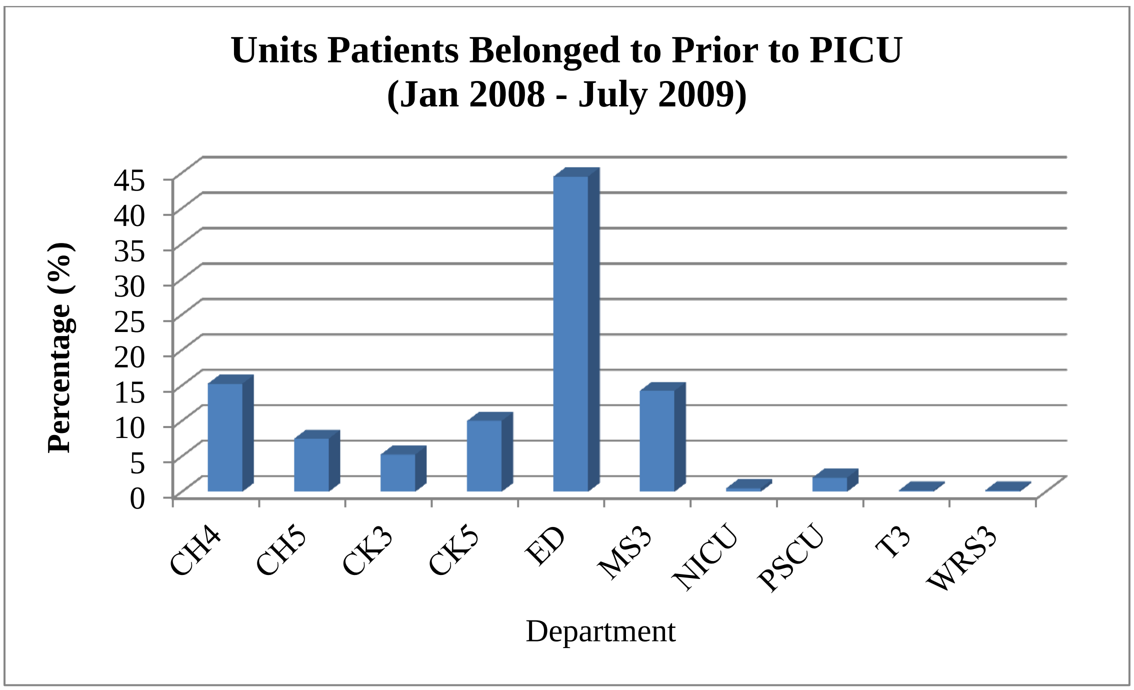

Figure 3.32 Units from Which Patients Transferred Into the PICU

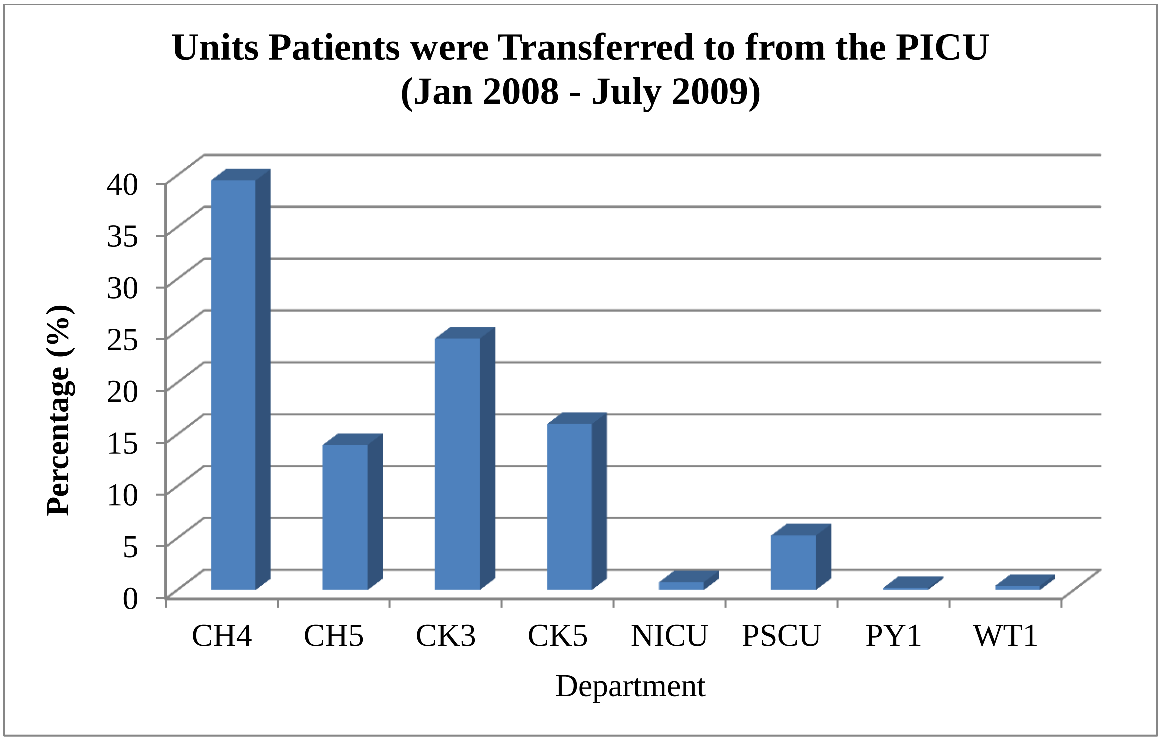

Figure 3.33 Units from Which Patients Transferred Out Of PICU Into

Focusing only on the sources of highest transfers in (ED) and transfers out (CH4), it can be seen (Figure 3.34) that the transfers from the ED were the highest in the late night to early morning at 2300 to 0200, with little variation. However, transfers to CH4 are minimally done in the morning but increase significantly in the afternoon, peaking at 1500 and coinciding with the peak discharge level of the overall statistics.

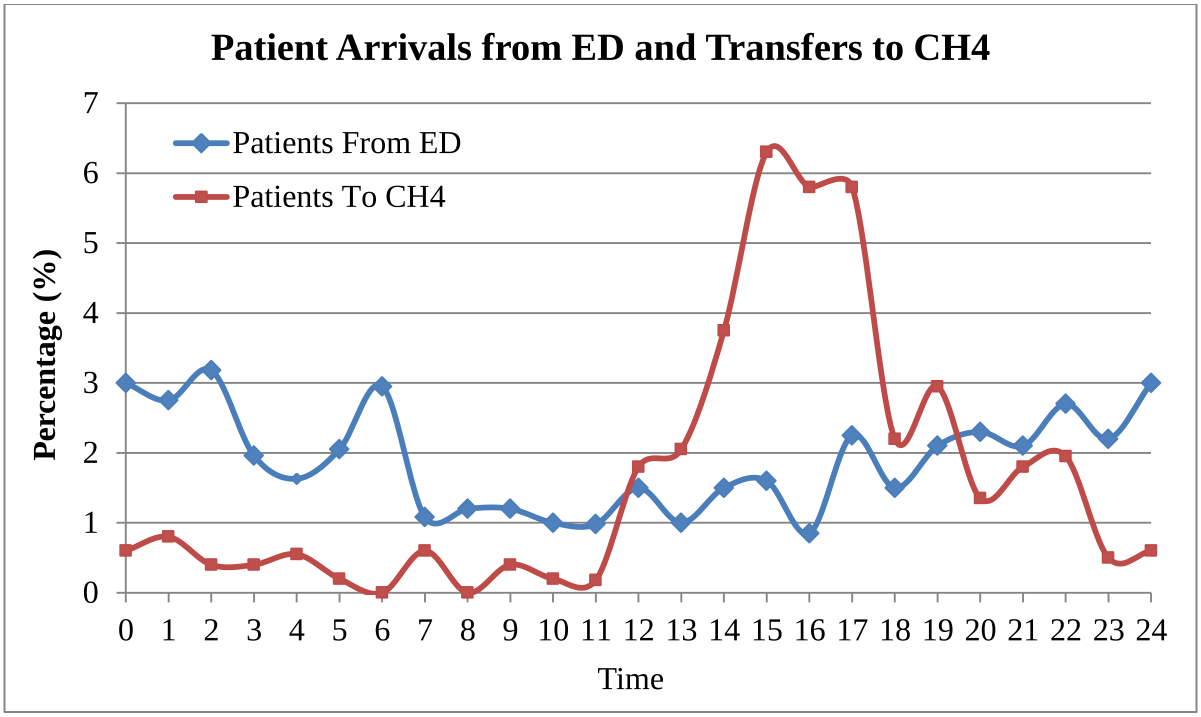

Figure 3.34 Patient Arrivals from ED and Discharges to CH4

Stepping back to a broader perspective, the following two graphs present the patterns for patients being transferred into and out of the PICU from all the individual units. Patients being transferred from MS3 to PICU peaked at about 1600 where 4% of all transfers to PICU occurred. Coincidentally, this was the same time that most patients were transferred out of the department. The non-drastic variability in the transfers into the department is a result of none of the peaks from individual units occurring simultaneously. This is definitely not the situation with patients transferred out of the PICU. Very little activity occurs in the morning while transfers to all units are done primarily throughout the afternoon

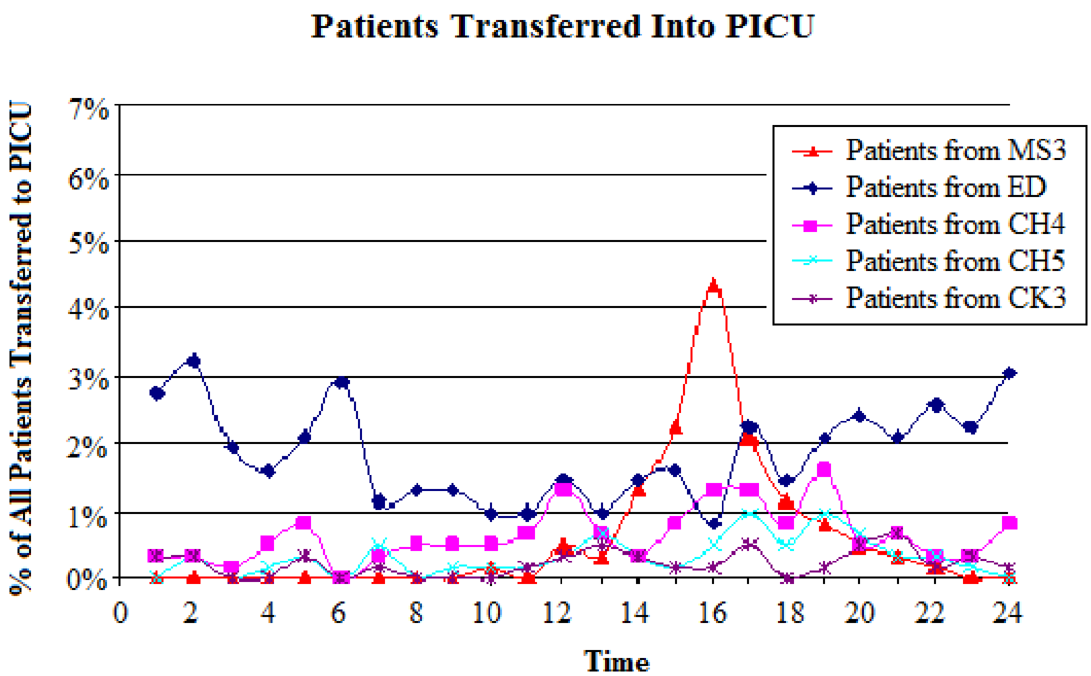

Figure 3.35 Patients Transferred Into PICU

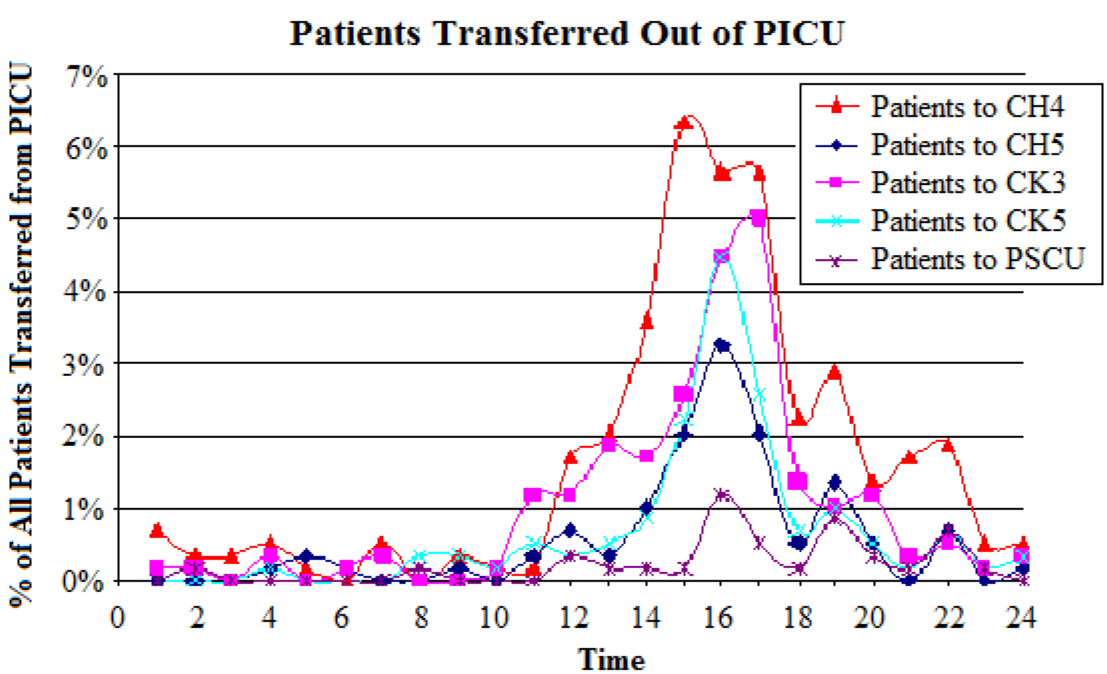

Figure 3.36 Patients Transferred Out of PICU

In response to the issue of post-operative monitored bed requests and availability, a number of surgeons (as PICU bed customers) were interviewed to identify the needs of their surgical discipline and discover thoughts they might have on potential improvements. Some of the more impactful ideas included performing more pre-op sleep studies to provide respirologists with more information to base their post-op bed needs judgment on. Also mentioned was the option of implementing telemetry to allow for centralized monitoring to reduce the impact of any staffing shortages. It was expressed that earlier notification of whether or not a case requiring a post-op bed can proceed would be beneficial. The complete interview transcripts can be seen in Appendix B.

3.2.8 Ward (CK3) Analysis Project

Through meetings with the CK3 staff, areas of non value added activity in surgical flow were identified using Lean methodology and the 7 Forms of Waste discussed in Section 3.2.2. As a result, a few priority improvement ideas were developed. One of these ideas was the need for a working group to improve flow of children from PACU to CK3 and Day Surgery. The working group representatives were able to present opportunities for improvement from each unit's perspective. Transferring of postoperative patients at shift change and ensuring ward beds rather than stretchers are used more often for transferring larger patients following specific surgical procedures were identified as a challenge for all areas. It is noted that this practice increases the comfort and satisfaction of the child and family, enhances the safety of the transfers for staff and patients and may expedite the time between transfers. The importance of pre-emptive planning was emphasized.

Other improvement ideas include organizing the filing system for patient care information to make it easier to find information, especially for new staff and moving supplies closer to the desk to reduce unnecessary motion and travel. As well the development of a family information poster for the CK3 family lounge and revisions to the CK3 family information pamphlet were brought up.

One of the resulting projects from the Lean application to CK3 was a using 5S in the ward supply room to organize supplies and equipment and their distribution. Discussions included agreeing upon how many supplies are restocked and how the quotas are determined and if there should be changes to the quota based on practice changes? Staff reviewed the list of items that have not been ordered in the past five to six months to identify what is no longer in usage and which items are simply used that rarely. The prevailing concern from staff was that they would not have an item when it was needed and delays related to supply discharge would keep them from getting receiving urgent supplies quickly.

3.2.9 Pre-Admit Clinic (PAC) Analysis Project

The Pre-Admit Clinic (PAC) (including the Anaesthetic Pre-Admit Clinic (APAC)) is of vital importance to the patient flow within the surgical process because it makes initial contact with the patient (or their family) and is responsible for the preparation and scheduling prior to the day of surgery. PAC was uniquely able to take advantage of lean tools because the department was moving into a new workspace and was starting to use a new practice called telehealth to perform assessments on patients in remote locations.

To understand the functions of PAC the process flow was mapped out and a value-stream map was created (Appendix A).

One of the constraining issues faced by the PAC staff was the slating guidelines. Current protocol suggests a one week prior to operation day deadline for booking elective cases. Anything of shorter notice impacts the PAC staff's ability to contact families for PAC and APAC appointments as well as the opportunity for pre-op education. Thus a database was created to collect statistics pertaining to the booking request form inputs. As well, data was extracted from the SIMS database to analyze the booking form arrival time range.

Observing the total number of booking forms received by the slating clerk in PAC, an average of about 90 forms were received per week (Figure 3.37) with Figure 3.38 showing the percentage of days in which a specified number of forms were received, the largest of which (besides 0) is 23 booking forms per day.

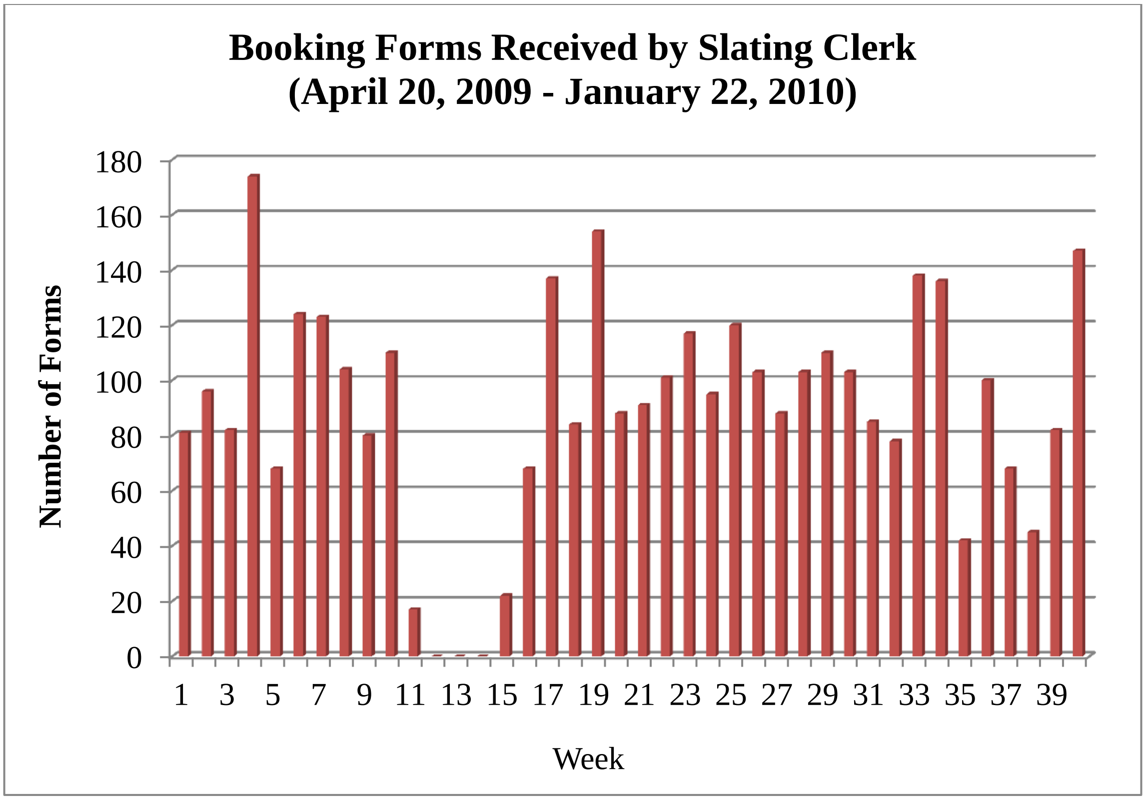

Figure 3.37 Booking Forms Received per Week

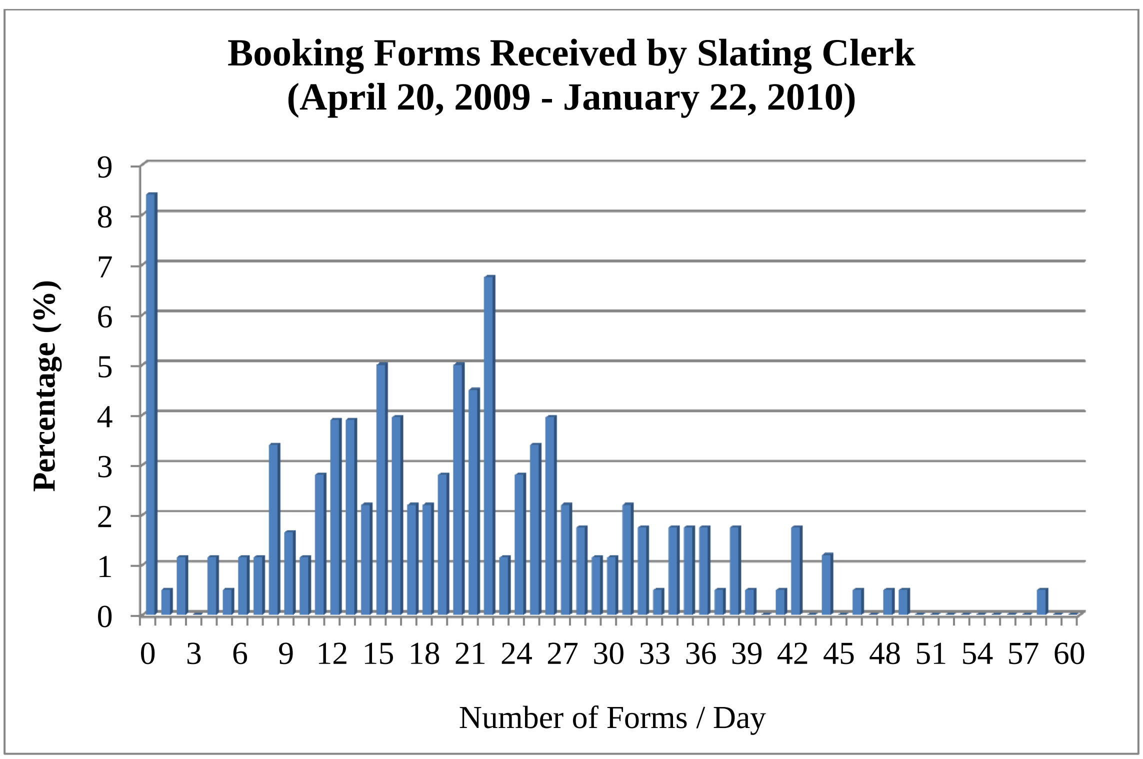

Figure 3.38 Number of Booking Forms Received per Day (by Percentage)

The data collected from the SIMS hospital database shows that between April 1, 2009 and January 29, 2010, 18.4% of booking forms received for elective surgical cases were received within 7 days (Table 3.5), placing a strain on the Pre-Admit Clinic's ability to perform their required functions.

Table 3.5 SIMS PAC Booking Form Data

SIMS Scheduler (April 1, 2009 – January 29, 2010)		
Entered Within	Count	%
7 days or greater	4306	81.60 %
Less than 7 days	969	18.40 %
Total	5275	

Using the values collected using the customized PAC database, an analysis of the booking time frames for elective surgical procedures was performed using the time differences between the OR date and the date the booking form was received. The results (shown in Table 3.6) indicate that PAC is often not informed of surgical cases until within a week of surgery, sometimes with less than 2 days to react.

Table 3.6 PAC Database Booking Form Arrival Time Period

Difference in Days	Count
0-2	56
2-4	43
4-6	65
6-8	193
8-10	107
10-12	80
12-14	194
14+	1542

The issue created by receiving the booking forms in close proximity to the day of surgery is that it leaves the Pre-Admit Clinic with little time to perform their duties and react to any additional needs the patient might have or any further surgical preparation that must be done, such as ensuring the patient receives APAC assessment, any necessary studies, blood work, history and physical, etc. Comparing the times of the OR surgery date and the time that the PAC nurse is able to complete the chart review helps determine a "slack time" during which PAC has the flexibility to perform additional tasks. Figure 3.39 and Figure 3.40 show the average amount of slack time that occurs for different booking form arrival periods. As expected, the average slack time decreases as booking forms are received closer to the OR date. It was calculated that the average slack time decreased from 10.11 days when the booking form was received more than 12 days prior to the OR date to as little as 0.9 days when received less than 4 days in advance.

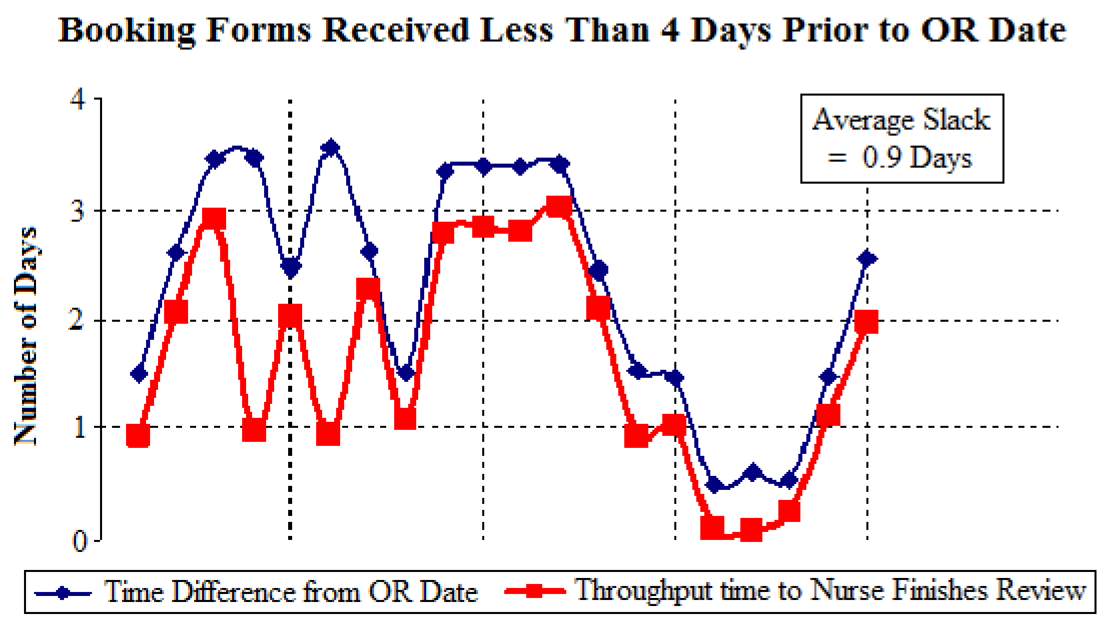

Figure 3.39 Slack Time for Booking Forms Received Less Than 4 Days Prior to OR Date

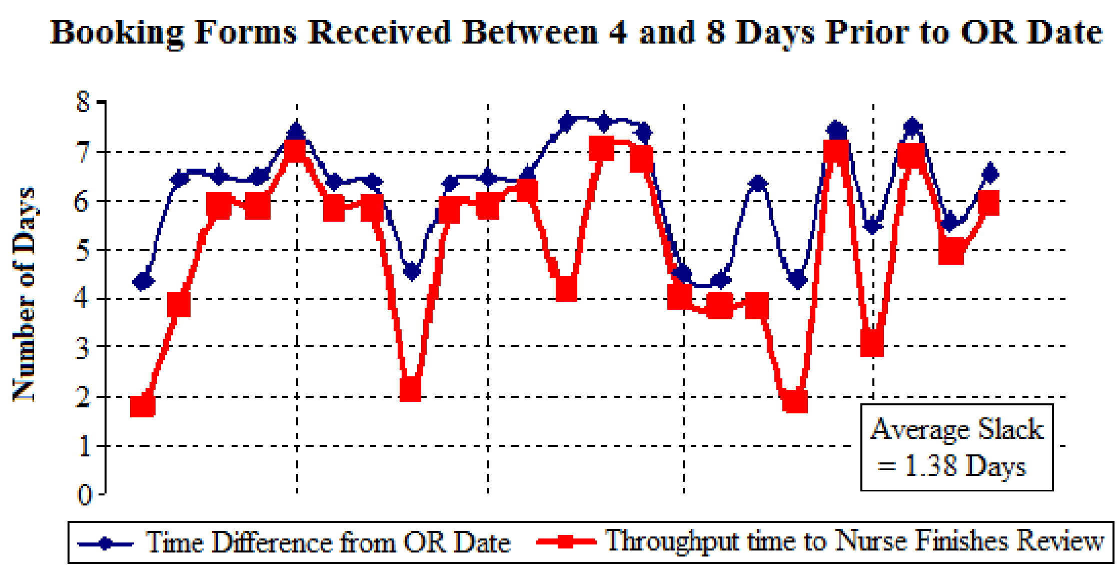

Figure 3.40 Slack Time for Booking Forms Received Between 4 and 8 Days Prior to OR Date

The Pre-Admit Clinic often faces delays related to ensuring that a patient has a proper history and physical completed. Standardizing the processes by which patients acquire these documents and by which PAC collects them would reduce the variability and subsequent delays. The current method involves all copies of the history and physical form being faxed to the Pre-Admit Clinic. Often times the faxed copies have no surgical date included resulting in time spent by the PAC nurses trying to identify the surgical date so that the charts can be processed and the forms can be filed by date. Other complications related to faxing, such as multiple ambiguous copies of the history and physical with possible correlation arriving at once. If the history and physical examination forms are not available on the date of surgery it often results in non-operative delays.

To solve the complications that accompany PAC receiving forms via fax, an electronic booking form was created. The paper-based forms were often difficult to read and were missing information, forcing the clinic staff to have to contact the surgeon's office to fill in the blanks. The electronic booking request form (Appendix A) solved these problems by utilizing computerized text and containing mandatory fields which must be filled in by the user in order for the form to be submitted.

3.3 Patient Flow at Maples Surgical Centre

I spent some time observing the patient flow and the practices used at the Maples Surgical Centre, a private plastic surgery clinic in Winnipeg, MB. It was an extremely beneficial experience and very interesting to be able to observe the differences between a private clinic and a public hospital. I created a value-stream map for the process which can be seen in Appendix A. The value stream for the private clinic flow is basically an ideal flow for the public hospital. Because the private clinic only deals with the simplest cases and is monetary objective-based, the patient flow is well streamlined. The major areas of difference which I noticed between Maples and the Winnipeg Children's Hospital were the speed of the changeover process and the elimination of pre-operative steps and repetitive questions. When a patient enters the Maples Centre, they enter an individual waiting room and are seen and questioned only once by the surgeon and anaesthetist. As well, the private OR's contain virtually all of the necessary items (ie. sutures, dressings, etc.) so there is no need to have a nurse leave the OR to retrieve something in the middle of surgery. Also the private clinic utilizes stand-by patients to fill in for any cancellations and improve OR utilization.

3.4 Summary

In conclusion, this chapter served as a comprehensive outline of the projects that were performed at the Health Science Centre Children's Hospital and described how lean was used to make a difference in the patient flow. An overview of the lean definitions and concepts used within the projects is provided. Divided by department, the process of identifying non-value added activities within the system by way of staff feedback is a central part of this chapter. Outlined within the chapter are the improvement projects stemming from the staff interaction and some of the more influential implementations within the patient flow. This includes electronic booking forms, the standardized procedure of the operating room clean-up, the transportation of patients to the OR, and the first-case start time accuracy.

Chapter 4 Pediatric Intensive Care Unit Simulation

4.1 Introduction

The pediatric intensive care unit (PICU) accepts patients from various sources when space is available, cares for them with the resources they have, and discharges them when the patient has recovered enough to be considered non-intensive. Figure 4.1 shows this in a simple pictorial form.

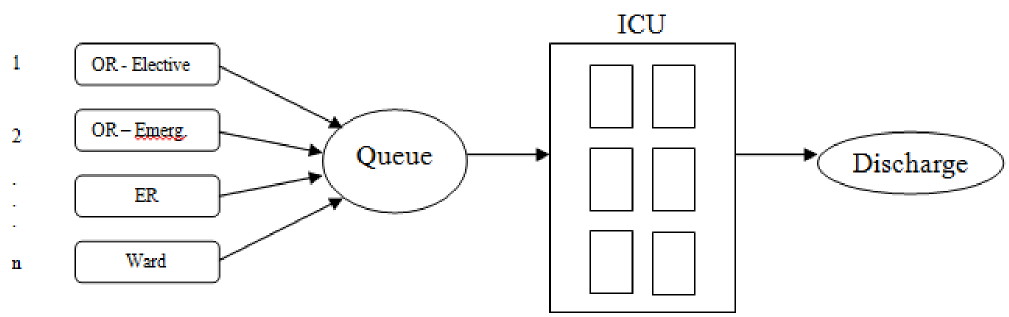

Figure 4.1 PICU Macro Patient Flow

This chapter is a summary of the steps taken to complete a simulation of the PICU at the Children's Hospital in Health Sciences Centre, Winnipeg. The simulation utilizes a model created from data collected by staff in the department. It views the PICU from a macro perspective and is used to observe the changes in variables such as patient arrival rate and number of staffed beds. The results will show how varying unit staff will affect the number completed and cancelled cases, the amount of additional resources that would be needed to compensate for an increase in patients, and how resource allocation affects results.

Within this chapter, Section 4.2 will provide a background as to how simulation was conceived as a solution to the cancellations occurring because of the PICU. A clear definition of the unit's resources, constraints, and variables are provided in the Design of Experiment in Section 4.3. This is followed by Section 4.4 which progresses through the steps involved in creating and analyzing the preliminary, current state, and future state simulation models. Lastly a summary is provided to outline the results achieved.

4.2 Background

The purpose for creating a simulation of the Pediatric Intensive Care Unit at the Health Sciences Centre is to gain a better understanding of the patient flow within the department in order to reduce the number of unexpected cancellations. As the system works now, frequently elective surgical cases are cancelled the day of surgery when it is determined that no post-op PICU bed is available. This leads to additional expenses incurred by the hospital due to rework and frustration for the surgeons, staff, and patients and their families. Hospital management posed the questions:

1. If additional beds in the PICU were staffed,
    a. What would be the impact on cancellations?
    b. What would the bed occupancy be?
    c. What would be the economic impact?
2. Explore how this economic impact can be internally resourced
    a. What impact would a 4 bed monitored unit for medical patients on CK4 have on surgical cancellations?

3. If any major changes are contemplated (dedicated beds, etc.), what would their impact be?

I realized that using my experience with simulation software I could create a simulation model that could not only be used in a capacity versus demand manner but would also be a valuable tool for theoretically altering PICU conditions and resources. This might include determining whether having dedicated beds for elective surgical cases would be a more efficient way of allocating resources or what the necessary additional resources would be in an epidemic situation.

4.3 Design of Experiment

The PICU consists of 10 beds occupied by patients who are cared for by 6 nurses and a charge nurse who works at the front desk. An average of 1:1 nurse to patient ratio means that typically 6 of the 10 beds are in use at any given time while the other 6 remain empty. The unit is staffed 24 hours a day, 7 days a week with all but scheduled elective OR patients arriving and departing at all times. Patients originating from the OR (both elective and emergent), the ER, hospital wards, other internal hospital departments, and external hospitals request the use of a PICU bed. These patients may enter into a queue and experience a wait of roughly 2 to 4 hours. They are then admitted to the PICU when any of the beds become available. No PICU beds are reserved for any specific type of request. OR elective cases are performed only during weekdays from 0730 to 1530, except Wednesdays when the start time is not until 0900. Patients remain in a PICU bed until their condition has improved sufficiently and are discharged.

Synthesizing:

- Resources: 6 staffed beds, 4 extra beds, 6 nurses
- Entities: Patients
- Patient Mix based on origin of arrival consisting of 6 categories (the OR (elective and emergent), the ER, hospital wards, other internal hospital departments, and external hospitals)
- Each category of patient characterized by pattern/rate of arrival and length of stay
- The entities arrive and depart at any time with the only scheduling limitation being elective surgical cases which are only admitted during OR hours Monday to Friday
- No bed allocation is used so any bed is available to any type of patient

Variables to be altered are the rate of arrival of each category and the bed management or allocation of the PICU beds. Increasing the rate of arrival will mimic expected future trends or a pandemic situation. This will result in observations of the number of cancellations and bed occupancy as well as an estimate of how many additional resources will counteract the increased rate. Assigning a single bed or multiple beds for strictly the use of elective operating room procedures is a possible managerial tactic due to the scheduled and relatively reliable nature of this patient population. Analysis of this bed allocation would reveal if this method was more efficient.

The ICU has no way of efficiently observing its performance measures from a macro perspective and adjusting its capacity to meet changing demands. A simulation model can supply an understanding of whether the ICU unit has adequate resources by providing statistics on how often the unit is at full capacity, bed utilization, and the average number of patients and time spent in queue waiting for a bed to open. Using the historical data collected, a patient mix based on origin will indicate patient arrival rates, length of stay distributions, and accordingly, cancellation numbers based on the number of available staffed beds. A simulation model will also provide an excellent means of experimentation. It will allow managers to examine the effects of altering department resources and patient statistics without having to disrupt anything in real life, valuable in situations such as pandemic planning. Lastly, a simulation model has the additional potential to be used for optimization purposes. Using a standard measure, such as dollars, the cost of adding resources to reduce cancellations can be weighed against the alternative.

A model useful for simulating the ICU would require entities to represent the patients, ICU staff, and beds. Patients within the model would possess the attributes rate of arrival, length of stay after being placed into a bed, and some sort of classification in order to differentiate between patients and provide further accuracy (in this case patient origin). The importance of the ICU staff is dependent on the number of beds in the ICU. The number of staffed beds is the useful value. As well, if the number of beds is the limiting factor, fluctuating the number of staff should have no effect on the simulation. Including staff in the model, however, requires attributes such as daily scheduling (shift length, breaks, etc.) and a resource-weight intensity (the number of nurses needed to "process" a patient). In this ICU model the number of staffed beds is the rate determining variable and will be varied in order to observe the effect on the number of cancellations and the bed occupancy. Because the elective patient flow is the only non-random variable, it is the only patient stream which could have a scheduling aspect applied to it. This will be incorporated into the model when evaluating a scenario in which one or multiple ICU beds are dedicated to elective surgical patients.

ICU data has been collected over a two year time period (January 2008 to December 2009). This data contains where the patient was transferred to the ICU from, the date and time of patient arrival, the date and time of patient discharge, and where the patient was discharged to. From this data, length of stay statistics and distributions can be calculated. Additionally, patients can be classified by where they originated, which has an effect on length of stay. For example, patients transferred in from out-of-province and external hospitals will be more severe cases and should require an extended length of stay. Information on surgical cancellations has also been acquired. Combining the number of cases cancelled due to no ICU bed being available and the number of accepted cases provides a measure of demand and patient rate of arrival values. This patient arrival value can then be increased by a percentage or accelerated and slowed down during certain time periods to observe the effect on case cancellations at various levels of bed capacity. The accepted average nurse to patient ratio in the ICU is one to one and the staffing level for the majority of the two year time period was five plus charge. This means that while the unit contains 10 beds, the unit capacity is an average of five staffed beds capable of caring for five patients. Additional funding was granted and the staffing level was increased near the end of the period to ten nurses plus a charge nurse to fully utilize all 10 beds. This scenario will be examined when the number of beds factor is varied.

4.4 Simulation Model

4.4.1 Preliminary Model Creation

An introductory simulation model was created and tested to determine whether it could perform as needed and produce the desired results. The first model offered insight into exactly what forms and amounts of data were necessary to properly define the PICU system and helped to provide the framework for more advanced models.

4.4.1.1 Data Collection

The data that was retrieved for the preliminary model came from "The Portal", the source which feeds hospital statistics to the Canadian Institute for Health Information (CIHI). The data was very generalized, consisting only of the number of patients which entered the PICU on a given day, where the patient came from, and the average length of time spent in the PICU by all patients admitted that day. Data was extracted from a 14-month period (February 2007 to March 2008). This period represents an accurate sample of the current system because it consists of the period after the new surgical facilities were implemented.

4.4.1.2 Data Analysis

The data was used to calculate an average of 1.15 patients entering the PICU per day and an average length of stay of each patient of 4.15 days. This immediately indicates that the current six bed unit has the capacity to handle the "normal" (or average) flow of patients but may still suffer from timing related issues such as upper limit variation of patient length of stay (i.e. if a couple of longer-stay patients are occupying beds the capacity is quickly decreased).

4.4.1.3 Simulation Model Construction

The simulation performed was done using Flexsim[1] software. The data was entered into a module called ExpertFit[2] which aids in fitting the data to a type of distribution. Neither the patient arrival nor length of stay data was able to accurately conform to a standard type of distribution. Therefore, an empirical distribution was necessary. This type of distribution basically calculates what percentage of situations the variable occurred and randomly selects values from within this range within a simulation. This process can be seen in the images in Appendix C.

The PICU physical environment was constructed in a three dimensional Flexsim[3] model using floor plans acquired through HSC, as seen in Figure 4.2 and Figure 4.3. The model consists of six fully-staffed PICU beds and 12 nurses.

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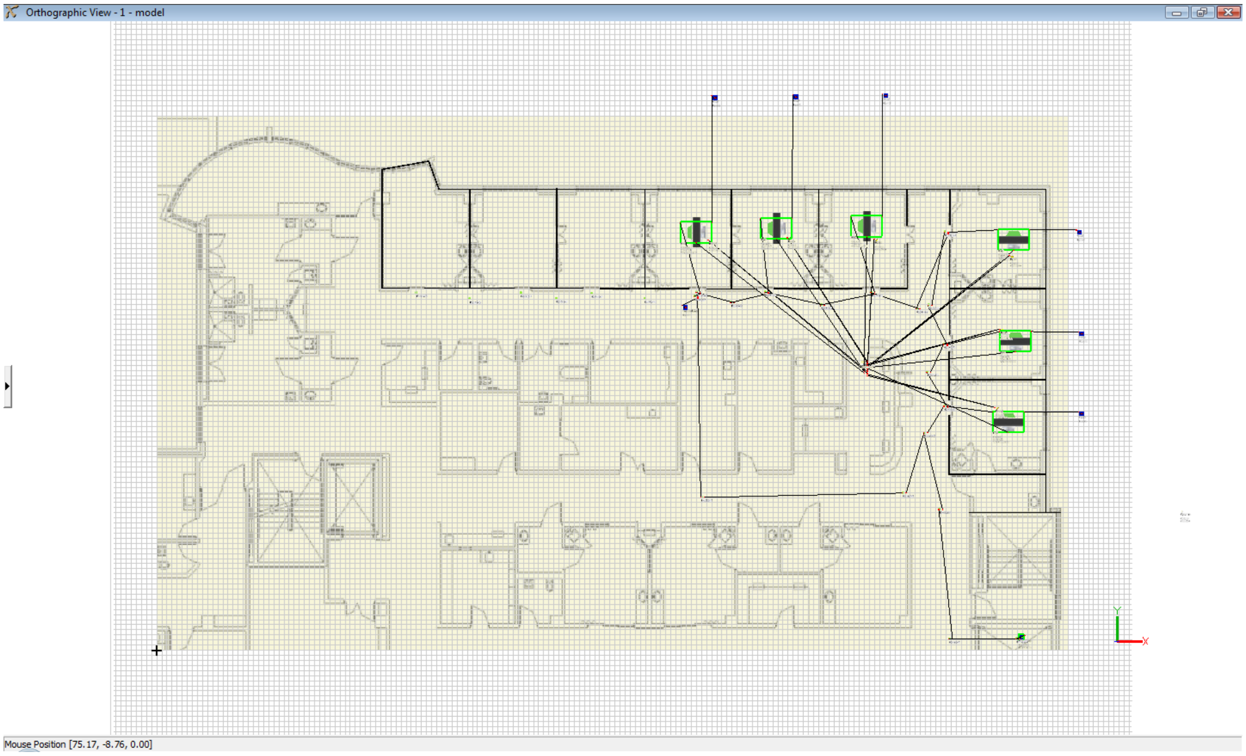

Figure 4.2 Preliminary Model Orthographic View

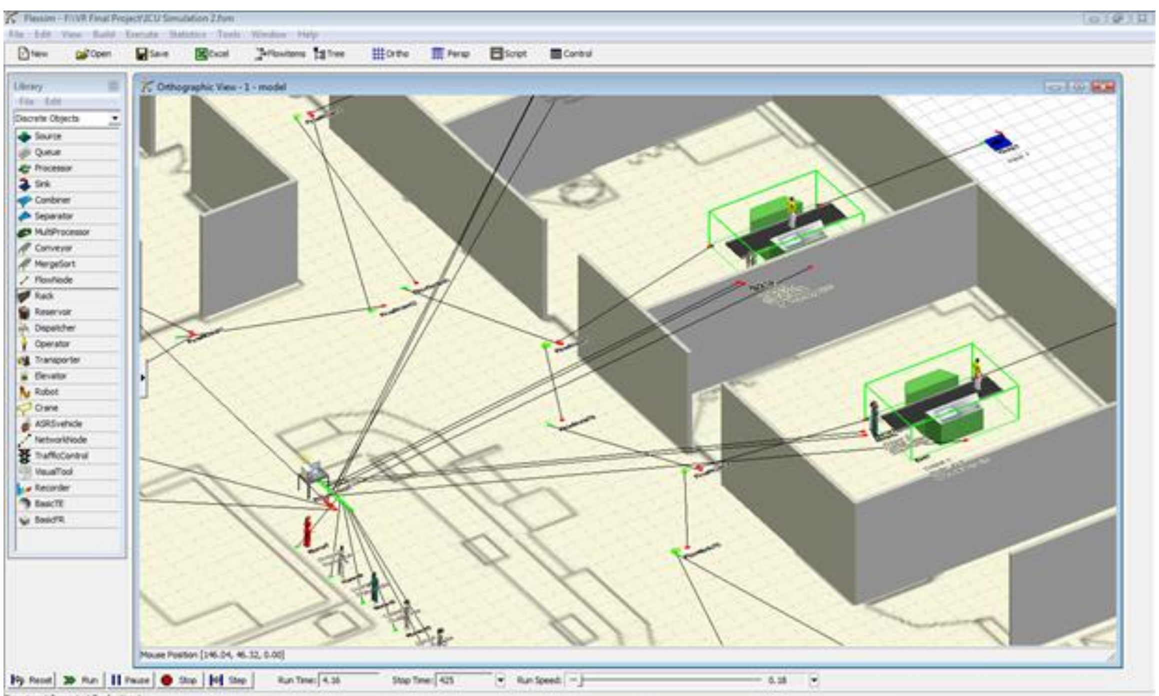

Figure 4.3 Preliminary Model 3-Dimensional View

Having the data in correct format after using ExpertFit[4], the "Arrivals" empirical distribution was applied to the "create" module at the beginning of the process and the "Length of Stay" distribution to each of the "beds", the cycle time of each processor. As a result, in the simulation, a "patient" is created between 1 to 3 times per day, in accordance to the empirical distribution, and goes from one bed to the next until it either finds an open one or until it reaches the end. Once entering a bed, the patient requires 2 "nurses" (or operators) and remains there for a random amount of time within the Length of Stay empirical distribution before exiting the system. A feature that I added was a delay loop. If a patient attempts to access all six beds and finds that they are all occupied, the patient will enter a return loop which will delay them for two hours and then allow them to try and access the beds again. This is to simulate the real-life procedure in which a surgical case is delayed while managers attempt to free up a bed. If after the second pass there is still no bed available, then the patient exits the system and the case is "cancelled".

The simulation was performed for 100 replications in order to get a large enough sample to produce significant results.

4.4.1.4 Simulation Results

The results that were produced by the simulation model indicate that an average of about 52 patients over the 14-month period were "cancelled". Because the information

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provided to the simulation was based on patients that were actually accommodated by the PICU and not cancelled, this value is more of an indication of how the system is stressed. These patients were cared for even though the system might not have the capacity to handle them. Charts in Appendix C show the results of the two simulation runs over confidence intervals of 90% and 99%.

4.4.1.5 Model Validation

In order to validate that the simulation was performing as intended and adhering to the input data, the values used for the length of stay and patient arrivals throughout the simulation runs were plotted on a chart. As shown in Appendix C, the average length of stay was 4.10, close to the actual value of 4.148. The average number of patient arrivals over the time frame was 499.5, slightly higher than the actual value of 491.

4.4.1.6 Simulation Analysis

The roughly 50 cancellations identified by the simulation model are a measure of the stress placed on the capacity of the PICU department. To perform an analysis and test different hypothetical situations the effect of adding additional fully-staffed beds was observed. Even though, based strictly on averages, 6 beds was sufficient capacity and the cancelations were due more to timing issues than lack of resources, it was speculated that adding one additional bed at a time would slowly decrease the number of cancellations and set up an optimization opportunity. However, after adding just one additional bed, the number of "cancellations" dropped to 0. Therefore, it would suggest that if the PICU consisted of seven fully-staffed beds, the stress placed on the system by patient variation would be significantly reduced. Charts in Appendix C display the statistics associated with the additional bed.

4.4.1.7 Simulation Discussion

The results of this simulation show that the current PICU department handles an average of about 50 patients within a 14 month period which it does not have the capacity to handle due to patient arrival and length of stay variation.

The simulation model used, however, is far from complete. Patient data from other sources, such as the PICU hand-written log book, was used to validate the input data for the patient arrivals and length of stay. Further classifying patients based on their monitoring needs and their procedure type would be beneficial. More staffing details, such as scheduling, sick time and holiday statistics, would make the model more accurate. As well, other resources available, such as monitored bed units on the wards, must be taken into consideration.

The current simulation model is an excellent start for understanding the data behind the operations of the PICU department and testing hypothetical situations. Further validation and details incorporated into the simulation model will bring the simulation model closer to its real-life counterpart and enable more accurate results.

4.4.2 Current State Model Creation

The current state model uses the supplied data and constraints to mirror the real-life system it is meant to simulate and build off of. The model must be verified by its creator to ensure that all of its features act the way they were intended and the software runs accordingly. It must also be validated to guarantee that it properly represents the system that it is intended to simulate. Verification is "building the model correctly" and validation is "building the correct model".

4.4.2.1 Data Collection and Analysis

Data covering a two-year time period was obtained from a handwritten logbook maintained in the PICU. Nurses record the name of the patient, the patient's date of birth, hospital ID #, diagnosis, the name of the doctor, where the patient was admitted from, the date and time of admission, the date and time of discharge, and where the patient was discharged to. A scan displayed below (Figure 4.4) shows how the data was recorded.

Doctor	Adm. Fm	date of birth	date	time	date	time	# days	To
	PICU	23-July-2005	01-01-08	0001	01-03-08	1530	2	CK-5
	PICU	02-Nov-2005	01-01-08	0001	01-17-08	1515	16	PSCU
	PICU	14-APR-2002	01-01-08	0001	01-31-08	1130	31	CH-5
	PICU	30-Nov-2007	01-01-08	0001	01-08-08	1810	7	CH-4
	PICU	03-DEC-2007	01-01-08	0001	01-07-08	1420	7	PSCU
	ER	29-MAR-2003	01-02-08	2335	01-03-08	1130	1	CH-4
	ER	23-Apr-2001	01-02-08	0520	01-06-08	1505	3	CK-3
	ER	21-Sep-2002	01-03-08	1845	01-11-08	1530	8	CK-5

Figure 4.4 Example Raw Data

The PICU charge nurse records the date and time that every patient is admitted to and discharged from the unit. They also include where the patient is admitted from and where the patient is discharged to as well as a total sum of patient days spent in PICU. As well, personal patient information (not shown) such as name, hospital number, date of birth, diagnosis, and attending doctor are recorded. The process of analyzing the data began with the arduous task of inputting the raw data into a Microsoft Excel[5] spreadsheet. Once in this format, the data could be organized and necessary statistics could be calculated.

Given the patient arrival and departure date and times, the overall length of stay was calculated. Given the time of arrival of each patient, inter-arrival times were calculated. Patient volume levels were found (number of beds in use versus time) and helped to verify the overall nurse to patient ratio. The entire patient population was divided up into 6 groups based on the source of origin. For each of these 6 groups the specific arrival rate and length of stay were calculated.

Once organized, the data was fed into the software ExpertFit[6] which determined the best-fitting statistical distributions to represent the data in the simulation. Distributions were found for the inter-arrival time and length of stay time for each classification of patients, as seen in Figure 4.5.

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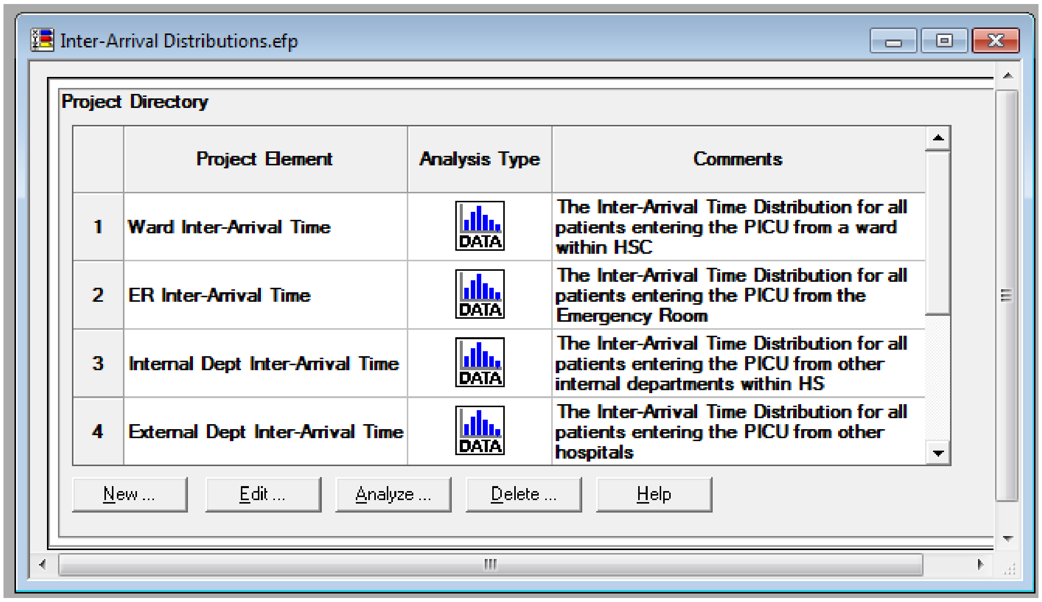

Figure 4.5 ExpertFit Distributions

After entering in the data (Figure 4.6a), basic statistics are supplied (Figure 4.6b), such as number of observations, minimum, maximum, mean, and median. Next a histogram can be plotted (Figure 4.7) to see the overall shape of the data.

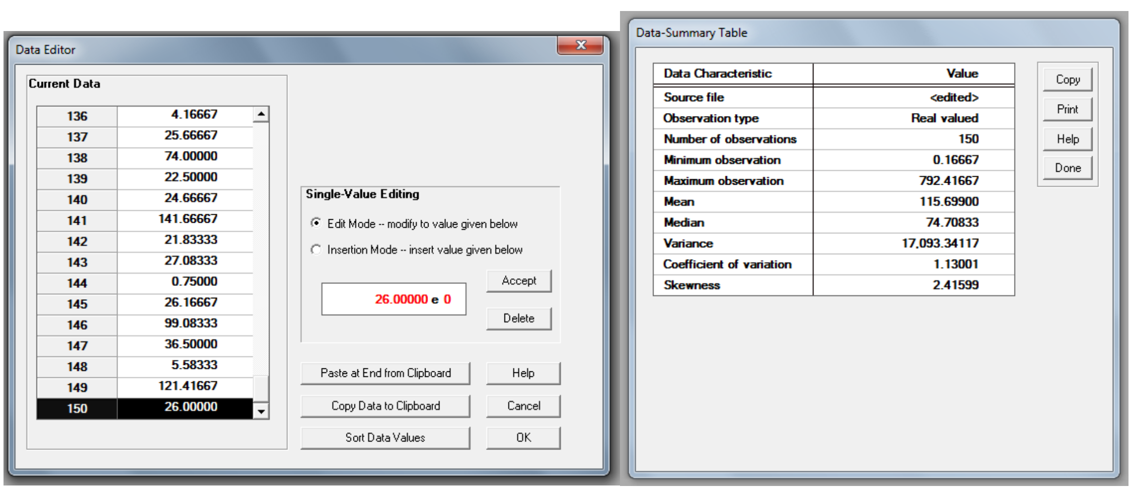

Figure 4.6 (a) Data Entry and (b) Data Statistics

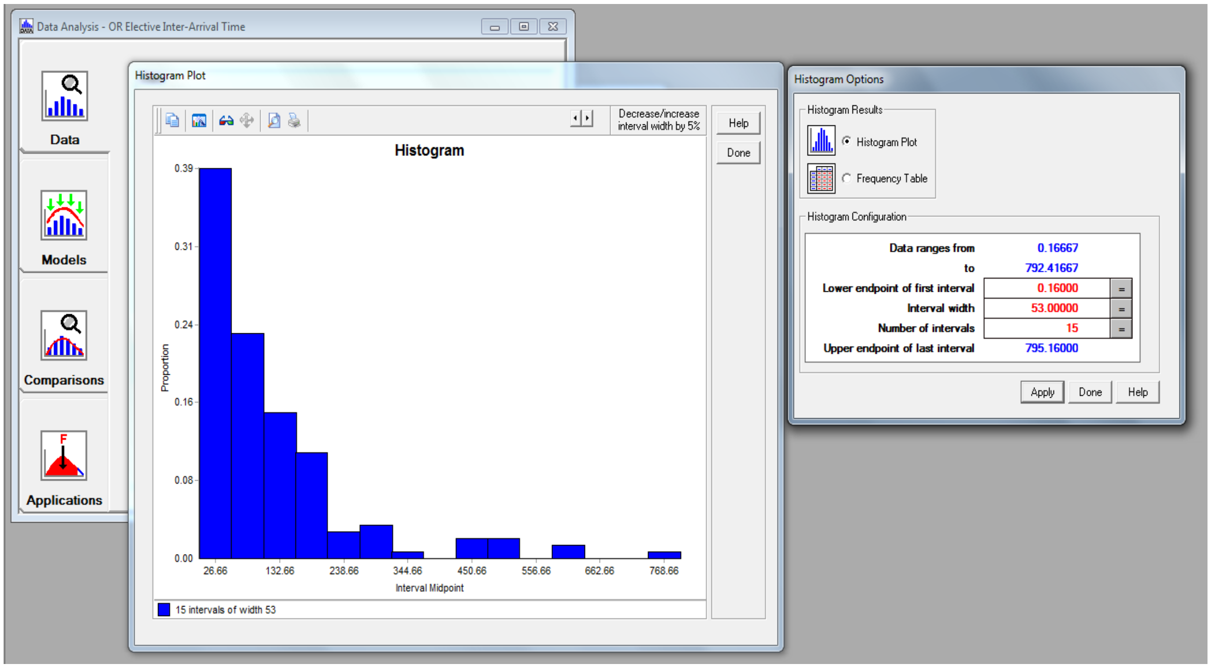

Figure 4.7 Histogram

Lastly, the ExpertFit[7] software provides a list of possible distributions (Figure 4.8) with a corresponding score indicating how well the distribution fits the data. Also provided are the distribution parameters and the necessary code needed to enter into the Flexsim[8] simulation (Figure 4.9).

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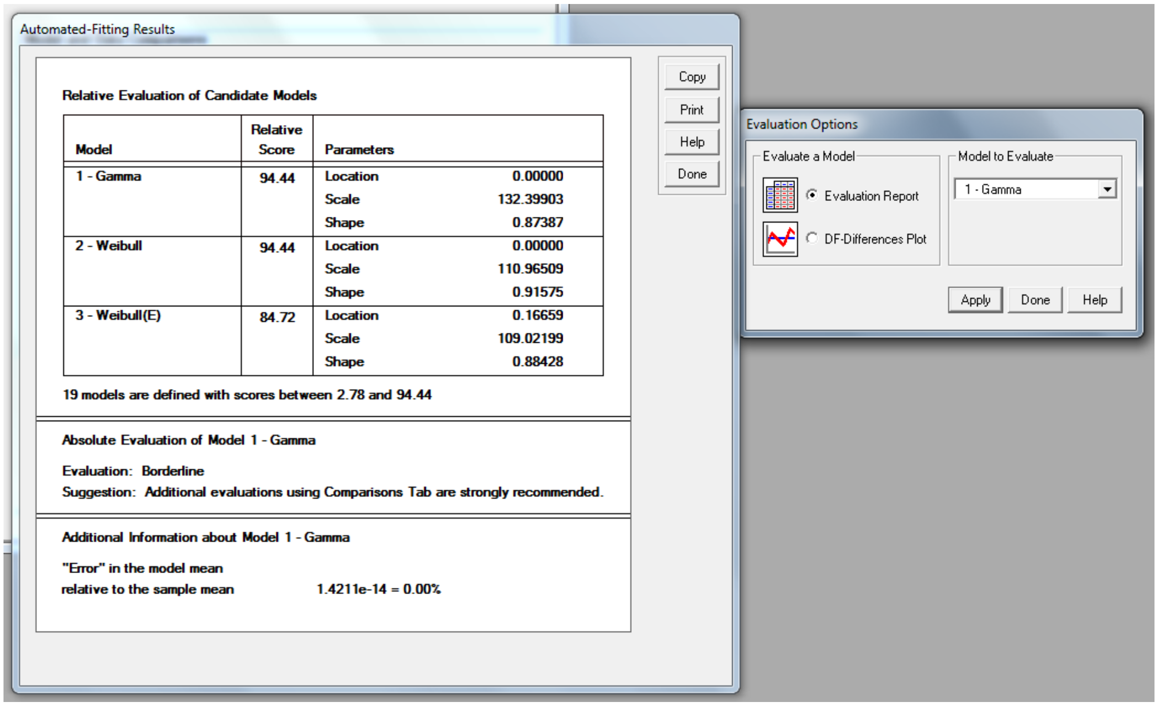

Figure 4.8 ExpertFit Distribution Scores and Parameters

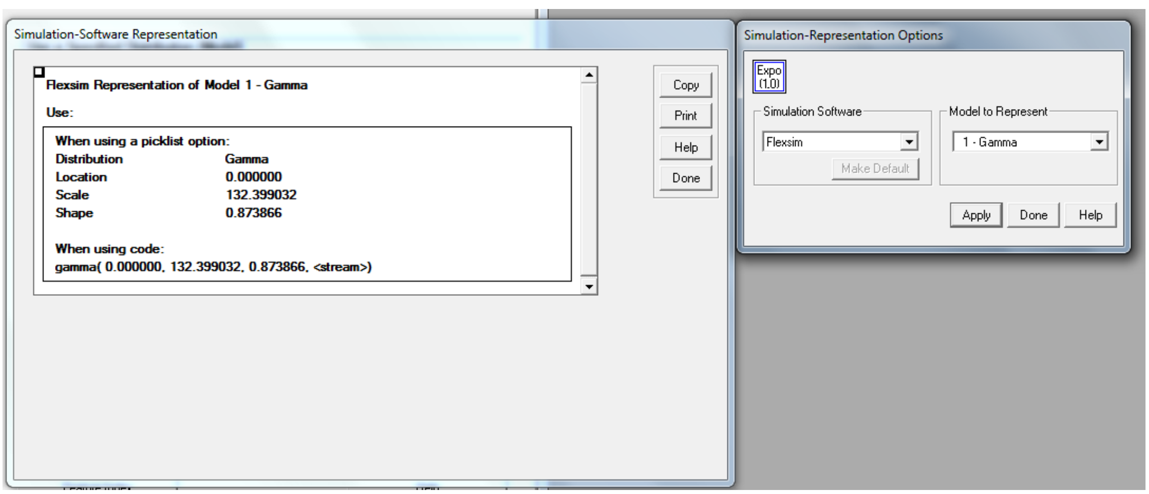

Figure 4.9 Flexsim Code

4.4.2.2 Model Features

This section looks at the detailed features of the PICU and how the incorporation of these features into the simulation model was validated. A “Divide and Conquer” approach was taken to creating and validating the model, meaning the model was split up into smaller, simplified parts and then slowly built upon and combined. Most of these substantiation tests were performed on simplified models to ensure that the theory was correct and would perform as intended when entered into the larger simulation model all while remaining unhindered by the clutter of a complex model.

a) Patient Arrival Verification

Each of the six patient classifications based on patient origin have their own unique rate of arrival and thus, their own verification. Each of the six classifications was given a source with the data distribution provided by ExpertFit[9] inserted into the inter-arrival time. Each of these sources was run in simulation time while recording the time at which patients arrived. This data was plotted using Excel[10] to display the average inter-arrival time versus simulation time. Shown in Figure 4.10 is the graph created for the internal department patients. From the raw data, the average inter-arrival time of patients from internal hospital departments is just over 425 hours. The graph indicates that the average inter-arrival time fluctuates during the early stages of the simulation but settles on about 425 after 100,000 simulation time units (or hours). Based on this finding, it can be concluded that the patient rate of arrival for the internal department classification of patients requires a warm-up period of 100,000 simulation hours.

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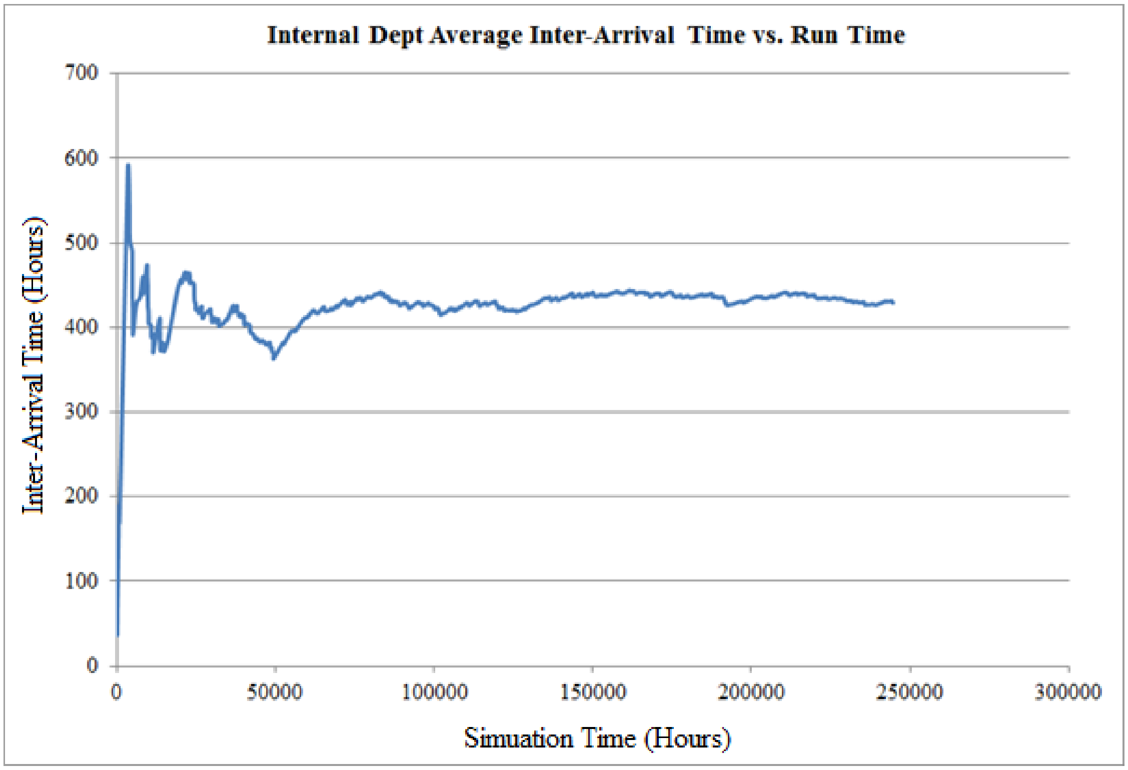

Figure 4.10 Internal Department Simulation Average Inter-Arrival Time

Performing this procedure on all 6 patient origins, the necessary overall simulation warm up period can be determined. The longest of the 6 values should be used to ensure all sources have sufficient time to reach their steady state with accurate average rates.

Visually within the simulation, patients entering the system must have accurate characteristics. For this to happen, upon patient creation, the source must be supplied with the code to set the item size so that the patient is to scale within the model. As well, any desired modifications to distinguish between patient groups, such as colour, must be entered.

To determine the overall demand requiring the resources of the PICU the patients that were cancelled due to no staffed bed availability must be accounted for. To do this, the number of cancelled cases was determined from PICU records and added to the raw data. To find the inter-arrival time including this population of patients which never actually entered the real-life system, a random number generator was used to assign a random arrival date and time. This allowed the same calculations to be performed on the overall demand as on the actual processed patients. The average demand using the randomized arrival date and times was 63.1 versus the average demand time of 63.1 calculated by extrapolating the actual raw data.

b) Patient Length of Stay Verification

Upon entering the simulation, each patient classification was assigned its own value, called an itemtype. For example, patients entering the PICU from the wards were assigned an itemtype of 1.00 while ER patients were assigned an itemtype of 2.00. The length of stay at each bed is based on the patient's itemtype. A simplified model was created to test this application, shown in Appendix C. Only three sources were used, with itemtypes 1, 2, and 3.

A Cases by Value criteria was selected for the processing time of the processor. Thus, the processor retrieves the itemtype of each object which enters and applies a processing time distribution assigned to that case. For this simplified model, all itemtype 1 objects require a processing time with a normal distribution of mean 10 and standard deviation 0.

All itemtype 2 objects require a mean of 30 and all itemtype 3 objects require a mean of 50. The code for this operation can be viewed in Appendix C.

Running the simulation, the result shows that the processor operates on three very distinct categories of parts with three very separate, unique processing times. The model works as intended and the three visibly distinct object processing times are observed, displayed in Appendix C. Translating this simplified example into the more complex PICU model, the objects become patients, the processors become beds, and the processing times become length of stays. Six cases are required, one for each patient origin, which return the length of stay distributions found in ExpertFit[11].

c) Staff Allocation (Resource Weight Intensity) Verification

Looking at the patient volume statistics for PICU, it was apparent that the suggested staff to patient ratio of 1:1 was roughly correct (6:5.8). However, the number of patients in the unit ranged from a minimum of 0 to a maximum of 10. Thus, simply having six staffed beds in the model sets an upper limit of six patients and is not accurate enough. As well, it is possible to have 10 patients cared for in the unit despite an average 1:1 nurse to patient ratio because this value is simply an average and can range between 2 patients per nurse to 2 nurses per patient. To accommodate for this, an approximate resource weight intensity (RWI) had to be developed for each of the six patient groups. Based on the

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RWI, the simulation model could allocate a variable number of staff to each patient based on the itemtype.

This theory was practiced using the simplified model shown in Appendix C. Fitting the RWI data into the simulation model, the number of operators required to process a patient was set using a user-defined global table. This enables the simulation to vary the RWI amongst patients based on the defined itemtype, unique to patient groups (ie. certain patient groups require 2 nurses, others 1, and others 0.5). This is performed using the code displayed in Appendix C where "NoProcessOps" is the global table (also shown in Appendix C) and the setvarnum command sets the number of required operators ("nrofprocessoperators").

The first step in finding a RWI for the patient groups using the collected data was to calculate the total sum of patient hours needed per patient group, followed by the corresponding percentage of overall patient hours. Next the number of staff per patient value was assigned based on the average length of stay value (indicative of complexity) and experience, as seen in Table 4.1. It was also necessary for the resulting sum to be as close to equaling the 100 percent of the overall patient hours as possible. Because half a nurse cannot be assigned to one bed in the simulation model, the number of staff was doubled so that 12 operators were in use, each representing half a nurse. Thus, for example, all patients arriving to the PICU from external sources require 4 nurses to be cared for in the simulation.

Table 4.1 Determining Specific Staff to Patient Ratios (RWI)

	Percentage of Overall Patient Hours	# of Staff / # of Patients	
Ward	30.21975521	1	30.21975521
ER	33.52838813	0.5	16.76419407
Internal	5.707319226	2	11.41463845
External	14.95313653	2	29.90627306
OR-Elective	6.983298411	0.5	3.491649206
OR-Urgent	8.608102485	1	8.608102485
	100		100.4046125

d) Arriving Patient Delay Queue

In real life, when an OR case is scheduled but the PICU is full on the day of the procedure, the case is delayed while the PICU managers try to discharge a patient to free-up a bed. This delay usually lasts a few hours, after which if there are still no available beds the case is cancelled. In the simulation model, when a patient attempts to access a bed but finds they are all occupied, that patient is redirected to another queue. While in that "Delay Queue", the patient waits a user-defined amount of time before attempting to access a PICU bed for the second time. If all beds are still occupied the patient exits the queue and moves into the cancellation sink. This feature is performed using code applied to triggers within the two queues, shown in a picture of the model in Appendix C.

Upon exiting the first queue, each object is given a label called "release_time" which is set to the time at which the object exits the queue plus a set wait time, in this case 4 hours. When entering the delay queue, an object triggers code which finds the difference between the actual time and the release time label. This code sends delay messages until the time difference is zero at which time a release message is sent. All of the exit ports for the delay queue are closed and only opened when triggered to do so by the release message sent to it. Objects exit the delay queue through the opened port 1 and travel to a third queue where the attempt to access an open bed once more before being cancelled.

A very minor problem that could occur with the delay technique utilized is that patients must wait the designated delay time. In real life, a patient can be moved to a bed as soon as it becomes available. In the simulation, a bed could open while a patient is in the delay queue but be filled by a newly arriving patient, causing the delayed patient to find all beds still full after waiting. A solution to this would be to add multiple delay queues to shorten the length of time between attempts at accessing a bed. This situation would occur so rarely and have such a small effect on the results that the simulation is left as it is.

e) Re-Routing Cancelled Patients after Delay Loop Verification

In a simulation set on the PICU floor plan, patients make a first trip around the department attempting to enter a bed, undergo a delay, and then make a second trip in search of a bed before potentially being cancelled. A decision point is necessary after the first trip and before the delay. At this juncture, it must be determined if the patient has attempted to access a bed once or twice. To do this, a label is applied to objects passing this point.

Creating a simplified model shown in Appendix C, upon creation objects are given an initial label titled “delayed” which is set at 1. After the first attempt at accessing a bed and finding all to be full, the patient reaches the decision point Flow Node. Objects exit the Flow Node via the port equal to the "delayed" label; port 1 to the delay loop and port 2 to the cancellation queue. The label "delayed" is changed to 2 upon exiting the Flow Node through port 1 (and objects are re-coloured black in the picture). After waiting for set time, in this model dependent on the distance of the path travelled, the delayed patient attempts to access a bed for the second time. Upon being denied for a second time and reaching the Flow Node again, objects are redirected through output port 2, based on the "delayed" label value of 2, and into the cancellation queue (and re-coloured green).

f) Elective OR Working Hours Schedule

Elective cases are performed in the OR weekdays between the hours of 0730 and 1530, except Wednesday when the slate does not start until 0900. Thus, a schedule must be applied to the Elective OR source which creates this group of patients to confine arriving patients to these hours.

Time tables are easily created in Flexsim[12] and, in this case, titled OR Working Hours. Using a graphical editor divided into time slots of 15 minutes (displayed in Appendix C) the desired working hours can be shaded in. To verify that the source is working correctly, a chart showing simulation time versus number of patient arrivals was created. This chart (Figure 4.11) shows that the time table dictates when patients can arrive based

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on focusing in on a distinct 2-week time period, with the long periods of reduced slope being weekends and shorter periods of alternating high and low slopes are weekdays.

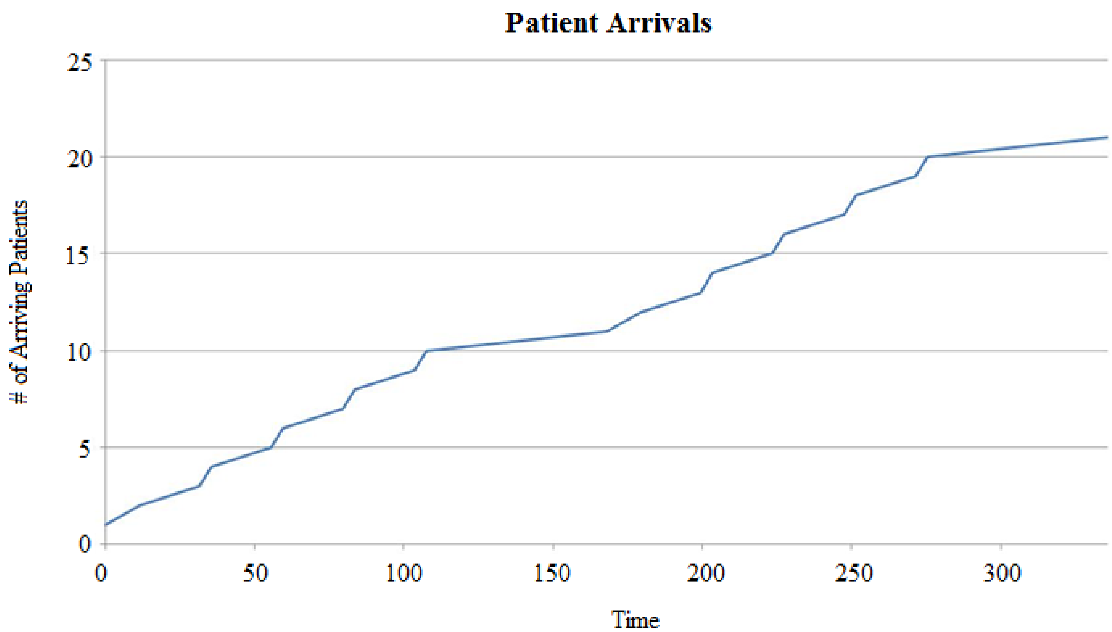

Figure 4.11 Patient Arrivals Dictated by Time Table

4.4.2.3 Current State Model Creation

Once all of the individual model features are validated and shown to fulfill all parts of the system definition, the features can be assembled into an overall working simulation model. Once pulled together, the model is checked to ensure it works as a whole and parameters such as warm-up period and run length are applied to specify in what manner the simulation will run.

To initially bring the specific sub-sections of the model together, the components were imported into a simplified layout, seen in Figure 4.12.

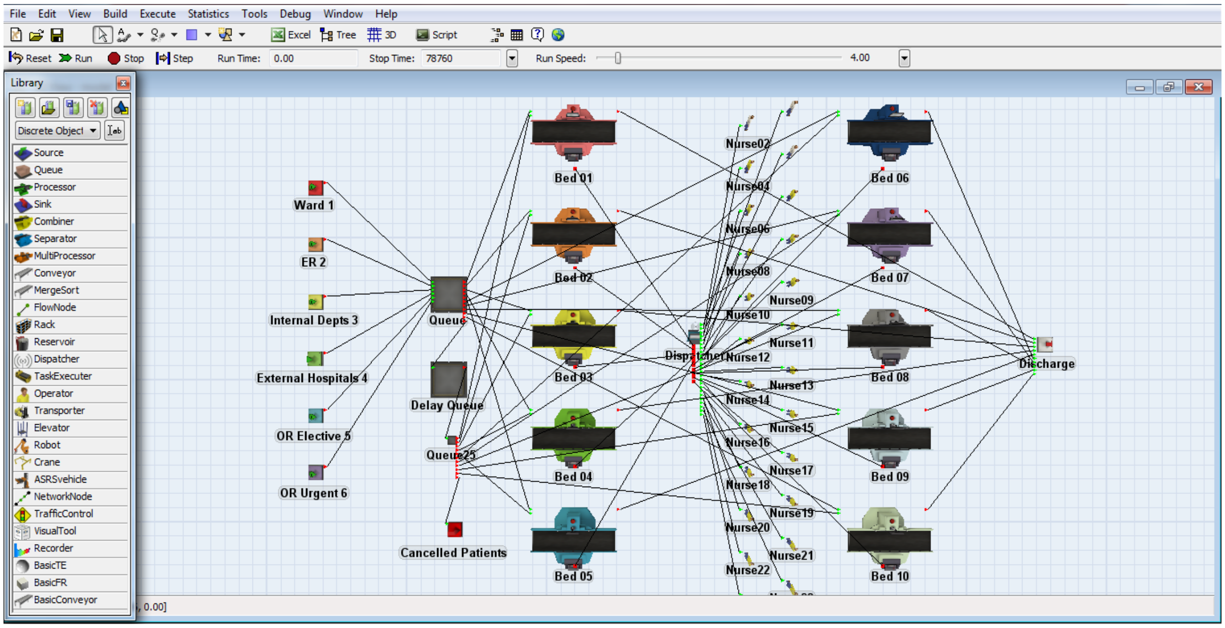

Figure 4.12 Simplified Final Simulation Layout

To further customize the simulation, the next draft of model was created over the PICU floor plan (Figure 4.13). This required more flow nodes to be inserted to direct the patients within desired confines, such as down hallways and through doors (Figure 4.14 and Figure 4.15).

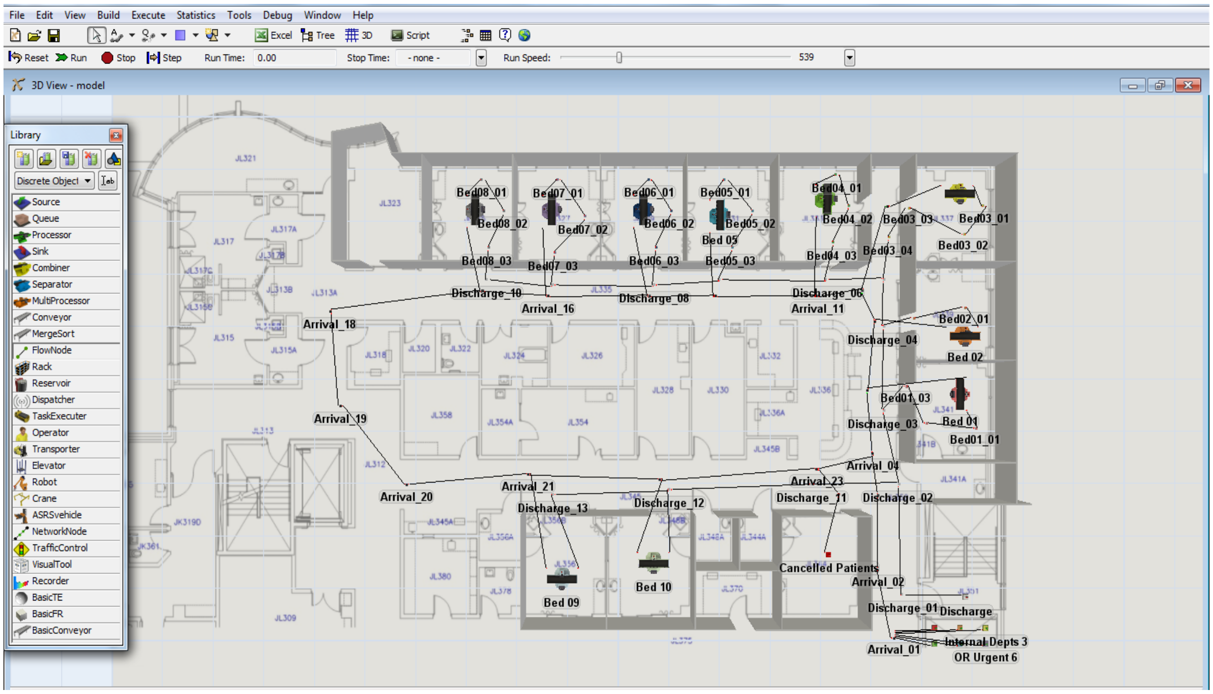

Figure 4.13 Final Simulation Layout Using PICU Floor Plan

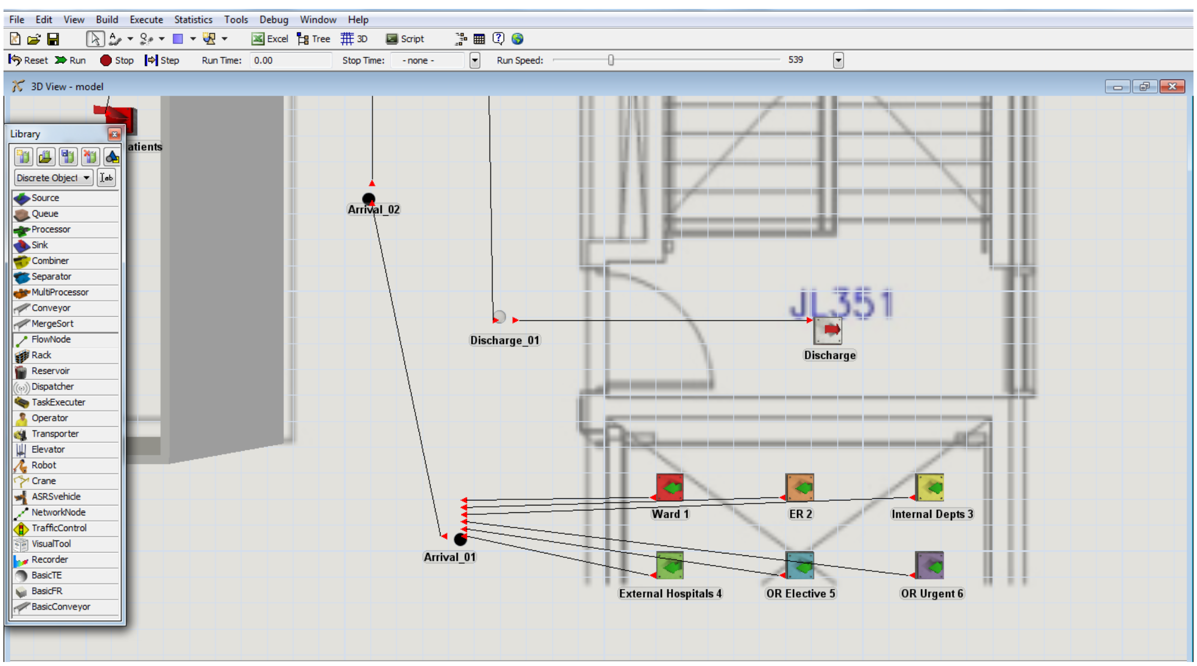

Figure 4.14 Sources, Discharge Sink and Flow Nodes

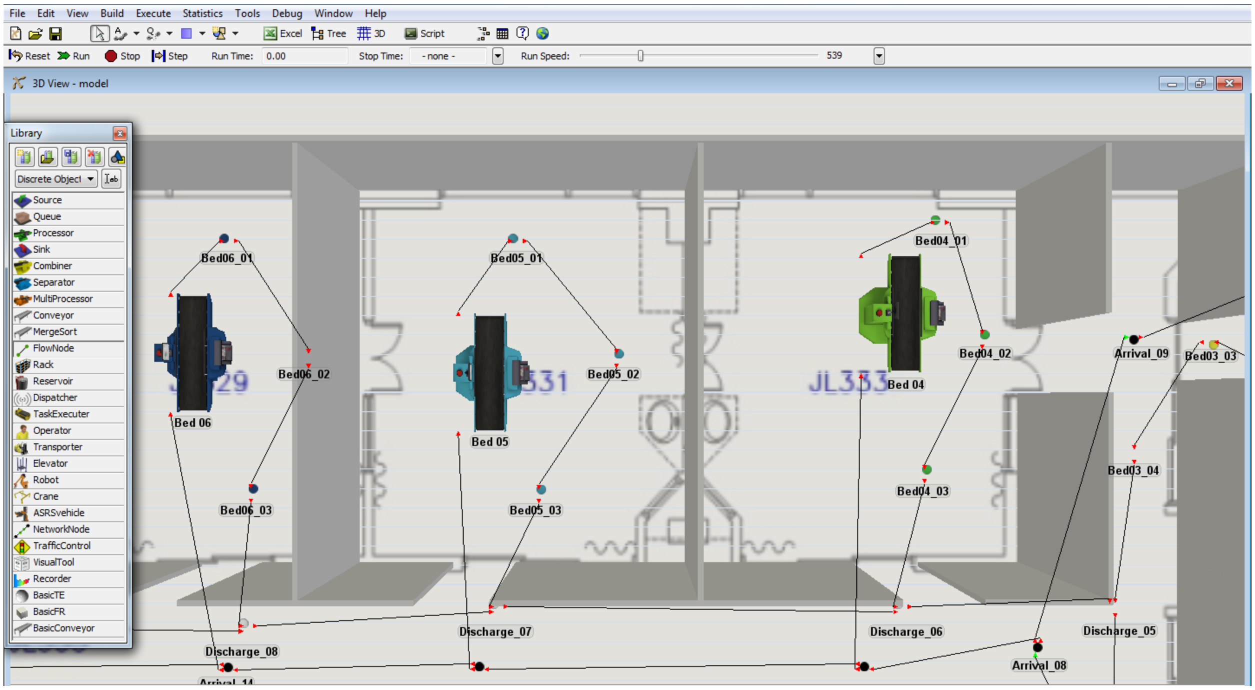

Figure 4.15 Directing Patients Through Hallways and Doors

4.4.2.4 Simulation Run Characteristics

There are three basic characteristics required to define a simulation run in Flexsim[13]; run length, warm-up period, and number of repetitions. One aspect of selecting values for these variables is what makes sense from a simulator's perspective. Choosing higher values can do no harm and can provide added security. However, higher values can also dramatically increase the time it takes to perform a simulation unnecessarily. Another aspect in selecting values is analytical; matching the raw data collected to data provided by the simulation.

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The first variable focused on is run length. PICU data was collected for a 2 year time period. Extrapolating this data for a simulation run length of anything greater than 2 years leads to an added risk. A run length must also be long enough to take into account any time-related fluctuations or season variability within the actual system. Taking all this into account, a straight forward run length of 1 year (or 8760 hours) was selected.

Next an accurate warm-up period length must be determined. The warm-up within the model is most needed for the source objects. The sources create the patients entering the system and are governed by the inter-arrival distributions calculated using ExpertFit[14] and based on the raw data. Running a basic simulation and recording the statistics for the source objects shows the inter-arrival time of patients entering the simulation. Using a spreadsheet, a running average of these inter-arrival times can be found and graphed, as shown in Figure 4.16 and Figure 4.17. Observing these graphs, a necessary warm-up period is identified as the run time at which the data stabilizes and levels off at the average inter-arrival time. For example, the ER average inter-arrival time calculated using the raw data is 52.2 hours. Figure 3.22 shows the simulation inter-arrival time at the ER source steadies at about 52 hours at about the 10,000 hour mark. Thus running the simulation for 10,000 hours as a warm-up will allow the source to reach a steady, desirable performance.

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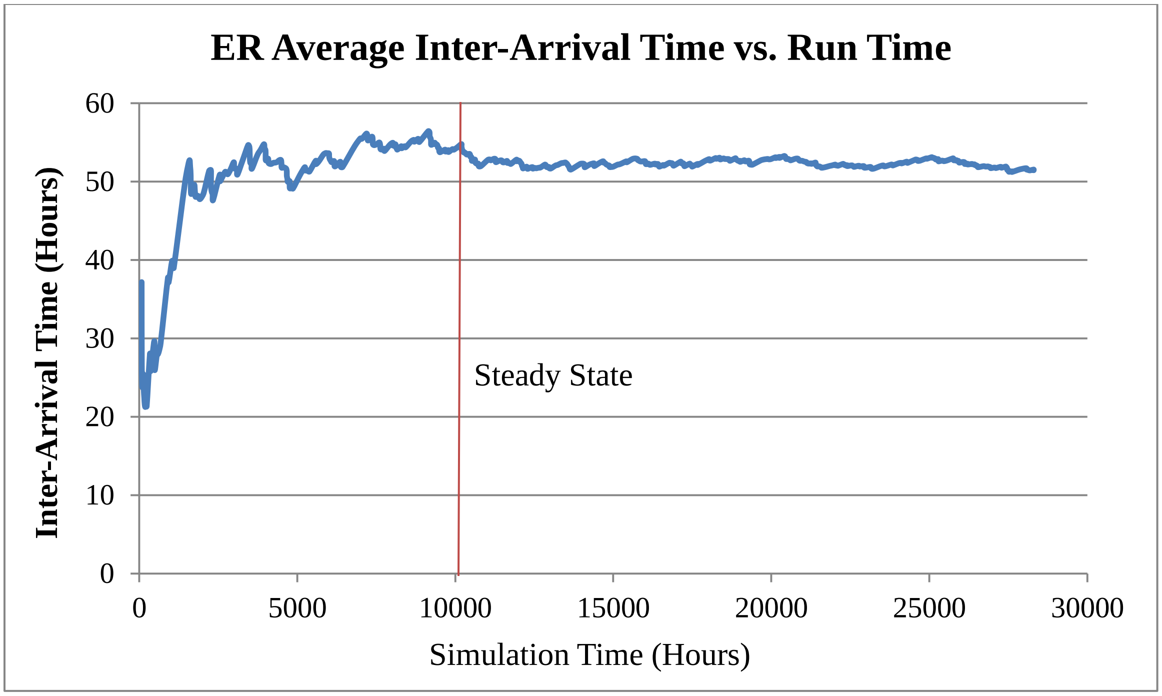


Figure 4.16 Average Simulation Inter-Arrival Time for ER Patients

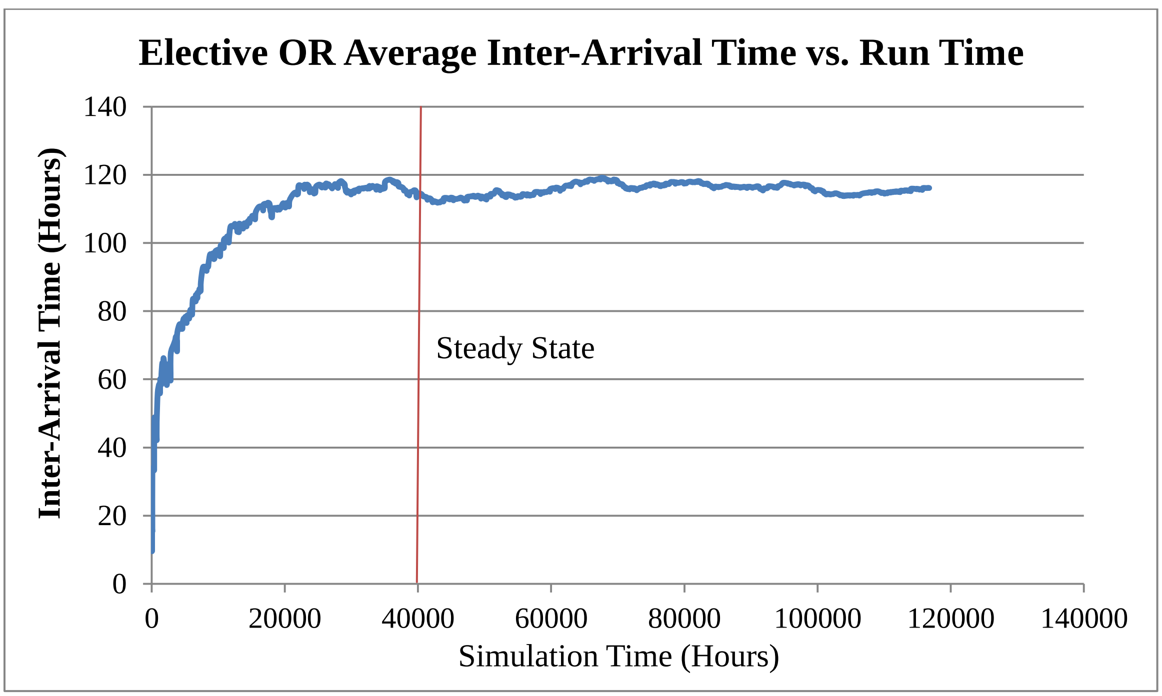


Figure 4.17 Average Simulation Inter-Arrival Time for Elective OR Patients

Comparing average inter-arrival charts for all sources, the ideal overall warm-up period is determined. Table 4.2 shows the recommended warm-up periods for all of the simulation sources. Selecting the highest recommended value ensures that all sources will have sufficient time to warm-up. Thus running the simulation for 70,000 hours before recording the desired performance measures will ensure that the model is warmed up and working as intended.

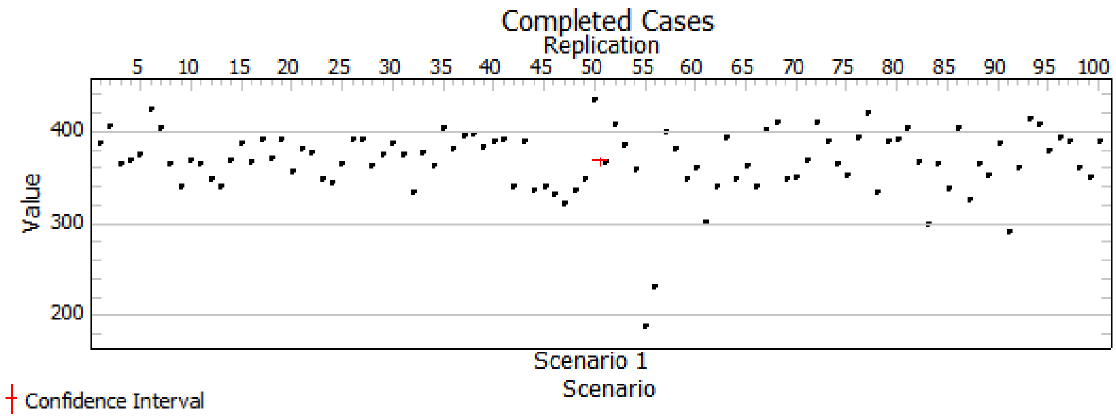
Table 4.2 Recommended Warm-Up Period Summary

	Recommended Warm-Up
ER	10,000
Ward	10,000
Internal	60,000
External	65,000
Elective OR	30,000
Elective OR Demand	5,000
Urgent OR	70,000

Lastly the number of repetitions must be designated. This value must be high enough to supply enough data points to render the simulation results valid. It must also be reasonable enough to not require hours if not days for each simulation run. Running the simulation for a lower number of repetitions and then slowly increasing the number can show when the values become unaffected by additional iterations. For the PICU simulation minimally 50 repetitions should be performed, preferably 100 repetitions.

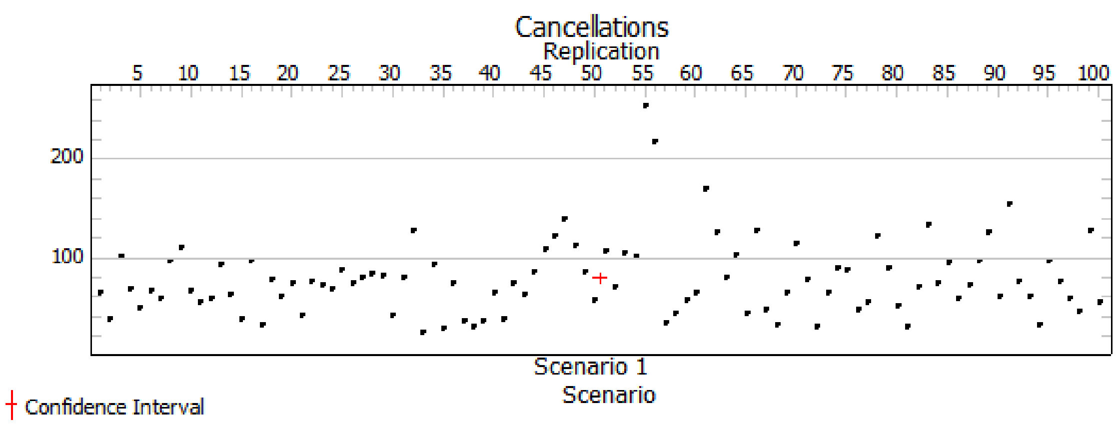
4.4.2.5 Simulation Results

With 100 repetitions and a 70,000 hour warm-up period, the results of the current state simulation were 368 ± 5 completed cases (Figure 4.18) with 80 ± 6 cancellations (Figure 4.19). The total number of patients was 448, equal to the average number of cases per year in the raw data. Other metrics include an average of 46.5 % occupancy over all 10 beds (59.5% over the first 6 beds) and an 83.8% nurse utilization. A closer look at bed occupancy shows that Bed 1 was the highest and was in use 71% of the time and was waiting for staff an additional 17% of the time.



	Mean	St. Dev.	Confidence Interval (90%)	Min	Max
Scenario 1	368	35	363 - 374	191	434

Figure 4.18 Current State Simulation Completed Cases Results



	Mean	St. Dev.	Confidence Interval (90%)	Min	Max
Scenario 1	80	38	74 - 86	27	254

Figure 4.19 Current State Simulation Cancellation Results

4.4.3 Future State Model Creation

4.4.3.1 Model Variable Changes

In order to observe the effects of specific changes made to the PICU simulation model, variables were altered and the results were monitored. The primary purpose of adjusting the input data and constraints of the simulation is to analyze the demand versus capacity relationship under different circumstances. The essential modification made to the system would be to modify the department resources, thus increasing or decreasing the capacity. Another scenario that is desirable to observe is an increase in incoming patients (demand) and how adjusting resources can mitigate this influx. Lastly the strategy behind the department's resource allocation is tested.

a) Number of Staff

The original resources for the PICU department included 10 beds with 6 full time nurses. Having a variable number of nurses required to care for patients (resource weight intensity) resulted in all 10 beds being used on rare occasions. However, with an average 1:1 nurse to patient ratio the number of staff is perceived to be the limiting resource. Thus, increasing the number of staff and observing the effect on cancellations and bed occupancy in the simulation model can indicate the benefits of increasing capacity. As well, it will also provide a sense of when the gains are the highest and at what point they start to taper off.

The values for patient arrival rate and length of stay obtained from the raw data were held constant in the model. Running the simulation for 100 iterations for the time length of a year (8760 hours) with a 70,000 hour warm-up period, the number of staff was progressively increased in increments of one. The following table (Table 4.3) shows a summary of the results:

Table 4.3 Results Summary Table for Increasing Number of Staff

			Cancellations			
# of Staff	Warm-Up Length	# of Reps	Mean	Std Dev	90% Conf Int	Total Cases
6	70000	100	80	38	74-86	448
7	70000	100	56	31	51-61	449
8	70000	100	39	22	35-42	452
9	70000	100	28	21	25-31	451
10	70000	100	23	14	20-25	452
11	70000	100	16	10	14-17	447
12	70000	100	16	11	15-18	448

Starting with the original 6 nursing staff members, the average number of cancellations over the 100 iterations is 80 patients. Increasing the number of staff steadily decreases the number of cancellations until the level of 10 nurses, after which the improvements become smaller and less conclusive. This is shown graphically in Figure 4.20. Additionally, as the number of case cancellations decreases, the number of completed cases naturally increases, as displayed in Figure 4.21.

As the number of staff is increased the PICU bed occupancy and staff utilization also changes. For the first few beds in the unit (Bed 1, 2, 3), the bed occupancy increases as more nurses are added because they incur less time waiting for staff to become available and are thus able to process more patients. The last beds in the unit (Bed 9 and 10) experience a drop in bed occupancy as the number of nursing staff is increased due to the starving effect. The staffed beds before them are more efficient and thus there is not a high enough demand to keep them as busy. All of this is displayed in Figure 4.22. As well, Figure 4.23 shows the rate at which the individual staff utilization decreases as more nurses are added.

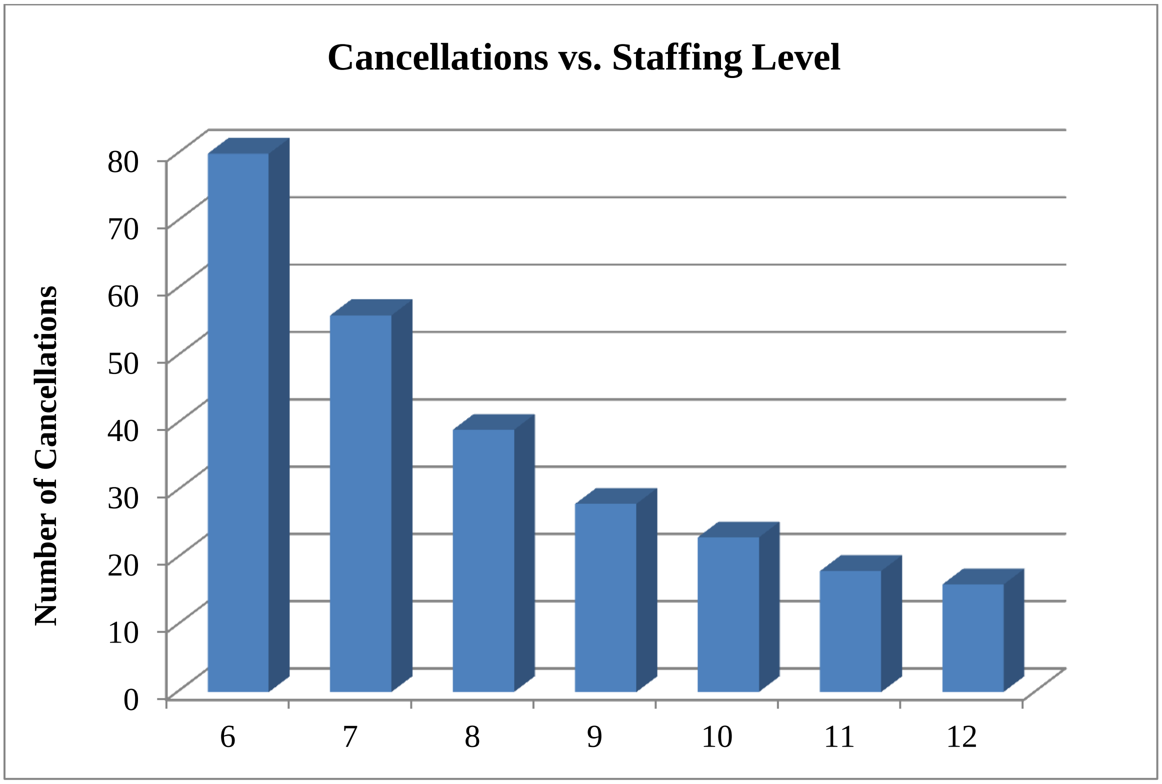


Figure 4.20 PICU Patient Cancellations versus Staffing Level

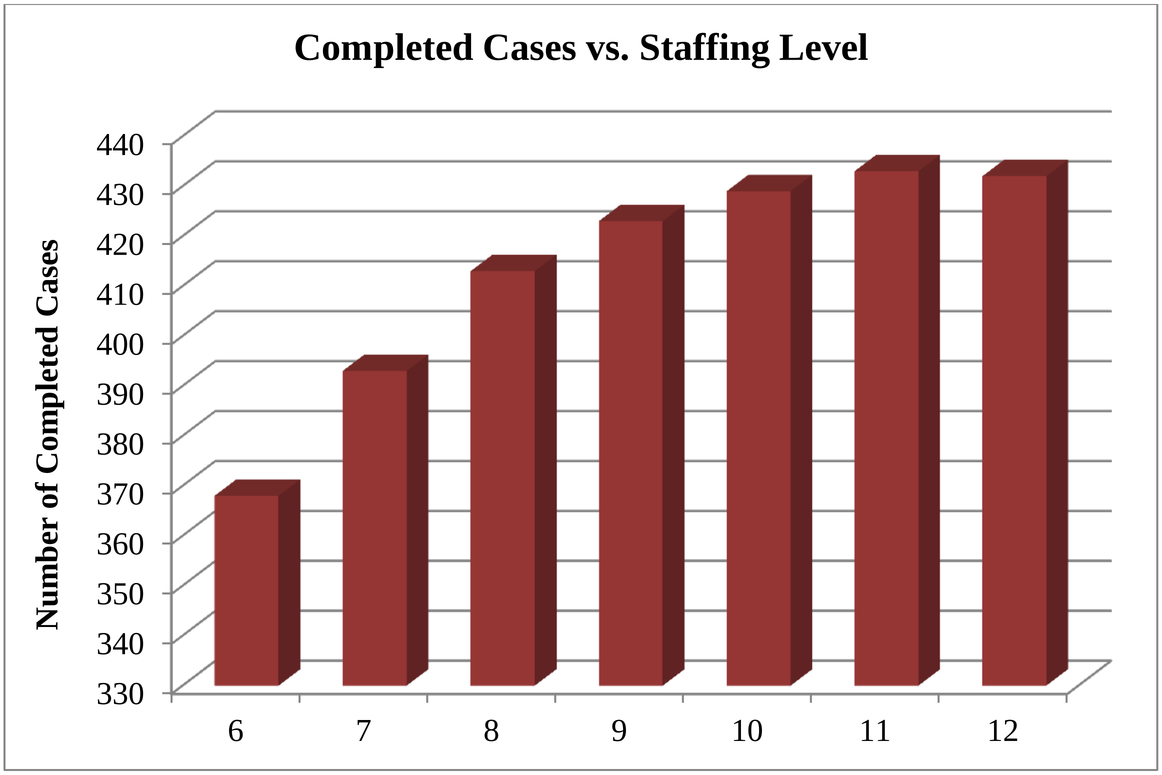


Figure 4.21 PICU Completed Cases versus Staffing Level

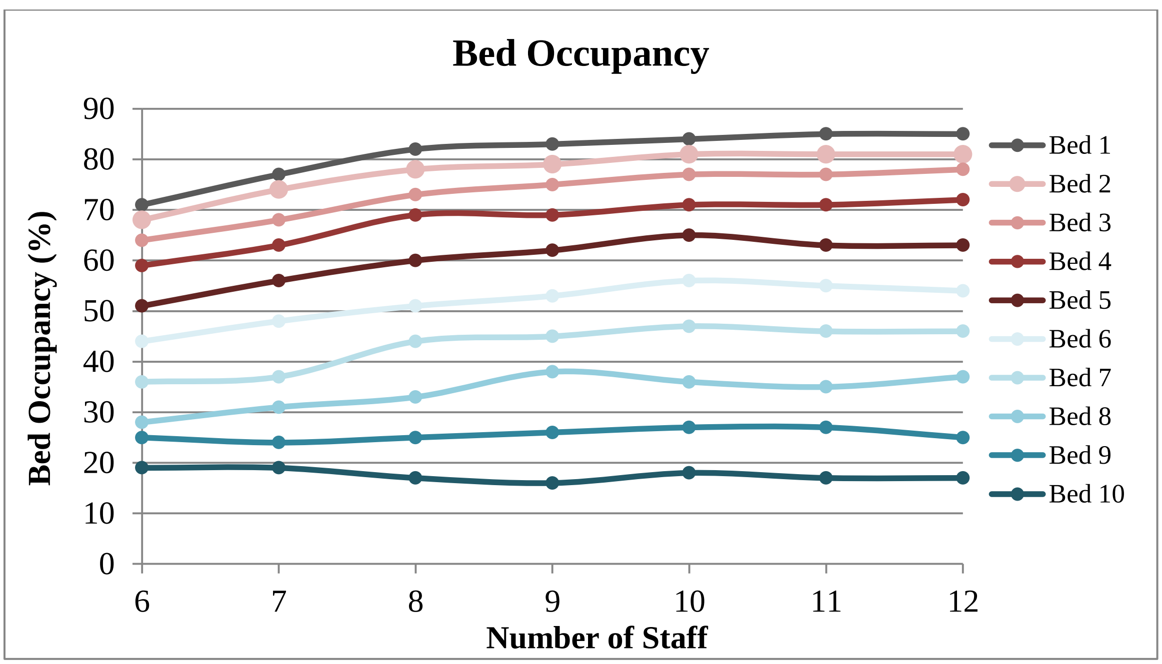


Figure 4.22 PICU Bed Occupancy versus Staffing Level

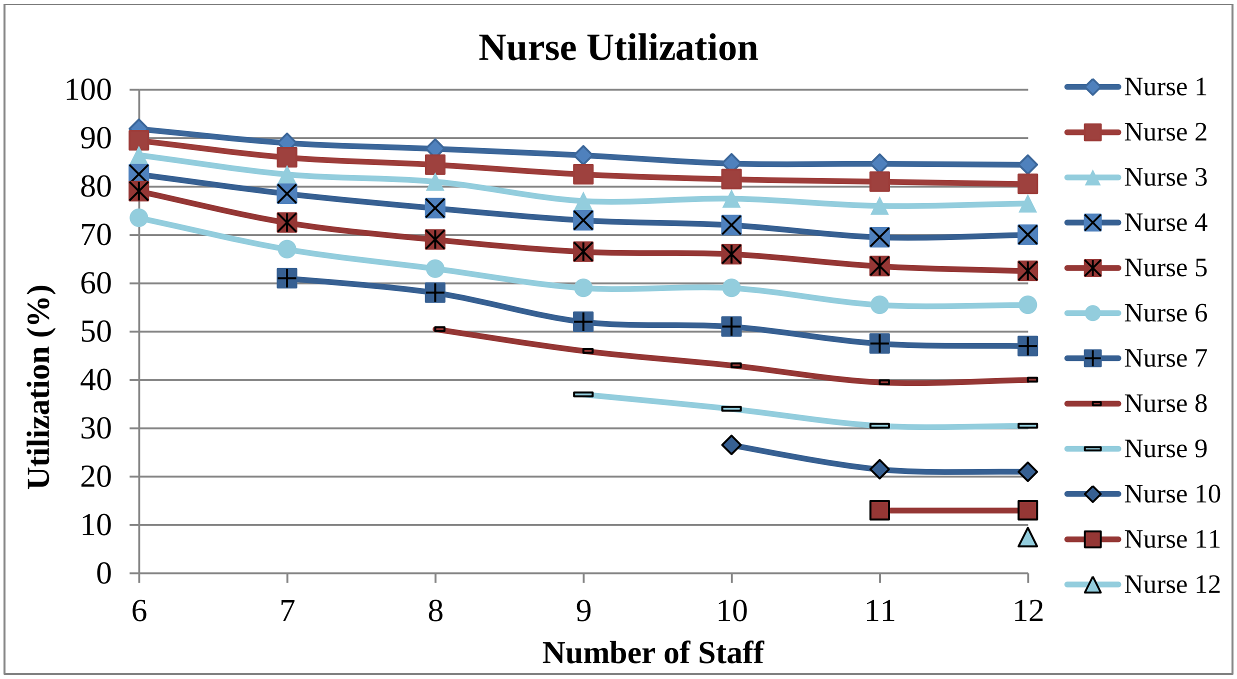


Figure 4.23 PICU Staff Utilization versus Staffing Level

The most significant decreases in cancellations are experienced at the initial increases in staff but occur until the 11 nurse level is reached, as shown by Figure 4.24. Therefore, depending on the cost of each additional staff member added, it can be concluded that with the current 10 bed unit, staffing 11 nurses is the best way to keep the system flowing and reduce cancellations while maintaining a certain level of staff utilization.

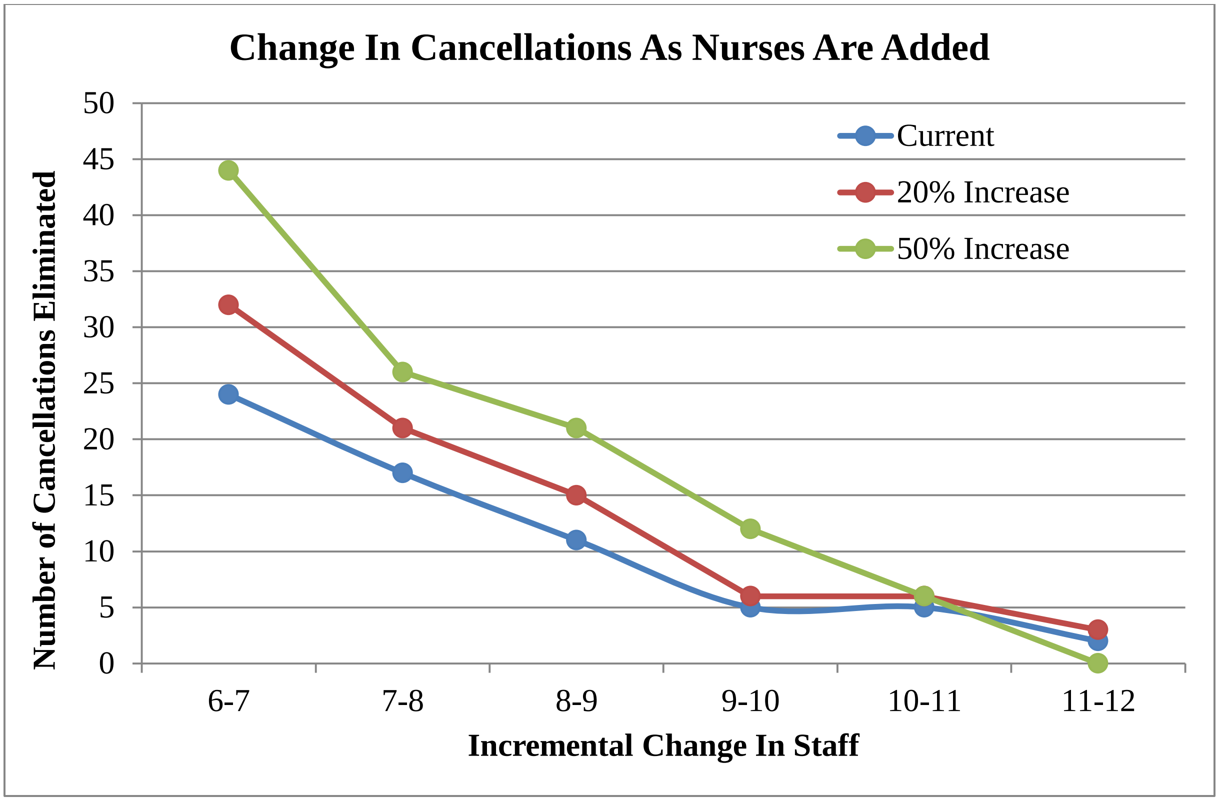


Figure 4.24 Reduction of Cancellations With Incremental Staff Increases Over Varying Increases of ER Patient Arrivals

b) Patient Arrival Rates

In the event of a wide-spread public illness, the rate at which patients arrive to a healthcare system can foreseeably increase drastically. To adequately plan for such a situation, a simulation can be performed to monitor the system under uniquely stressful conditions. This can be accomplished by changing the distribution which dictates the rate at which patients enter the system.

In the PICU simulation, patients originating from the ER would be the ones most affected by any outbreak. Depending on the desired amount of increase, random patient arrival times can be created and inserted into the data to create a new distribution that represents an increased population size. Table 4.4 shows a summary of results acquired from running the simulation while varying the rate of ER patient arrivals.

Table 4.4 Increased ER Patient Arrival Results

			Cancellations				Completed Cases		
# of Staff	Warm-Up Length	# of Reps	Mean	Std Dev	90% Conf Int		Mean	Std Dev	Total Cases
6	70000	100	80	38	74-86		368	35	448
7	70000	100	56	31	51-61		393	31	449
8	70000	100	39	22	35-42		413	24	452
9	70000	100	28	21	25-31		423	24	451
10	70000	100	23	14	20-25		429	18	452
11	70000	100	18	12	16-20		433	20	447
12	70000	100	16	11	15-18		432	21	448
Increased Number of ER Patients									
20% Increase									
6	70000	100	104	42	97-111		379	36	483
7	70000	100	72	32	66-77		412	34	484
8	70000	100	51	26	46-55		434	28	485
9	70000	100	36	21	32-39		451	25	487
10	70000	100	30	18	27-33		453	24	483
11	70000	100	24	15	21-26		454	19	478
12	70000	100	21	12	19-23		462	20	483
50% Increase									
6	70000	100	143	43	136-150		389	41	532
7	70000	100	99	37	93-105		433	36	532
8	70000	100	73	29	68-78		460	28	533
9	70000	100	52	24	48-56		483	24	535
10	70000	100	40	21	36-44		492	22	532
11	70000	100	34	15	31-36		498	21	532
12	70000	100	34	13	32-36		499	21	533

The following figures (Figure 4.25 and Figure 4.26) show the increase in PICU cancellations and completed cases over a range of staffing levels with a 20% and 50% increase in arriving ER patients. The disparity in cancellations is much greater with less staff members although the percentage of overall cases is closer. The difference between total cases completed is more even throughout the range of staffing levels with the greatest disparity occurring with the most nurses employed.

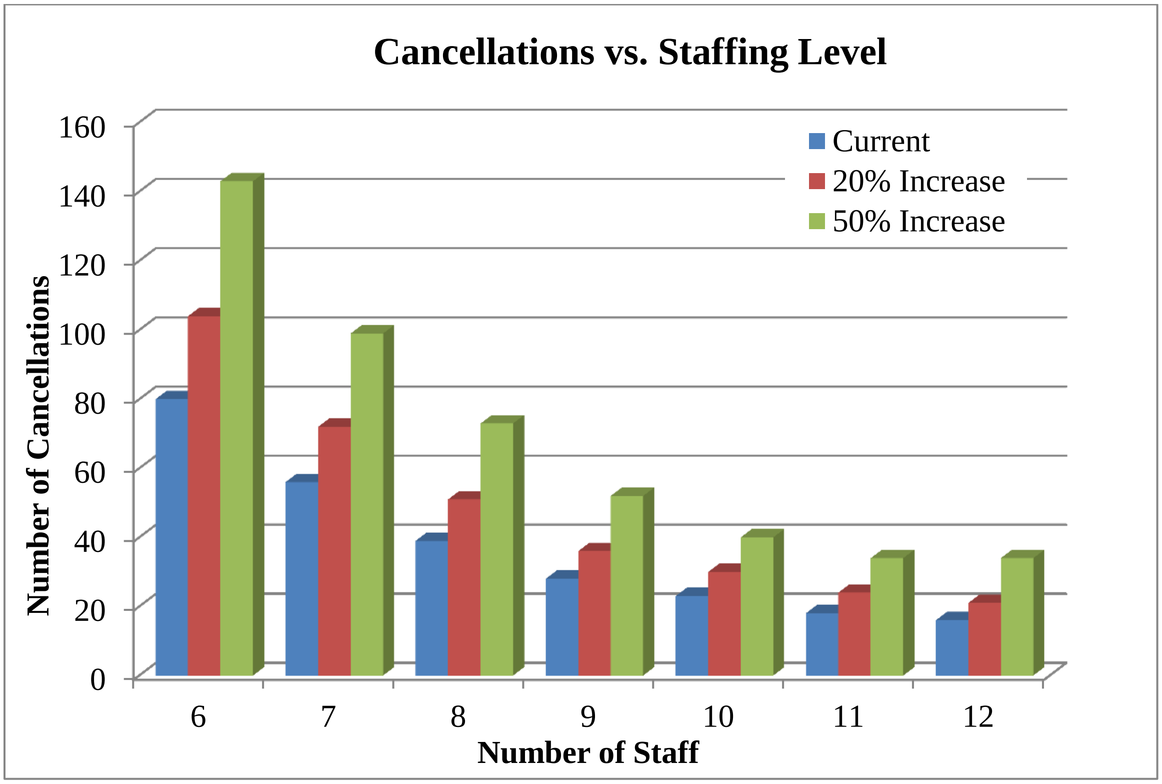


Figure 4.25 Increasing Cancellations Due to Increased ER Patient Arrivals

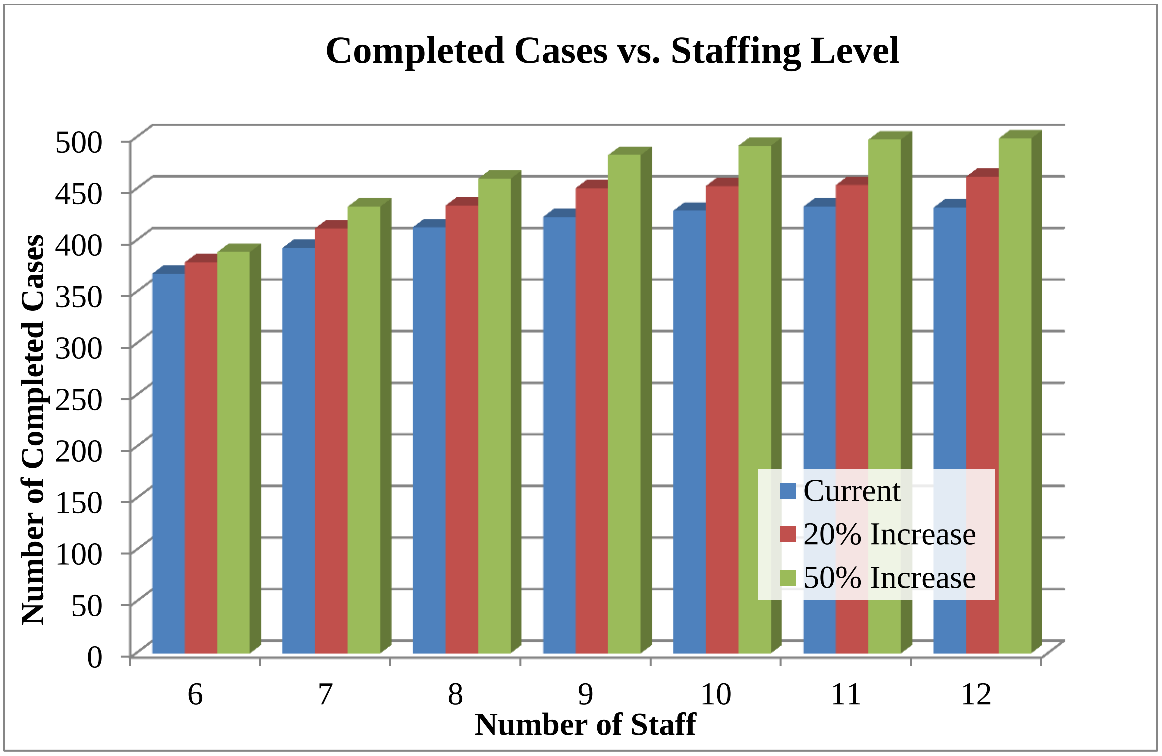


Figure 4.26 Increasing Completed Cases Due to Increased ER Patient Arrivals

The last chart (Figure 4.27) shows the number of cancellations versus staff for the three different rates of arrival. This layout allows a better perspective on the necessary additional resources that would be required to return the system back to its standard operational levels under such duress. For example, if 8 nursing staff is typically employed in the unit, an average of 39 cancellations is experienced over the time range (1 year). Experiencing a 20% increase in ER patients over that time frame, increasing staffing by about one nurse (maybe 0.8 EFT) should return performance back to where it was. With a 50% increase, just over 2 nurses would have to be added to make up for the additional demand.

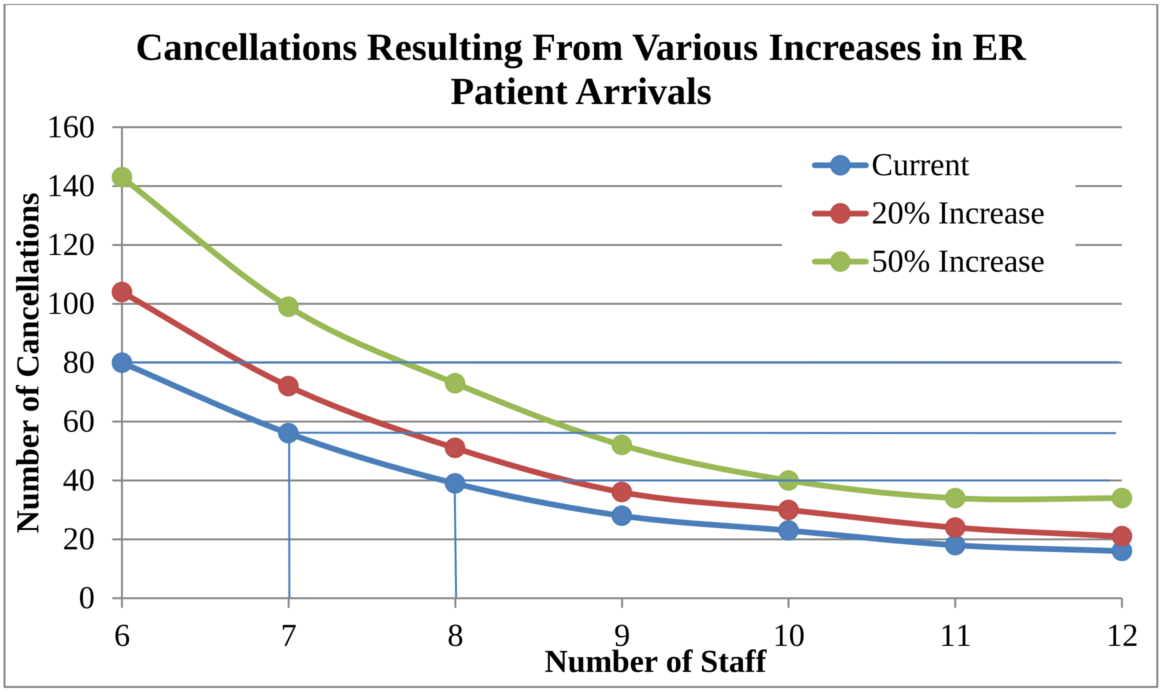


Figure 4.27 Comparing Cancellations Resulting from Increased ER Patient Arrivals

c) Bed Allocation

The current management style of the pediatric intensive care unit does not reserve any beds for any specific patient populations. Elective surgical OR patients are the only group of patients which are regulated by a schedule. This patient population also tends to have a more predictable length of stay in the PICU. These factors make it possible a plausible option to assign one of the PICU beds to strictly handle elective OR cases. Simulation can be used to observe the effect of designating resources to work solely with a group of patients as well as varying the rate of patient arrival to improve efficiency.

To start with, the current state simulation model was used and altered so that one of the PICU beds could only be accessed by patients arriving via the Elective OR source, as shown in Figure 4.28. The newly-formed elective OR patient flow also includes its own delay queue to hold a patient for 4 hours if the bed is already occupied and send the patient to the cancellation sink if the patient is still unable to access the bed after the delay.

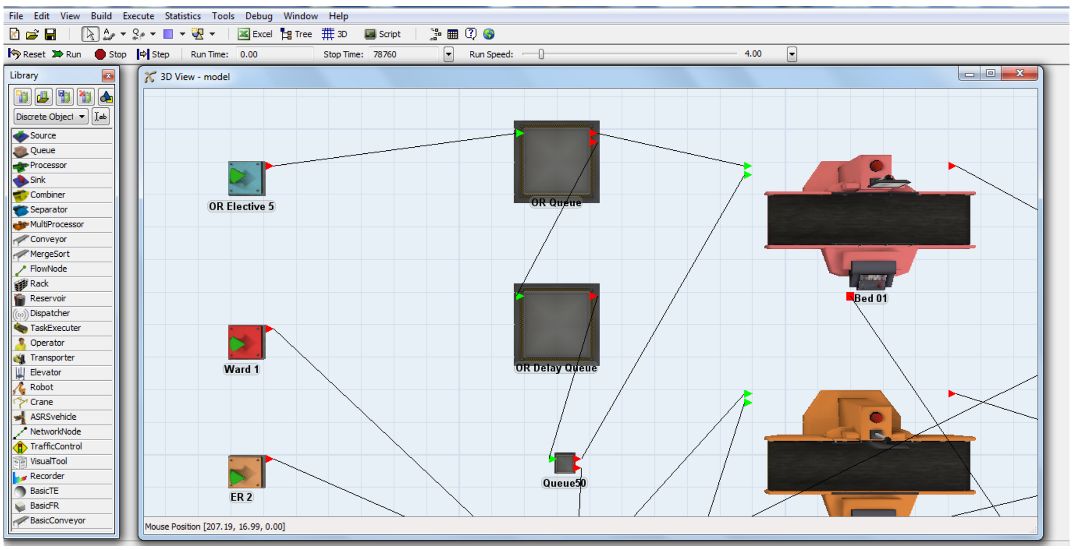


Figure 4.28 Dedicated OR Bed Model

Originally, the OR bed is able to access all of the staff when required to process a patient. This aspect was changed in subsequent simulation runs to observe the effect of dedicating staff to the bed as well. The original model also uses the elective OR patient arrival rate calculated from the raw data. Further trials are performed with increased patient arrivals to determine the effect on bed occupancy and staff utilization.

The first simulation run with 1 of 10 PICU beds dedicated to elective OR patients and 6 PICU nurses was 8760 hours in length with a warm of period of 70,000 hours. The results were 111 total annual cancellations and 340 completed cases. The dedicated OR bed was in use 22% of the time and spent 22% of the time waiting for a nurse to become available. This indicates that while there is not enough staff in this model, there is also probably not enough demand to efficiently utilize the dedicated bed. Increasing the staffing level to 10 nurses resulted in a decrease to 41 total cancellations, shown in Figure 4.29. In addition, the percentage of time spent waiting for a nurse dropped to 1.1% and the bed utilization increased to 27%. This points to the conclusion that while there are now enough staff, the elective OR patient demand is still too low to justify dedicating a bed to this patient population. Playing with the system, 1 of 10 nurses was assigned to work solely on the dedicated elective OR bed. This led to an increase in the number of cancellations by 8 with only a 1% increase in bed utilization. Clearly the designated nurse can be better used caring for all types of patients.

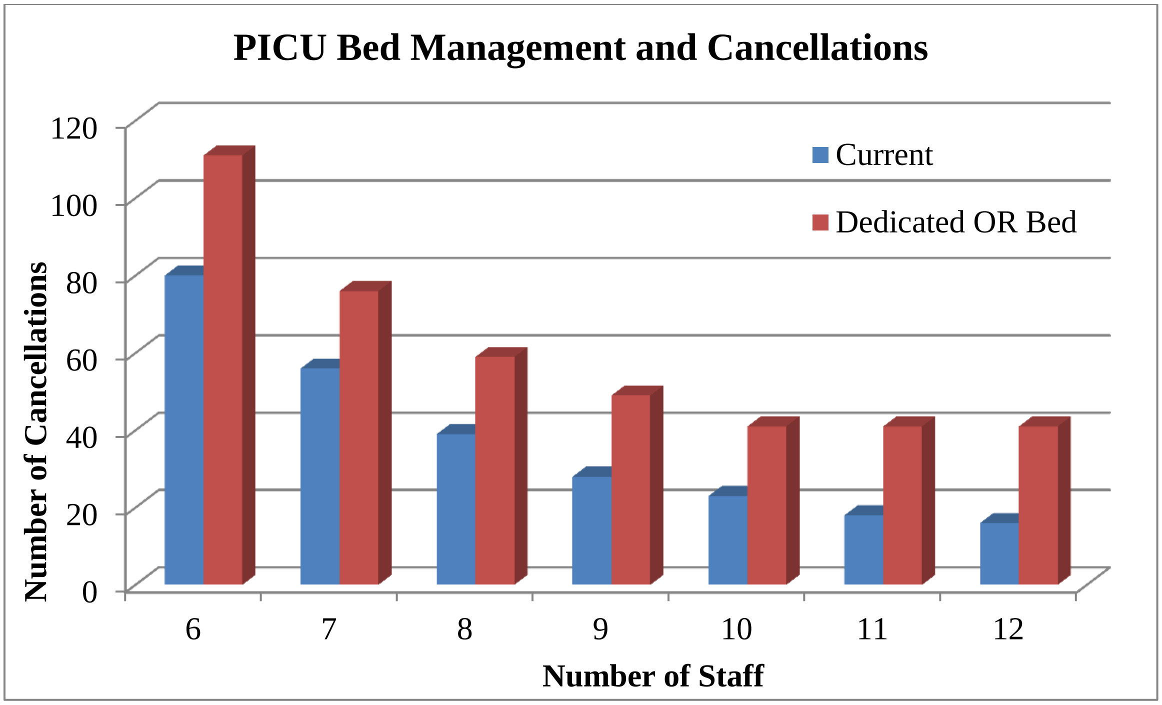


Figure 4.29 Cancellations of Different PICU Bed Management Techniques

Once it was determined that the demand associated with elective OR patients was insufficient to achieve high enough utilization numbers for a dedicated bed, the patient arrival rate was increased to examine the effects of performing more procedures requiring a PICU bed. Increasing the elective OR patient rate of arrival by 20% at a 10 nurse staffing level resulted in a bed utilization of 32% and 48 cancellations. Increasing the arrival rate by 50% increased both measure to 37% bed utilization and 65 cancellations. Increasing the arrival rate by 100% resulted in a 44% bed utilization and 89 cancellations. Accordingly, while having a dedicated PICU for elective surgical cases would allow for an expansion and more cases to be performed, the number of resulting cancellations outweighs the additional number of completed cases. The elective OR patient flow is still too unpredictable to assign it a dedicated bed. Performing a simulation with a more rigid OR schedule and a simplified sample of elective OR patient with more standardized stay times might show a dedicated bed to be advantageous. For example, by simply limiting the arrival of elective OR patients to 1 every 2 days, the total number of completed cases jumps to 477 with only 78 cancellations and a 66.6% bed occupancy. Comparing these results to the last dedicated OR bed simulation, that's an improvement of 40 additional completed cases with 11 fewer cancellations.

4.5 Summary

This chapter provided a summary of the steps taken to create a model and complete a simulation of the PICU at the Children's Hospital in Health Sciences Centre. The simulation is based on data collected directly by the PICU staff in the department and validated using the current state model. Descriptions of the unique features integrated into the simulation model show the steps taken to mirror the model to the real-world system. The results show the effect of varying staff level on indicator metrics such as the number of cancellations and bed occupancy. It also outlines how many additional resources would be needed to compensate for an increase in patient admissions. Lastly, the model evaluates various resource allocation rules and finds the current undesignated system to be best under the existing conditions.

Chapter 5 Pediatric Intensive Care Unit Bed Availability Prediction Tool

5.1 Introduction

The pediatric intensive care unit (PICU) is a critical resource in caring for patients both post-operatively and in emergency cases. It is the randomness associated with the emergency cases that creates uncertainty within the PICU. The awareness of the exact state of the PICU is currently very vague and often it is never known for certain whether a surgical case requiring a post-op monitored bed can be performed until hours after it was scheduled to start.

The purpose of this chapter is to provide a description of the creation of a tool which can be used by surgeons and everyone involved in the PICU admissions decision-making process to allow for a more pre-emptive understanding of the state of the unit. By creating an anticipatory operations management tool, surgeons will have access to more information leading up to a case requiring a monitored bed and hopefully PICU managers will experience less perpetual stress from having to react to ever-changing conditions and relaying the status on to those involved.

The conceptual idea is that the resource will be able to supply the probability that a monitored bed will be available on the day that it has been requested, providing some sort of progression analysis (red/yellow/green light). In an elective surgery situation, this will provide a surgeon with the information on which to base the decision of whether to continue as scheduled or postpone the case and schedule a replacement. Equally, if not more important, if it can be determined at an earlier stage whether a surgery is able to proceed or, if not, allow patients and their families to receive sooner notice that the surgery must be cancelled. No one wants to hear that they have to wait longer for their surgery and ideally no cases would get cancelled, but at least with earlier notice it would eliminate some of the difficulties of patient fasting and then traveling into the hospital on the morning of the surgery and finding out it was all for nothing.

Given a patient mix based on patient origin of arrival and statistics on rate of arrival and length of stay for each patient category, statistical distributions can be calculated for each type of patient. Thus determining the current conditions of the PICU (how many patients, types of patients, and current length of stay), the historical data can be projected into the future to determine the probability of beds being available at a later date.

5.2 Bed Availability Prediction Tool

5.2.1 Theory

In healthcare as in manufacturing, the system is subjected to inherent variability. Some of this variability is due to known causes, such as varying practices, while some of it stems from random, unforeseeable causes. Probability theory has "shown that chance variations follow a definite pattern" (Lawson, 2001). The tossing of a coin is a random trial. A single coin toss performed correctly is unpredictable however after a large number of tosses the results will be approximately 50% heads and 50% tails. Thus both heads and tails will have a probability of occurrence of 50%.

The coin toss example can be converted to an application useful for the PICU. Instead of hypothesizing whether the *result* will be heads or tails, we postulate whether a bed will be available or occupied. The number of beds available would be the *random variable*, a numerically measured outcome. The *sample space* would be 0,1,…,n (n being the number of PICU beds) representing all possible outcomes of how many beds are available at the conclusion of the trial. An *event* is any one of the outcomes of the trial within the sample space. The *probability* of an event is a number between 0 and 1 which represents the certainty with which the event will occur. With respect to the coin toss example, the probability of heads, P(H) equals the probability of tails, P(T) which equals 0.50. The sum of all probabilities within a sample space must be 1 [P(H) + P(T) = 1]. For the purpose of the PICU, the probability of beds being either available or occupied is based on required user input to outline the current department conditions and the length of stay distributions previously obtained from the raw PICU data.

To find the probability of a single event occurring, all possible combinations of outcomes, or bed availability, must be accounted for. Expanding the coin toss example to include a second coin toss requires the probability addition and multiplication rules for independent events. The addition rule states that the probability of A or B occurring is equal to the probability of A plus the probability of B, $P(A \cup B) = P(A) + P(B)$. The multiplication rule states that the probability of A and B occurring is equal to the probability of A times the probability of B, $P(A \cap B) = P(A) \times P(B)$. Therefore, for the event of 0 heads occurring in two coin tosses to happen, the probability would be equal to

P(0) = P(T) x P(T) = 0.5 x 0.5 = 0.25. The event of 1 head occurring in two coin tosses can happen multiple ways, tails first then heads second or heads first then tails second. Therefore, P(1) = P(T) x P(H) + P(H) x P(T) = 0.5 x 0.5 + 0.5 x 0.5 = 0.5. Thus after two coin tosses, the chances of having only one coin result in heads are 50%. The probabilities of events are summarized in Table 5.1 (Lawson, 2001).

Table 5.1 Probabilities of Events for 2 Coin Tosses

<table>
<tr><th colspan="2">1st Coin Toss</th><th colspan="2">2nd Coin Toss</th><th></th><th colspan="2">Joint</th></tr>
<tr><td>Event</td><td>Prob.</td><td>Event</td><td>Prob.</td><td></td><td>Event</td><td>Prob.</td></tr>
<tr><td>T</td><td>0.5</td><td>T</td><td>0.5</td><td></td><td>0 Head</td><td>0.5 x 0.5 = 0.25</td></tr>
<tr><td>T</td><td>0.5</td><td>H</td><td>0.5</td><td rowspan="2">}</td><td rowspan="2">1 Heads</td><td rowspan="2">0.5 x 0.5 + 0.5 x 0.5 = 0.5</td></tr>
<tr><td>H</td><td>0.5</td><td>T</td><td>0.5</td></tr>
<tr><td>H</td><td>0.5</td><td>H</td><td>0.5</td><td></td><td>2 Heads</td><td>0.5 x 0.5 = 0.25</td></tr>
</table>

Translating this to the PICU, the probability of having no beds available is equal to the probability of each bed being occupied at the designated date and time multiplied by each other. The probability of having 1 bed available is equal to the sum of all combinations resulting in one bed being available at the designated date and time. One such combination would be Bed 1 being available while all other beds are occupied. This would be equal to the probability of Bed 1 not being occupied multiplied by the probability of Bed 2 being occupied, and so on. The number of possible combinations is given using Pascal's Triangle, displayed in Figure 5.1. Pascal's Triangle is constructed by rows consisting of values obtained by adding the two values in the row above. Each row indicates the number of combinations for each event. Relating to the coin toss example and Table 5.1, Row 2 (2 events) is 1, 2, 1. This means there is 1 way of achieving 0 Heads, 2 ways of achieving 1 Heads, and 1 way of achieving 2 Heads. For a 10 bed PICU unit, there would be 1 way of having 0 or 10 beds available, 10 combinations resulting in 1 or 9 beds being available, up to 252 combinations for which 5 beds are available.

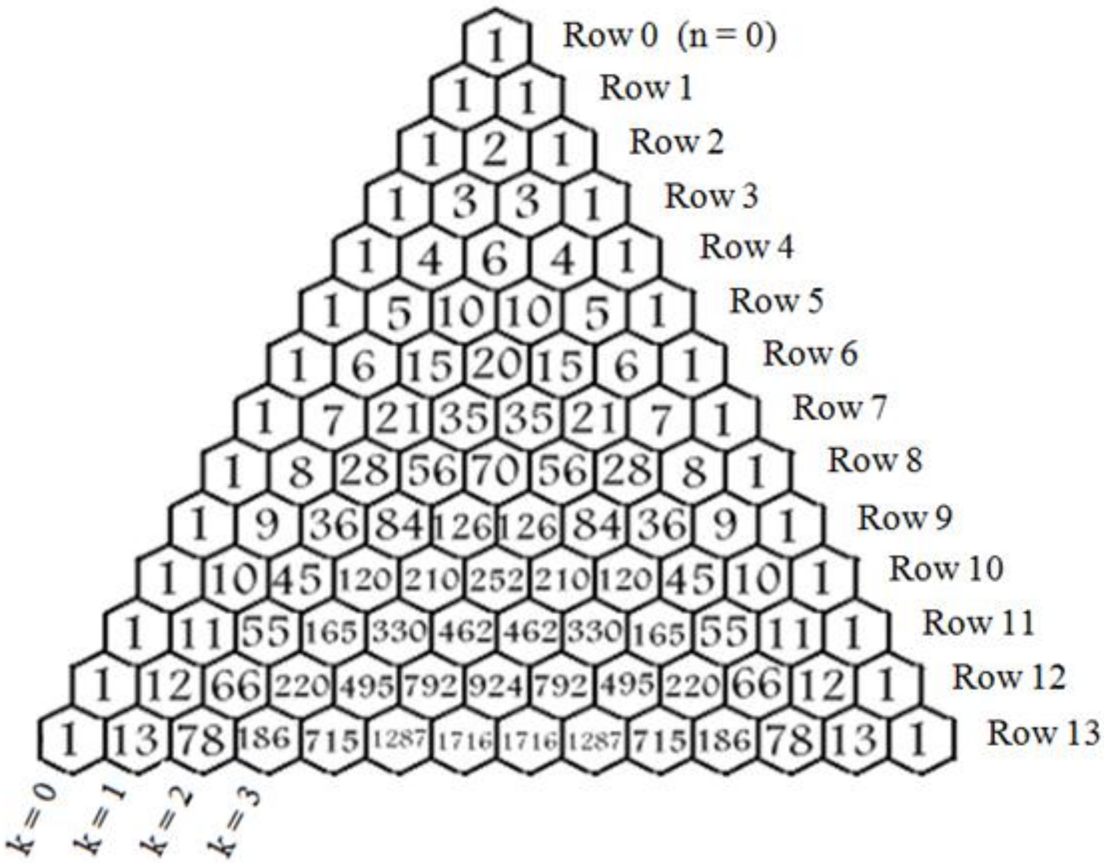


Figure 5.1 Pascal's Triangle

Individual values within Pascal's Triangle can also be calculated using the binomial coefficient (Equation 5.1a) of the probability mass function (Equation 5.1b).

(a) $$\binom{n}{k} = \frac{n!}{k!(n-k)!}$$ (b) $$f(k;n,p) = \Pr(K = k) = \binom{n}{k} p^k (1-p)^{n-k}$$

Equation 5.1 (a) Binomial Coefficient and (b) Probability Mass Function

The binomial coefficient, referred to as "n choose k" (also denoted as ${}_{n}C_{k}$), represents the number of ways of distributing *k* successful trials anywhere among the *n* trials. The probability mass function uses this to determine the probability of achieving exactly k successes and *n*-*k* failures out of a total of *n* trials. Using n choose k, *n* is the number of the row and *k* is the element in that row. So for 3 successful trials (or available beds) out of 10, the number of possible combinations is equal to "10 choose 3" which equals 10! / 3! x (10–3)! = 120. Another mathematical trick with Pascal's Triangle is that the sum of the numbers in all rows is equal to 2 to the nth power (2^n), when n is the number of the row. So the total number of combinations in row 10 would be 2^{10} = 1024.

5.2.2 Data Collection and Analysis

The data used for the prediction tool is the same two years' worth of PICU data used for the simulation in Chapter 4. The necessary information for predicting bed availability is the patient length of stay, broken up into groups based on some criteria, in this case patient origin. As well, an overall patient arrival is required.

The program ExpertFit[15] can be used to fit data distributions for the length of stay to each population of patients. The software can also create a probability mass function, as described in 5.2.1, based on the inputted raw data. Thus, supplied with the length of stay (in hours) that the patient would have reached at the date and time a request has been

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made for a PICU bed, ExpertFit[16] will provide the probability that the patient will have vacated the bed.

The other piece of information required for a prediction tool is the number of new patients that will enter the system between the time of analysis and the requested bed time. ExpertFit[17] can tell the user what the chances are of currently occupied beds being available in the future, however new patients that might occupy those empty beds before the request must be accounted for. For this, the overall average number of patients admitted to the PICU was calculated from the raw data.

5.2.3 Creating a User-Friendly Interface

The purpose of a bed availability prediction tool is to help with resource management on a daily basis. In order for a tool like this to be fully taken advantage of, it must be straight forward and easy to operate. To accomplish this, popular software is used. Users are more likely to be comfortable using this software. Easily identifiable user-input areas are also incorporated to prompt users for required data in a simple manner.

A Microsoft Excel[18] spreadsheet template was created to act as the background and layout for the bed availability prediction tool. The purpose of the spreadsheet is to divide up the sections of the probability prediction process and make it clear what information is

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required from the user and the location it should be entered into. The first step in the process is to determine the current conditions of the PICU. The second step is to indicate at what point in the future the user would like to analyze the potential conditions and how many new patients are expected to enter the PICU in the time between now and then. Next, ExpertFit[19] distributions are applied to the individual patients currently occupying beds to find the probability that they will be discharged by the requested future date. Lastly, statistical formulas are used to calculate the probability of events such as a certain number of beds being available and, accordingly, a range of beds being available (for instance greater than or equal to 3 beds). The results are plotted, taking into account the additional patients entering the PICU, and a final probability and stoplight indicate the chances of at least one PICU bed being available on the date of the request.

The Excel[20] template starts by developing a clear picture of the current state of the PICU. It does so by requiring the user to input the patient arrival details (date and time), as seen in Table 5.2 As well patient classification criterion is required, in this case the department of origin to match the PICU data and the simulation. The options for department of origin that the user has to select from are limited by a drop-down list, as shown in Figure 5.2.

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Table 5.2 PICU Patient Arrival Input Data

	Patient Arrival			
Bed	Date	Time		Dept. of Origin
1	02/03/2011	14:30	02/03/2011 14:30	ER
2	06/03/2011	20:45	06/03/2011 20:45	External Dept
3	09/03/2011	5:50	09/03/2011 5:50	OR-Urgent
4	13/03/2011	20:05	13/03/2011 20:05	OR-Elective
5	13/03/2011	21:15	13/03/2011 21:15	Ward
6	15/03/2011	8:45	15/03/2011 8:45	OR-Elective
7	16/03/2011	14:50	16/03/2011 14:50	OR-Urgent
8	18/03/2011	6:15	18/03/2011 6:15	ER
9	19/03/2011	20:35	19/03/2011 20:35	ER
10				

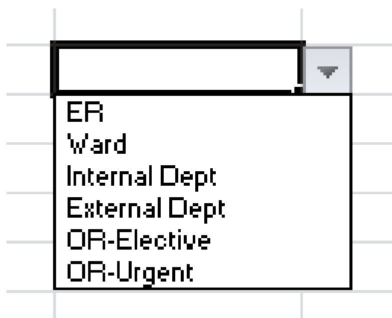

Figure 5.2 Selection of Department of Origin via Drop-down List

In order to hypothesize about the future state of a department, a specific forthcoming time is necessary. For scheduled cases, this is a straightforward piece of information, while for other events it might have to be estimated. The template prompts the user for the date and time of the requested bed, shown in Table 5.3. Accordingly, the time between “now” and the request is calculated. The overall average patient arrival rate is listed as well as the overall average patient demands per day which incorporates the cancelled cases within the data range. Using the average arrival rates and rounding the calculated value, the number of expected patients that are expected to enter the PICU prior to the request is indicated.

Table 5.3 PICU Bed Request Input Data and Anticipated Patient Arrivals

Requested Bed			
Date	Time		
25/03/2011	10:45	25/03/2011 10:45	
Time Before Request		2.8376020	
Patients / Day		1.229395604	
Demand / Day		1.402472527	
# of Expected Admitted Patients Prior To Request			4

The next part of the process requires statistical software, ExpertFit[21] in this case, to determine what the conditions of the department will be based on the current patient population. The current length of stay and what the length of stay will be at the time of the request are calculated. For each bed, the length of stay at the request is imported into the ExpertFit[22] software which, based on the patient's department of origin, returns a value specifying the probability that the patient will be discharged before the request date. This value represents the two years' worth of raw PICU data that was used in the simulation. For further probability calculations, the reverse (1-P(x)), the probability that the patient will not have been discharged) is calculated. All of this is displayed in Table 5.4.

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Table 5.4 ExpertFit Statistical Probability Data Input

Current LOS (Hours)	LOS at Request	P(x)=Probability Bed Will Be Available	1-P(x)
525.70	548.25	0.9507	0.0493
423.45	446.00	0.77573	0.2242
366.37	388.92	0.89104	0.1089
256.12	278.67	0.0484	0.9516
254.95	277.50	0.6903	0.3097
219.45	242.00	0.23	0.77
189.37	211.92	0.17446	0.8255
149.95	172.50	0.0832468	0.9167
111.62	134.17	0.02055	0.9794
0.00	0.00	1	0

Use the theory outlined by Pascal's Triangle and the probability of events described by the coin toss example, determining the probability of a single event requires finding all possible ways that event could happen. Using the graphical method shown in Figure 5.3, the events were translated to formulas relating the individual patient population probabilities and the probability of bed availability. These formulas were then entered into the Excel[23] spreadsheet and linked to the corresponding cells. Figure 5.4 shows the formula entered to find the probability of there being exactly nine beds available at the designated request date.

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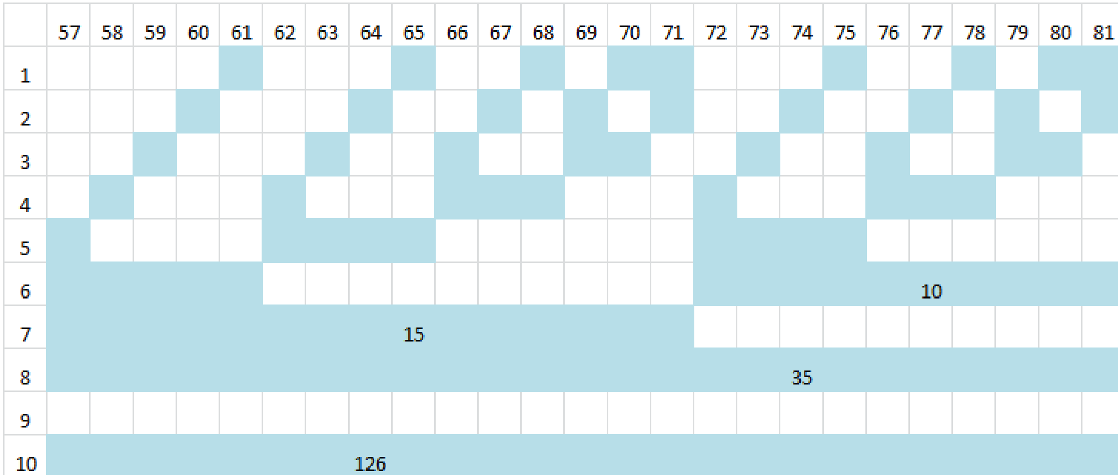
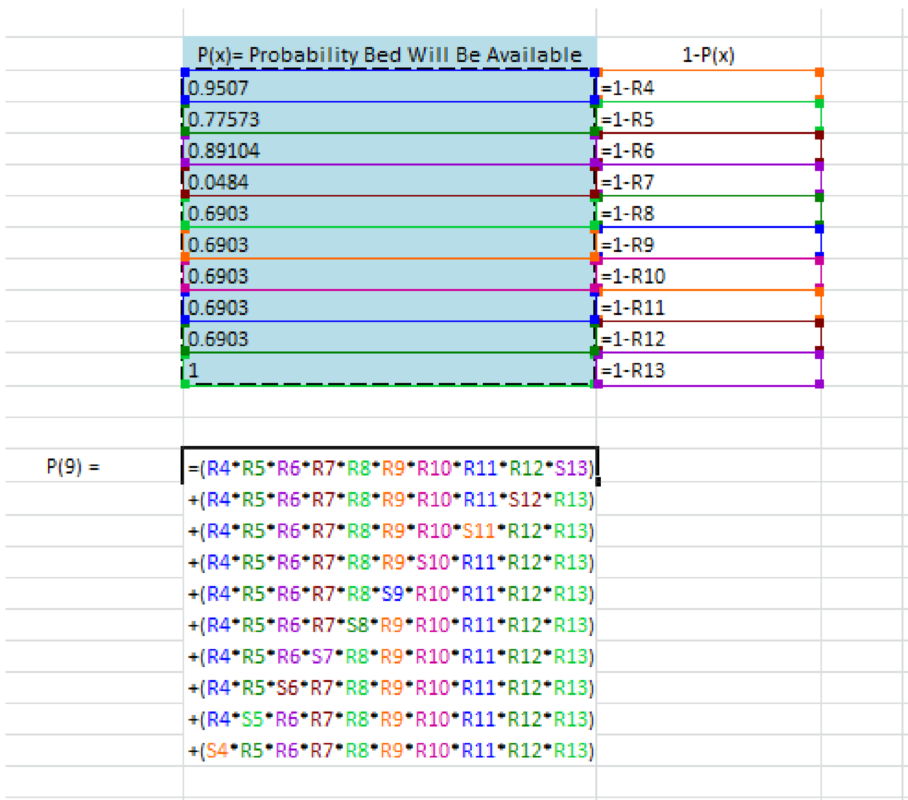


Figure 5.3 Graphical Representation of Pascal's Triangle Equations



	P(x)= Probability Bed Will Be Available	1-P(x)
	0.9507	=1-R4
	0.77573	=1-R5
	0.89104	=1-R6
	0.0484	=1-R7
	0.6903	=1-R8
	0.6903	=1-R9
	0.6903	=1-R10
	0.6903	=1-R11
	0.6903	=1-R12
	1	=1-R13
P(9) =	=(R4*R5*R6*R7*R8*R9*R10*R11*R12*S13)	
	+(R4*R5*R6*R7*R8*R9*R10*R11*S12*R13)	
	+(R4*R5*R6*R7*R8*R9*R10*S11*R12*R13)	
	+(R4*R5*R6*R7*R8*R9*S10*R11*R12*R13)	
	+(R4*R5*R6*R7*R8*S9*R10*R11*R12*R13)	
	+(R4*R5*R6*R7*S8*R9*R10*R11*R12*R13)	
	+(R4*R5*R6*S7*R8*R9*R10*R11*R12*R13)	
	+(R4*R5*S6*R7*R8*R9*R10*R11*R12*R13)	
	+(R4*S5*R6*R7*R8*R9*R10*R11*R12*R13)	
	+(S4*R5*R6*R7*R8*R9*R10*R11*R12*R13)	

Figure 5.4 Calculating Event Probability

This formula consists of 10 parts, as signalled by Pascal's Triangle and the binomial coefficient with k = 1 and n = 10. For the larger formulas, with upwards of 252 parts, a word processor was used to write the text and the formula was split up into two cells to adhere to Excel[24] constraints.

5.2.4 Results

The results of the Microsoft Excel[25] template are a summary of probabilities relating to bed availability and a progression indicator which advises the user whether progressing with the case requesting a PICU bed is sensible.

As a result of the formulas entered into Excel[26], two tables are created which are populated with probabilities for bed availability. The first chart, Table 5.5, lists the probabilities of there being an exact number of PICU beds available based solely on the current patients within the department.

Table 5.5 Example Results for Probability of Bed Availability

P(10) =	0.004985239
P(9) =	0.111508006
P(8) =	0.279655087
P(7) =	0.314493193
P(6) =	0.196234449
P(5) =	0.073290579
P(4) =	0.01646625
P(3) =	0.002120123
P(2) =	0.00013756
P(1) =	3.26622E-06
P(0) =	0

Table 5.6 shows an example of the second chart which is created. This chart uses a summation of the values in the first chart to determine the probability of there being a greater or equal number of beds available. For example, the probability of there being at least 6 beds available (P(>=6)) at the requested date is equal to the probability of there being 6, 7, 8, 9, or 10 beds available (P(6)+P(7)+P(8)+P(9)+P(10)). The latter columns of this chart also take into account the expected number of new patients which will enter the PICU by subtracting the value from the number of beds. In other words, this chart takes the expected future capacity based on current conditions and subtracts the capacity which will be occupied by the anticipated demand which will occur up to that point.

Table 5.6 Example Results for Probability of Multiple Bed Availability

P(10) =	0.004985239	10	6
P(>=9) =	0.116493245	9	5
P(>=8) =	0.396148332	8	4
P(>=7) =	0.710641525	7	3
P(>=6) =	0.906875973	6	2
P(>=5) =	0.980166552	5	1
P(>=4) =	0.996632803	4	0
P(>=3) =	0.998752925	3	-1
P(>=2) =	0.998890486	2	-2
P(>=1) =	0.998893752	1	-3
P(>=0) =	0.998893752	0	-4

The resulting values in the second chart are then displayed on a graph (Figure 5.5) plotting probability versus the number of available PICU beds. Two lines are plotted, one is the probability based only on the current patient volume and the other is based on the projected patient volume, incorporating the expected new patients.

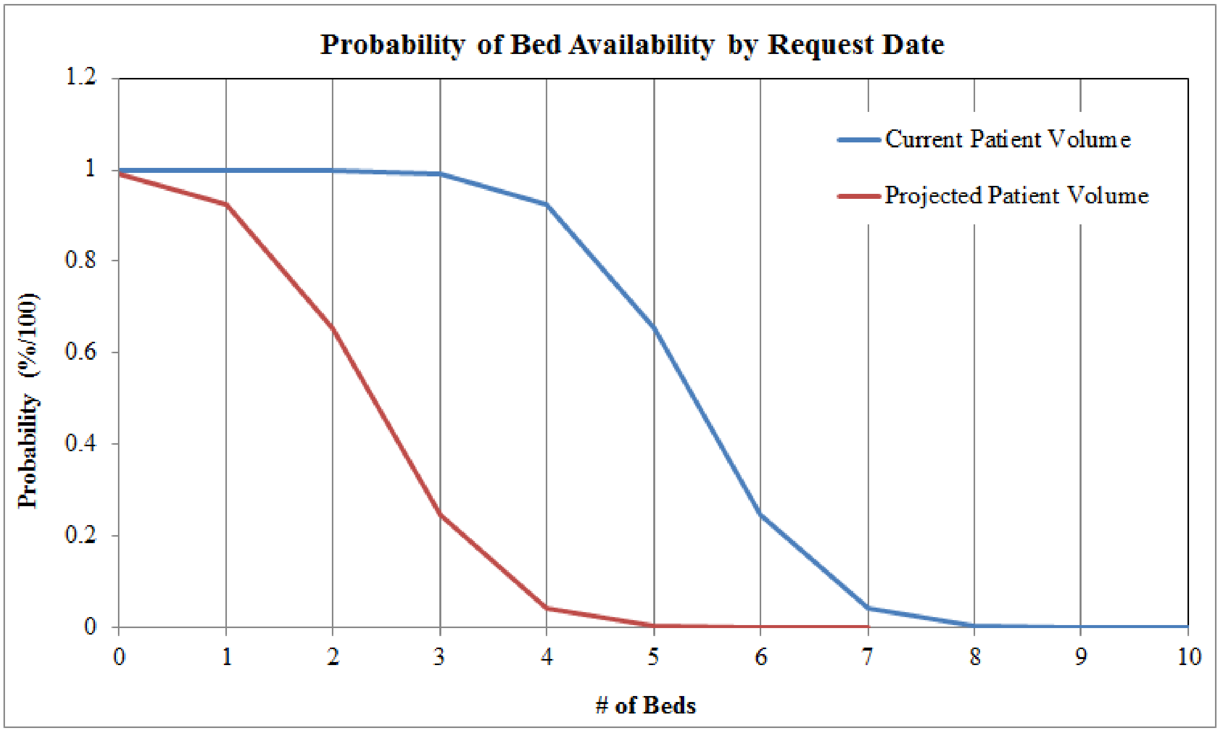


Figure 5.5 PICU Bed Availability Chart

The further in advance that an analysis is performed, the greater the distance will be between the lines due to a greater number of new patients not currently admitted. This will also decrease the accuracy of the probability calculations due to the fact the new patients will have a higher chance of being discharged.

In accordance with the overall expectations of the bed availability prediction tool, the final step is to indicate to the user whether it is advisable for the case on the request date to proceed or not. This is done so using pre-defined probability ranges. In the example shown in Table 5.7, cases are advised to proceed ("given the green light") if there is an 80 percent chance or higher that the PICU will have a bed available. Cases or warned that it is quite possible that a bed will not be available within the yellow range of 60 to 80 percent and are advised not to go ahead with a case if the probability is less than 60 percent.

Table 5.7 Decision to Proceed Stoplight

Ranges		Decision To Proceed With Case on Requested Date?		
< 60		Probability	98.02%	
60 – 80		Stoplight		
> 80				

5.3 Summary

A prediction tool such as the one created and described in this chapter could help ease the decision-making process of PICU managers by providing an earlier sense of what future conditions will be like. A simple spreadsheet with basic data entry cells could be used by anybody requiring only a small amount of additional help to fill in the ExpertFit[27] distribution data. The accuracy of the prediction results could be improved by expanding the amount of raw input data and adding more layers of patient classifications.

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Chapter 6 Conclusion

The original purpose of this thesis was to apply lean thinking to a healthcare setting and focus on improving the patient flow within the pediatric elective surgical system. As a direct result of this task, a more specific objective was acquired: to assess the problem of surgical cases being cancelled due to a lack of available staffed beds in the pediatric intensive care unit and determine how simulation could help.

6.1 Research Results

6.1.1 Incorporating Lean

The effect that lean concepts had on the patient flow at the Winnipeg Children's Hospital is described in Chapter 3. Central to uncovering the areas of improvement and non-value activities was the staff feedback involved in the individual department lean introductory meetings. Numerous examples of influential outcomes reinforce the usefulness of these types of projects. Outlined within the thesis are the improvement projects stemming from the staff interaction and some of the more influential implementations. These applications include:

- creating electronic booking forms,
- restructuring the internal OR communication guidelines,
- improving external OR communication for the transportation of ER and ward patients,
- standardizing the procedure used for the operating room clean-up, and
- increasing the first-case start time accuracy.

6.1.2 PICU Simulation

The results of the simulation provide a means of balancing the capacity and demand under varying conditions while taking into account the inherent variation. The simulation model does not necessarily produce a single solution, but a range of options to select from based on priority (reducing cancellations, economic, productivity, etc.). The simulation model provides a macro perspective of the PICU, observing the statistical performance of the overall department over a significant period of time.

Chapter 4 provides a summary of the steps taken to create the current state model to accurately portray the PICU in the Children's Hospital at Health Sciences Centre and to complete a simulation of the real-life system. Data collection, data analysis, model feature validation and verification were all important steps included in the simulation process. Accurately identifying and incorporating the major features of the PICU is the only way to ensure that the simulation model will act as close to the actual department as possible.

Altering the model parameters leads to the creation of future state models and situational analyses. The results show the influence that varying the number of PICU staff has on indicator metrics such as the number of cancellations and bed occupancy. The model is also used to account for an increase in patient admissions, such as in the case of an outbreak, and outlines how many additional resources would be needed to compensate. The last circumstances that the model was used to evaluate were various resource allocations. It was determined that the current undesignated system was the best option under the existing conditions.

6.1.3 Bed Availability Prediction

The statistical prediction tool was created to fill in the gap left by simulation by providing a micro perspective of the PICU department. From a day-to-day operational standpoint, managers rely on exact resource utilization and capacity and could benefit from the use of the prediction tool to foresee what the unit conditions will be in the upcoming days. This would allow them to be able to make a more informed judgement on the progression of certain cases, resulting in saving patients a lot of inconvenience while improving the utilization of the OR. The bed availability predication tool was designed with the intent of making it easy to use with a few simplified, outlined places for user input and an understandable result indicator.

6.2 Future Research

The largest opportunity for future research based on the work performed in this thesis is the addition of further details to more accurately represent patient populations. For both the simulation and bed availability probability statistics, having a larger and more acutely defined sample size would improve the quality of the results. Hospitals are such complex systems and patients are unique individuals making it difficult to generalize using patient populations. While this study used a single variable patient identifier (Department of Origin), other literature discusses defining patients even further and even giving them a score based on different criteria. In order for this to be possible, a substantial database would be needed to include enough patients in each individual sample size.

In addition to the data collection and analysis, adding smaller details to the simulation model would refine the results. While including small details to the model would not necessarily lead to any significant changes in the results. The nature of creating a simulation is that it will never completely mimic its real-world counterpart, which is constantly being reshaped itself. Further work could also be aimed at monitoring new simulation software and its application to healthcare. As computers and software advance, so do the capabilities of a simulation software. Lastly, expanding the scope of the study and including simulation models of connecting departments would lead to more accurate department interaction variables and the opportunity to test alterations on a larger scale.

References

Baldwin, L.P., Eldabi, T.A. & Paul, R.J. 1999, "Simulation modeling as an aid to decision-making in healthcare management: the Adjuvant Breast Cancer (ABC) trial", *Proceedings of 1999 Winter Conference on Simulation* IEEE, Piscataway, NJ, USA, 5-8 Dec. 1999, pp. 1523.

Ballard, S.M. & Kuhl, M.E. 2006, "The use of simulation to determine maximum capacity in the surgical suite operating room", *Proceedings of the 2006 Winter Simulation Conference* IEEE, Monterey, CA, USA, 3-6 Dec. 2006, pp. 433.

Bosire, J., Wang, S., Gandhi, T. & Srihari, K. 2007, "Comparing simulation alternatives based on quality expectations", *2007 Winter Simulation Conference, WSC* Institute of Electrical and Electronics Engineers Inc., New York, NY 10016-5997, United States, Washington, DC, United States, Dec 9-12 2007, pp. 1579.

Brailsford, S.C. 2007, "Tutorial: advances and challenges in healthcare simulation modeling", *2007 Winter Simulation Conference*IEEE, Washington, DC, USA, 9-12 Dec. 2007, pp. 1436.

Brailsford, S.C., Rauner, M.S., Gutjahr, W.J. & Zeppelzauer, W. 2007, “A combined discrete-event simulation and ant colony optimisation approach for selecting optimal screening policies for diabetic retinopathy”, *Computational Management Science,* vol. 4, no. 1, pp. 59-83.

Brailsford, S.C., Sykes, J. & Harper, P.R. 2006, "Incorporating human behavior in healthcare simulation models", *2006 Winter Simulation Conference, WSC* Institute of Electrical and Electronics Engineers Inc., New York, NY 10016-5997, United States, Monterey, CA, United States, Dec 3-6 2006, pp. 466.

Cahill, W. & Render, M. 1999, "Dynamic simulation modeling of ICU bed availability", *1999 Winter Simulation Conference Proceedings (WSC), December 5, 1999 - December 8* IEEE, Phoenix, AZ, USA, 1999, pp. 1573.

Coletti, G., Paulon, L., Scozzafava, R. & Vantaggi, B. 2007, "Measuring the quality of health-care services: A likelihood-based fuzzy modeling approach", *9th European Conference on Symbolic and Qualitative Approaches to Reasoning with Uncertainty, ECSQARU 2007*Springer Verlag, Heidelberg, D-69121, Germany, Hammamet, Tunisia, Oct 31-Nov 2 2007, pp. 853.

Connelly, C. 2005, “Hospital takes page from Toyota”. *The Washington Post*. www.washingtonpost.com/wp-dyn/content/article/2005/06/02/AR2005060201944.html.

Corrigan, A. 1978, “Harlem Hospital Bed-Reallocation Plan”. *Health and Hospitals Corporation of the City of New York, New York*.

Davies, R., Brailsford, S., Roderick, P., Canning, C. & Crabbe, D. 2000, "Using simulation modelling for evaluating screening services for diabetic retinopathy", *Journal of the Operational Research Society,* vol. 51, no. 4, pp. 476-484.

Davies, R. & Davies, H. 1994, “Modelling patient flows and resource provision in health systems”, *Omega, vol.* 22, pp. 123-131.

DeBusk, C. & Rangel Jr., A. 2005, “Creating a Lean Six Sigma Hospital Process”, healthcare.isixsigma.com.

Denton, B.T., Rahman, A.S., Nelson, H. & Bailey, A.C. 2006, "Simulation of a multiple operating room surgical suite", *2006 Winter Simulation Conference, WSC*Institute of Electrical and Electronics Engineers Inc., New York, NY 10016-5997, United States, Monterey, CA, United States, Dec 3-6 2006, pp. 414.

Dumas, M.B. 1985, "Hospital bed utilization: an implemented simulation approach to adjusting and maintaining appropriate levels", *Health services research,* vol. 20, no. 1, pp. 43-61.

Dumas, M.B. 1984, "Simulation modeling for hospital bed planning", *Simulation,* vol. 43, no. 2, pp. 69-78.

Eldabi, T., Paul, R.J. & Young, T. 2007, "Simulation modelling in healthcare: Reviewing legacies and investigating futures", *Journal of the Operational Research Society,* vol. 58, no. 2, pp. 262-270.

Eldabi, T. & Young, T. 2007, "Towards a framework for healthcare simulation", *2007 Winter Simulation Conference, WSC*Institute of Electrical and Electronics Engineers Inc., New York, NY 10016-5997, United States, Washington, DC, United States, Dec 9-12 2007, pp. 1454.

Ferrin, D.M., Miller, M.J. & McBroom, D.L. 2007, "Maximizing hospital finanacial impact and emergency department throughput with simulation", *2007 Winter Simulation Conference, WSC*Institute of Electrical and Electronics Engineers Inc., New York, NY 10016-5997, United States, Washington, DC, United States, Dec 9-12 2007, pp. 1566.

Fone, D., Hollinghurst, S., Temple, M., Round, A., Lester, N., Weightman, A., Roberts, K., Coyle, E., Bevan, G. & Palmer, S. 2003, "Systematic review of the use and value of computer simulation modelling in population health and health care delivery", *Journal of public health medicine,* vol. 25, no. 4, pp. 325-335.

Goldman, J., Knappenberger, H.A. & Eller, J.C. 1968, "Evaluating bed allocation policy with computer simulation", *Health services research,* vol. 3, no. 2, pp. 119-129.

Gorunescu, F., McClean, S.I. & Millard, P.H. 2002, "A queueing model for bed-occupancy management and planning of hospitals", *Journal of the Operational Research Society,* vol. 53, no. 1, pp. 19-24.

Griffiths, J.D., Price-Lloyd, N., Smithies, M. & Williams, J.E. 2005, "Modelling the requirement for supplementary nurses in an intensive care unit", *Journal of the Operational Research Society,* vol. 56, no. 2, pp. 126-33.

Hancock, W.M., Martin, J.B. & Storer, R.H. 1978, “Simulation-based occupancy recommendations for adult medical/surgical units using admissions scheduling systems”, *Inquiry*, vol. 15, no. 1, pp. 25-32.

Harper, P.R. & Shahani, A.K. 2002, "Modelling for the planning and management of bed capacities in hospitals", *Journal of the Operational Research Society,* vol. 53, no. 1, pp. 11-18.

Hubbard, D.W. 2009, *The Failure of Risk Management: Why It's Broken and How to Fix It*, Wiley.

Hubbard, D.W. 2007, *How to measure anything: Finding the value of intangibles in business,* Wiley.

Jackson, R.R.P. 1964, “Appointment systems in hospitals and general practice”, *Operational Research Quarterly*, vol. 15, pp. 219-237.

Kao, E.P.C. & Tung, G.G. 1981, "Bed allocation in a public health care delivery system", *Management Science,* vol. 27, no. 5, pp. 507-20.

Kelton, W. 2006, *Simulation with Arena (McGraw-Hill Series in Industrial Engineering and Management)* 4th edn, McGraw-Hill Science/Engineering/Math.

Khurma, N., Bacioiu, G.M. & Pasek, Z.J. 2008, "Simulation-based verification of lean improvement for emergency room process", *2008 Winter Simulation Conference, (WSC)* IEEE, Piscataway, NJ, USA, 7-10 Dec. 2008, pp. 1490.

Kleijnen, J.P.C. & Wan, J. 2007, "Optimization of simulated systems: OptQuest and alternatives", *Simulation Modelling Practice and Theory,* vol. 15, no. 3, pp. 354-62.

Kuljis, J., Paul, R.J. & Stergioulas, L.K. 2007, "Can health care benefit from modeling and simulation methods in the same way as business and manufacturing has?", *2007 Winter Simulation Conference,* IEEE, Piscataway, NJ, USA, 9-12 Dec. 2007, pp. 1449.

Lawson, J.S. & Erjavec, J. 2000, *Modern Statistics for Engineering and Quality Improvement (Statistics Series)* 1st edn, Duxbury Press.

Leaning, M.S., Yates, C.E., Patterson, D.L.H., Ambroso, C., Collinson, P.O. & Kalli, S.T. 1991, "A data model for intensive care", *International journal of clinical monitoring and computing*, vol. 8, no. 3, pp. 213-24.

Liu, Z., Zhang, Y. & Li, H. 2008, "Uncertainty modeling design with a probabilistic fuzzy neural network", *2007 IEEE International Conference on Control and Automation, ICCA* Institute of Electrical and Electronics Engineers Inc., Piscataway, NJ 08855-1331, United States, Guangzhou, China, May 30-Jun 1 2007, pp. 883.

MacStravic, R. 1978, “A Case for a Hospital Census Variation and Bed Needs Formula”, *American Journal of Health Planning* vol. 3, pp. 51-60.

Meredith, J. R. & Shafer, S. M. 2007, *Operations Management for MBAs* 3rd edn, Wiley.

Morrissette, M. 2009, “Time-release fix: 5S is the little big secret for improving health care”, *Industrial Engineer,* vol. 41, no. 8, pp. 34-38.

Pande, P.S., Neuman, R.P. & Cavanagh, R.R. 2000, *The Six Sigma Way* 1st edn, McGraw-Hill.

Pidd, M. 2004, *Computer Simulation in Management Science* 5th edn, Wiley.

Radzicki, M.J. & Taylor, R.A. 2008, “Origin of System Dynamics: Jay W. Forrester and the History of System Dynamics”, *U.S. Department of Energy's Introduction to System Dynamics*.

Ridge, J.C., Jones, S.K., Nielsen, M.S. & Shahani, A.K. 1998, "Capacity planning for intensive care units", *Managing Health Care under Resource Constraints* Elsevier, Netherlands, 03/01, pp. 346.

Robinson, S. 2004, *Simulation - The practice of model development and use*, Wiley.

Ruohonen, T., Neittaanmaki, P. & Teittinen, J. 2006, "Simulation model for improving the operation of the emergency department of special health care", *2006 Winter Simulation Conference, WSC* Institute of Electrical and Electronics Engineers Inc., New York, NY 10016-5997, United States, Monterey, CA, United States, Dec 3-6 2006, pp. 453.

Rusting, R. 1978, "Swing beds: rural hospitals seek solution to old problem of bed distribution", *Health Care Week,* vol. 2, no. 1, pp. 8-9.

Schuster, D.P. 1992, "Predicting outcome after ICU admission. The art and science of assessing risk", *Chest,* vol. 102, no. 6, pp. 1861-1870.

Seung-Chul Kim, Horowitz, I., Young, K.K. & Buckley, T.A. 1999, "Analysis of capacity management of the intensive care unit in a hospital", *European Journal of Operational Research,* vol. 115, no. 1, pp. 36-46.

Tu, J.V. & Guerriere, M.R.J. 1993, "Use of a neural network as a predictive instrument for length of stay in the intensive care unit following cardiac surgery", *Computers and Biomedical Research,* vol. 26, no. 3, pp. 220-9.

Tu, J.V., Mazer, C.D., Levinton, C., Armstrong, P.W. & Naylor, C.D. 1994, "A predictive index for length of stay in the intensive care unit following cardiac surgery", *CMAJ : Canadian Medical Association journal = journal de l'Association medicale canadienne,* vol. 151, no. 2, pp. 177-185.

Van Houdenhoven, M., Nguyen, D.T., Eijkemans, M.J., Steyerberg, E.W., Tilanus, H.W., Gommers, D., Wullink, G., Bakker, J. & Kazemier, G. 2007, "Optimizing intensive care capacity using individual length-of-stay prediction models", *Critical care (London, England),* vol. 11, no. 2, pp. R42.

Watt, K.F. 1977, "Why won't anyone believe us?", *Simulation,* vol. 28, no. 1, pp. 1-3.

Webb, M., Stevens, G. & Bramson, C. 1977, "An approach to the control of bed occupancy in a general hospital", *Operational research quarterly,* vol. 28, no. 2, pp. 391-9.

Wijewickrama, A.K.A. & Takakuwa, S. 2006, "Simulation analysis of an outpatient department of internal medicine in a university hospital", *Proceedings of the 2006 Winter Simulation Conference*, IEEE, Monterey, CA, USA, 3-6 Dec. 2006, pp. 425.

Wilson, J.C.T. 1981, "Implementation of computer simulation projects in health care", *Journal of the Operational Research Society,* vol. 32, no. 9, pp. 825-32.

Womack, J.P. & Jones, D.T. 2003, *Lean Thinking: Banish Waste and Create Wealth in Your Corporation*, Free Press.

Yates, C.E., Leaning, M.S., Patterson, L.H., Ambroso, C. & Kalli, S.T. 1991, "Data modelling for intensive care within the INFORM project", *Proceedings*, Springer-Verlag, Berlin, Germany, 19-22 Aug. 1991, pp. 116.

Appendix A - Incorporating Lean at Health Sciences Centre

OR Theatre Cleaning Guidelines

Tasks (in order):

- Confine and contain garbage, soiled linen. Place on cart.
- Confine and contain dirty anaesthesia equipment.*
- Push dirty case cart outside of room.
- Mop floor around bed, cautery, suction, anaesthesia machine, and any visibly-soiled areas. (for t-tube procedures, only visibly-soiled areas need to be mopped)
- Wipe visibly-soiled areas of OR lights.
- Wipe down furniture, OR bed, cautery, suction, other equipment used, and any visibly-soiled areas, using a different rag for each.
- Wipe anaesthesia equipment.*
- If necessary, mop floor again.
- Remove dirty mop head and place in laundry.
- Remove gloves and wash hands.
- Replenish supplies in anaesthetic machine and side cart.*
- Place clean linen on bed.
- Place plastic bags in buckets and large bag in holder.
- Replace laundry bags.
- Replenish supplies on cleaning cart as required.
- Move dedicated equipment back to storage.
- Take dirty case cart to MDR elevator and transport to basement.

*These tasks belong to the Anaesthesia Assistant.

Additional tasks at the end of a surgical slate each day are:

- Put Neptune through a cleaning cycle
- Wipe OR lights
- Wash the whole floor
- Wipe all furniture including prep trolley (remove items)
- Use vacuum on computer if necessary

Additional instructions include:

- Staff should wear gloves during the cleaning process.
- If a patient was MRSA/VRE positive, staff should also wear a gown.
- If the Anaesthesia Assistant is unavailable and at least 2 MSW staff are present, 1 MSW staff should carry out the Anaesthesia Assistant's tasks.
- If any MSW staff members have completed their portion of cleaning, they should assist the Anaesthesia Assistant where possible.

- During procedures, MSW staff members are welcome to enter the theatres and check the garbage, replenish anaesthesia supplies, and carry out any other helpful tasks.
- Only MSW staff should be present in the operating room during the cleaning process, unless absolutely necessary.

Specific tasks to be performed by the designated Anaesthesia Assistant position are as follows:

Tasks (in order):

- Confine and contain dirty anaesthesia equipment.
- Throw out used tubes.
- Put dirty pan and instruments on cart.
- Wipe anaesthesia equipment.
- Clean arm wrap.
- Wipe cables and entire anaesthetic machine.
- Remove gloves and wash hands.
- Replenish supplies in anaesthetic machine and side cart.
- Cover the machine tray with a cloth.
- Replace used supplies (tubes, pan, syringes, mask, sensors, etc.)
- Attach new arm band and sensors (based on size of next patient)
- Refill supplies in anaesthesia machine drawers
- Refill supplies in anaesthesia side cart and IV cart
- The tasks performed by the Anaesthetic MSW are as follows:

In the occurrence of a Malignant Hypothermia (MH) patient, the following procedures are performed:

- Remove the three canisters of Sevoflurane, Desflurane, and Isoflurane
- Remove machine circuit and filter
- Remove box of gas refills
- Remove Sucuciline
- Remove respiratory bags
- Remove used Sodabsorb
- Put all removed supplies on cart and indicate with a note which theatre it was taken from
- Take cart to anaesthesia room
- Run anaesthetic machine for 20 minutes

- Replace Sodabsorb
- Set up machine with MH safe respiratory bags, masks, and a new filter and circuit.

Tasks performed by the MSW's in addition to post-op clean-up:

- Help transport patients between departments
- Assist during operation as required (holds, positioning)
- Help lift patients during transport
- Restock supplies in storage area
- Transport equipment to other departments
- Stock cast cart and housekeeping carts in the morning
- Assist with offsite cases

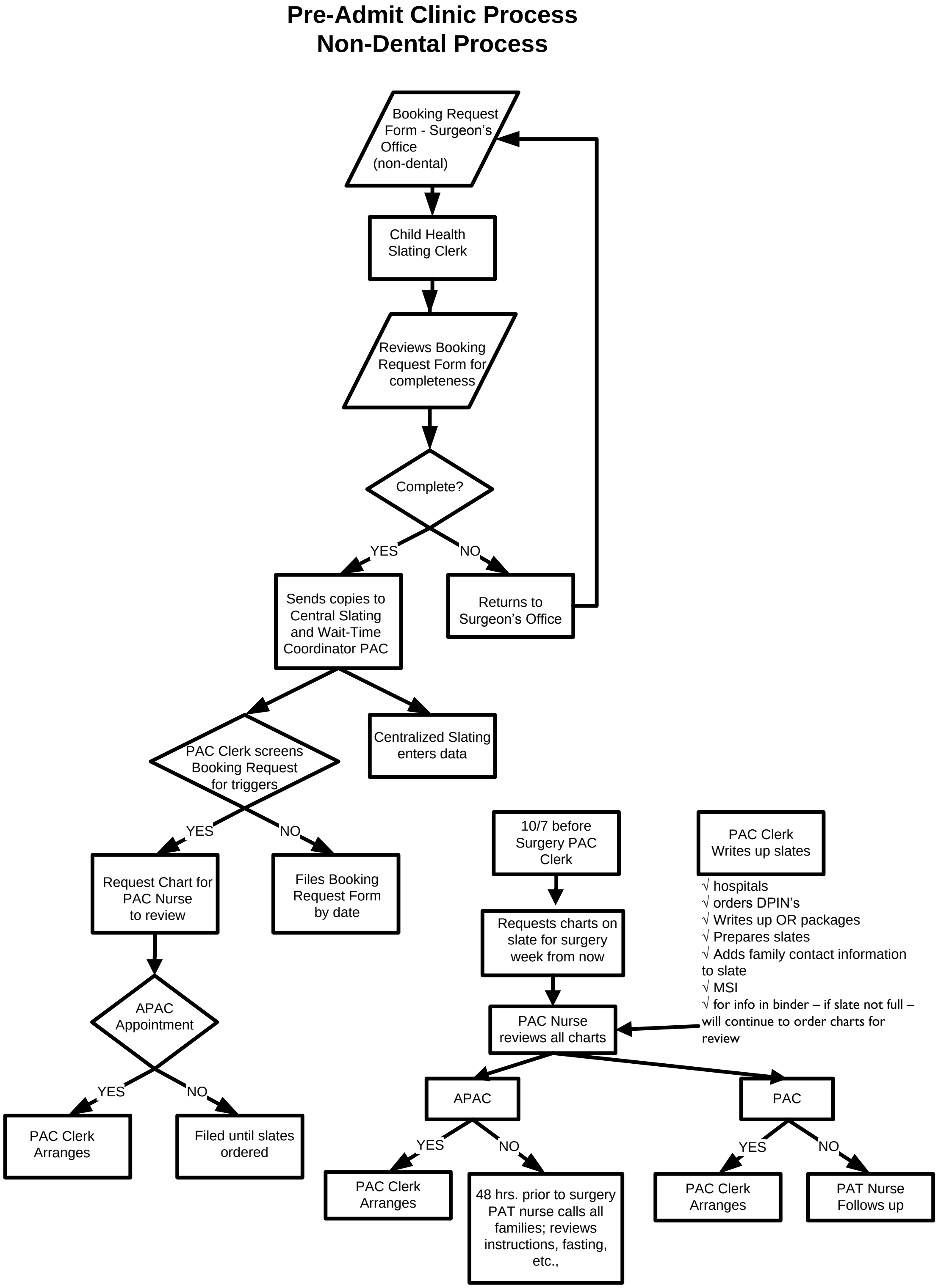


Figure A.1 Pre-Admit Clinic Process Flow Chart

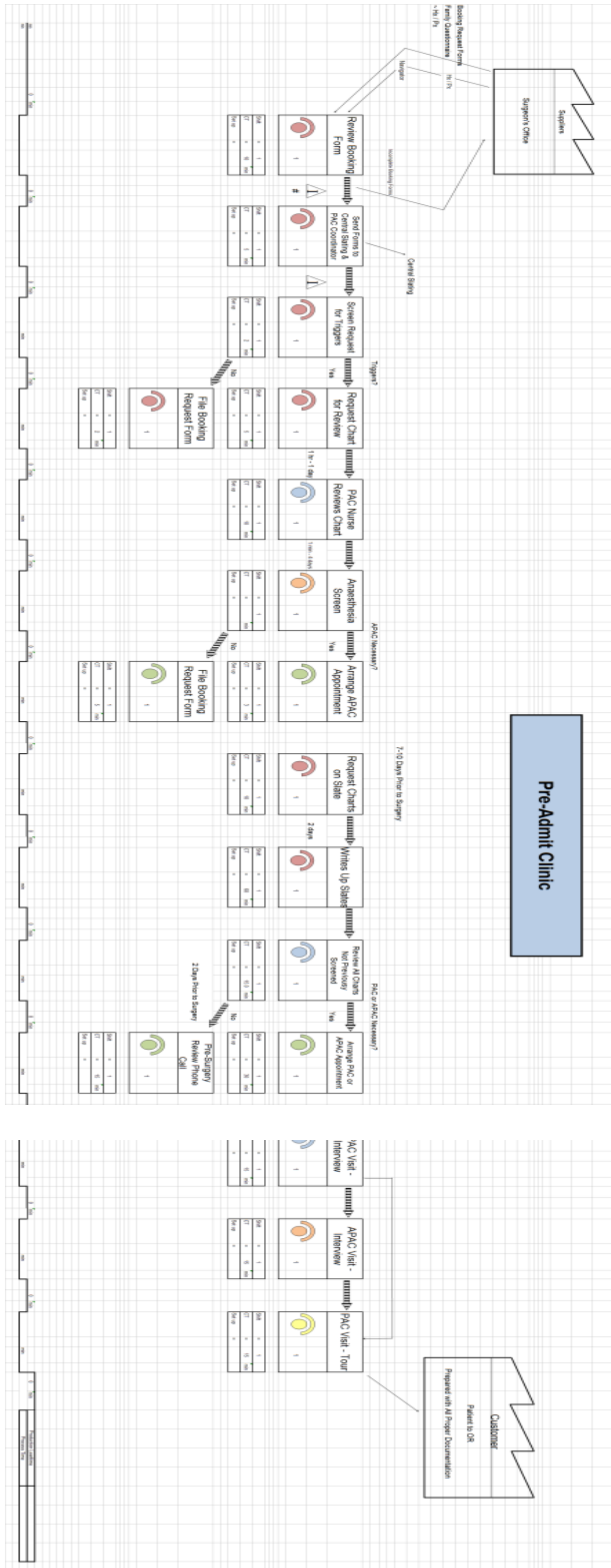
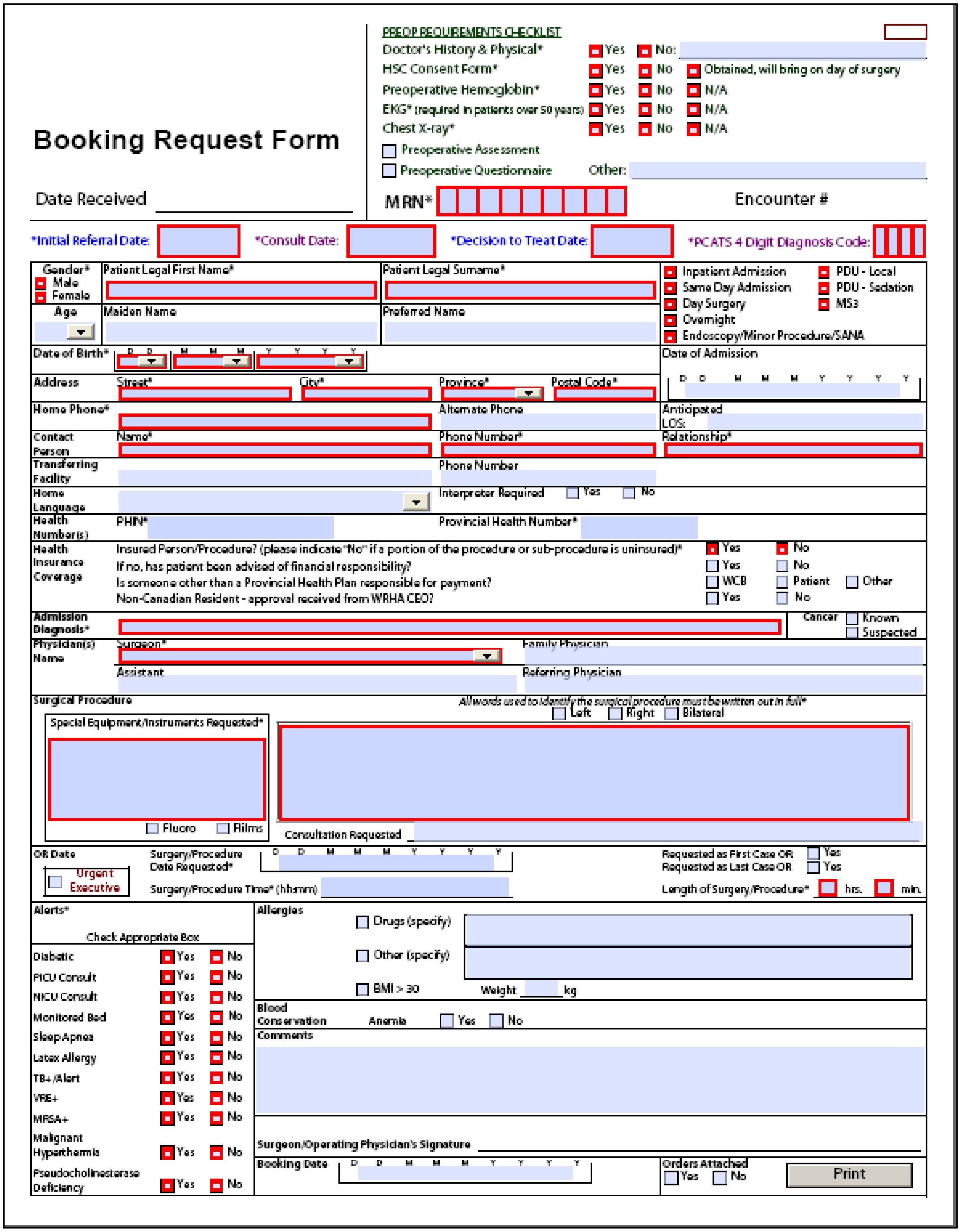


Figure A.2 Pre-Admit Clinic Current State Value-Stream Map



Booking Request Form

Date Received

PREOP REQUIREMENTS CHECKLIST

Doctor's History & Physical*	Yes	No:	
HSC Consent Form*	Yes	No	Obtained, will bring on day of surgery
Preoperative Hemoglobin*	Yes	No	N/A
EKG* (required in patients over 50 years)	Yes	No	N/A
Chest X-ray*	Yes	No	N/A

Preoperative Assessment

Preoperative Questionnaire Other:

MRN* Encounter #

*Initial Referral Date: *Consult Date: *Decision to Treat Date: *PCATS 4 Digit Diagnosis Code:

Gender* Male Female | Patient Legal First Name* | Patient Legal Surname* | Inpatient Admission | PDU - Local | Same Day Admission | PDU - Sedation | Day Surgery | MS3 | Overnight | Endoscopy/Minor Procedure/SANA

Age | Maiden Name | Preferred Name

Date of Birth* D D M M M Y Y Y Y | Date of Admission D D M M M Y Y Y Y

Address Street* City* Province* Postal Code*

Home Phone* Alternate Phone Anticipated LOS:

Contact Person Name* Phone Number* Relationship*

Transferring Facility Phone Number

Home Language Interpreter Required Yes No

Health Number(s) PHIN* Provincial Health Number*

Health Insurance Coverage
Insured Person/Procedure? (please indicate "No" if a portion of the procedure or sub-procedure is uninsured)* Yes No
If no, has patient been advised of financial responsibility? Yes No
Is someone other than a Provincial Health Plan responsible for payment? WCB Patient Other
Non-Canadian Resident - approval received from WRHA CEO? Yes No

Admission Diagnosis* Cancer Known Suspected

Physician(s) Name Surgeon* Family Physician
Assistant Referring Physician

Surgical Procedure *All words used to identify the surgical procedure must be written out in full*
Left Right Bilateral

Special Equipment/Instruments Requested*
Fluoro Films
Consultation Requested

OR Date Urgent Executive
Surgery/Procedure Date Requested* D D M M M Y Y Y Y
Surgery/Procedure Time* (hh:mm)
Requested as First Case OR Yes
Requested as Last Case OR Yes
Length of Surgery/Procedure* hrs. min.

Alerts*

Check Appropriate Box

Diabetic	Yes	No
PICU Consult	Yes	No
NICU Consult	Yes	No
Monitored Bed	Yes	No
Sleep Apnea	Yes	No
Latex Allergy	Yes	No
TB+/Alert	Yes	No
VRE+	Yes	No
MRSA+	Yes	No
Malignant Hyperthermia	Yes	No
Pseudocholinesterase Deficiency	Yes	No

Allergies
Drugs (specify)
Other (specify)
BMI > 30 Weight kg

Blood Conservation Anemia Yes No

Comments

Surgeon/Operating Physician's Signature

Booking Date D D M M M Y Y Y Y

Orders Attached Yes No

Print

Figure A.3 Electronic Booking Request Form

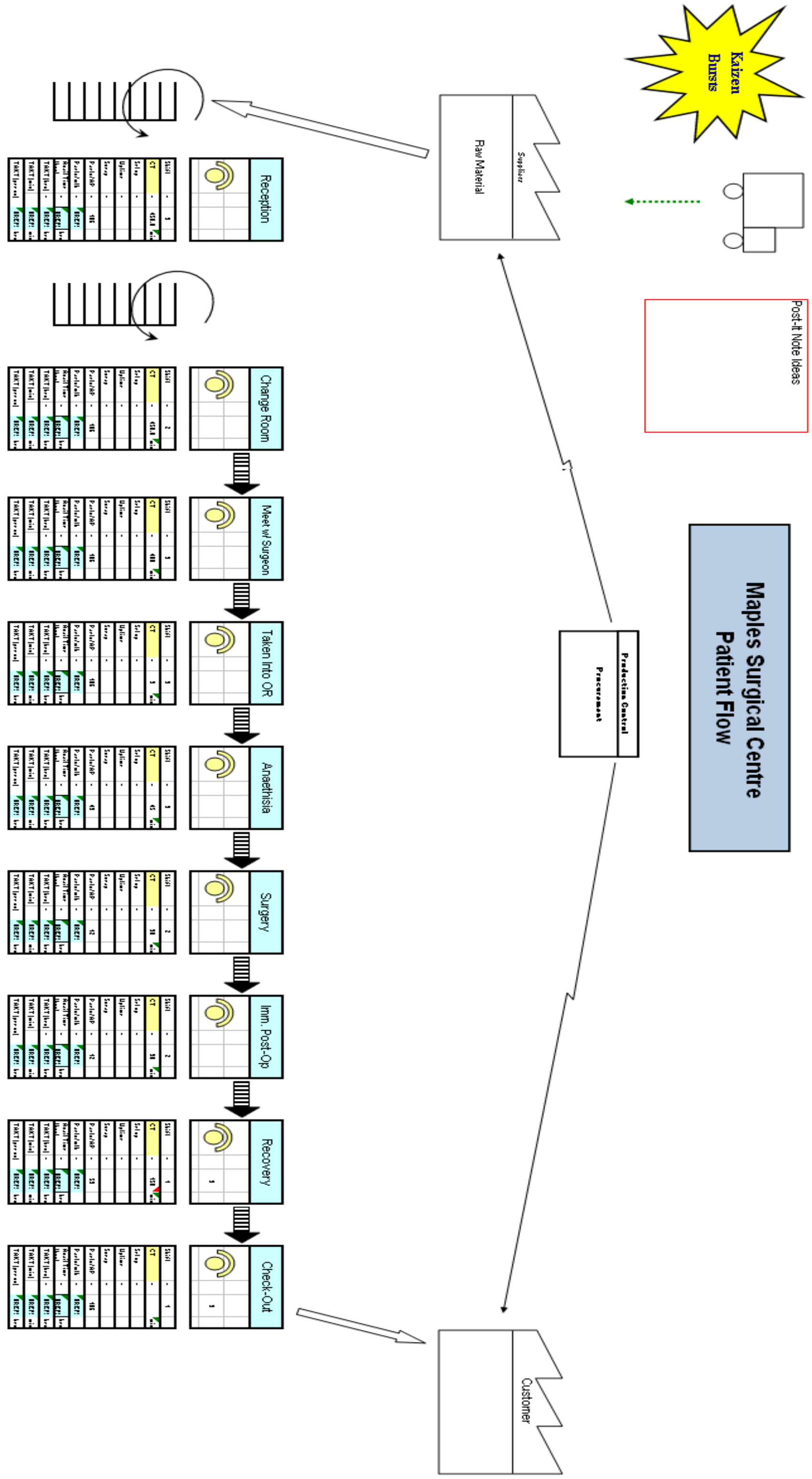


Figure A.4 Maples Surgical Centre Value-Stream Map

Summary of MSW Identified Potential Areas of Improvement

Rework

- Setting up a room multiple times due to unknown next case and end-of-the-day uncertainty or decision to change from one room to another
- Going to the ward for a child who needs to go to the OR and finding that a stretcher/wheelchair may be required.
- Going back and forth for equipment for off-site activities

Waiting

- Wait for supplies or equipment (extra case cart, fitted sheets, case list),list of equipment needed for the anaesthesia machine
- Wait for clarification/organization when retrieving equipment (implement a detailed info form)
- Waiting for the ward patient to be ready to go to the OR , families may be away from the unit when the OR staff go to pick up the patient
- Drugs not ready in pharmacy
- Wait for "dirty" cart to be removed before wiping.

Transportation

- Retrieving new/clean items (diapers, fitted sheets)

Overprocessing

- Notification of room requiring cleaning (cell phones)
- Using inefficient equipment (larger mop)
- Tracking breaks (communication among staff)
- Inexperienced phone carrier has to pass phone to someone else
- Nurses remain in room during cleaning

Inventory

- Oxygen tanks – identify CHOR tanks, leave tank on bed
- Shortage of patient sliders
- MDR communication, lack of weekend restocking

Motion

Overproduction

- Use sheet on floor for casting

- Investigate case needs with infection control

General Concerns

- Low morale among staff, results in high stress. Within MSW staff, stress stems from on-call hours

- Demand placed on Anaesthesia Assistant position

- Leadership, report to charge nurse who is busy with other tasks

- Communication between MSW' s, OR nurses, etc. (e.g. important items not being added to communication book)

- Multiple demands from different groups.

- Teamwork between PACU and MSW' s (e.g. MSW' s often asked to help PACU, but PACU does not help when there are no PACU patients and MSW' s are busy)

- Float pool staff-orientation

- Retrieving patients from the ward on weekends

- Switching OR rooms on evenings/weekends

- Picking up patients and OR or CT don't know about MRSI or other complications

- Taking patients off-site instead of children's OR corridor

Summary of OR Nurses Identified Potential Areas of Improvement

Rework

- Consents, histories and physicals examinations being lost
- Children coming to the OR fully clothed-but signed off on the pre-op checklist

Waiting

- Consents
- Case Carts to be picked for Evening/weekend cases
- Case Carts-MDR does not want to pick the case cart until just before the case is done-rationale do not want to do the work if the case might be cancelled-this frequently happens on the adult side but rare in Child Heath-there is no other site that does surgery on children-this may result in a delay while MDR picks a case cart-MDR has agreed to pick the case carts for E1and E2 cases
- Surgeons who go elsewhere between cases-child may remain anaesthetized longer
- Late starts
- Monitored bed requests
- Surgeons who arrive late and need to speak with families/get consents
- Practice Variations
- Lack of common definition of what start time means-impact of not starting on time.
- Consent not signed by a legal guardian
- Delay in MDR sending up a piece of equipment needed for a case

Overproduction

- If a case is not done by midnight-the case needs to be cancelled and a new case # given-could the case # be rolled over automatically?
- Time allotted for Orthopedic Emergency Time-orthopedics may lose their time because another surgeon was running late or the orthopedic surgeon was not available for emergency time
- Anesthesia resident and the anesthesiologist may interview the family separately and then the nurse speaks with the family and will ask similar questions-nursing feels that they need to interview families as they may ask a question in a different way and get different information
- Interviewing of families after they have been asked the same questions by anesthesia
- Nursing checks arm bands and ensures that the site has been marked, asks about allergies, reviews child's respiratory status, and airway management issues
- Review the chart sent by Day Surgery, Day Surgery staff has asked families the same questions
- Rely on the team, communication
- Unnecessary phone calls
- Answering surgeon,anesthesia,resident pagers and blackberries
- Multiple phone calls on the weekend-no clerk
- Phone calls from Day Surgery re: child's weight, history, physicals

Motion

- Consents, histories and physicals examinations being lost-rework required
- Issues related to MDR

Transportation

- Delays in accessing the second case carts which are stored in the elevator area-need to move case carts to locate the correct one-? Could the MSW staff person assigned to the room move the case cart to the assigned room and if it is not there notify the charge person?
- There is only one aide on the weekend-can the ward transfer the patient? Should it be a negotiated process? PACU aide may be able to assist
- When there are a number of shorter cases on the weekend-need additional support

Inventory

- The number of incorrect items being sent is decreasing
- Cast Cart-could it be topped up at MDR-there is a list of required sullies available
- Supplies stored in incorrectly
- Core specific service supplies-nurse in charge of the sub-specialty needs time to review these supplies
- Looking for Supplies in the Core-should an individual be assigned to the Core-what happens on evenings and weekends and you don't know where supplies are kept.

Improvement Projects

- Incomplete pre-op list

- Communication issues

- MDR issues

- Slating Process

Summary of Day Surgery Identified Potential Areas of Improvement

Correction/Rework

- Patients arrive in poor condition, de-hydrated from the OR, fluid deficits.

Better education of patients (lots of fluids before fasting)

- Duplicate phone calls.
- Equipment is old → portable SAT and new thermometers.

Waiting

- Patient arrives at 6:30 and resources aren't established until much later (monitored beds)
- Clarify arrival times (2 hours?), patients unclear of physicians instructions.
- Patients wait between clinic visit in morning and emergency slate, could go home in between.
- Patients arrive with no history and physical or Hgb completed.
- SIMS usage, computer access.

Transportation

- Lack of physical space, fixed "unisex" space
- Not equipped for increased level of acuity and number of patients (2 toilets).
- Proximity to PACU, could be old OR?
- Better signs to direct families

Overprocessing

- Wrong application of kytril, give med at different times.
- Standardize consent procedure (mandatory PAC?)
- Telephone calls re: porter, patients, extend white board and improve communication.
- Discharge requirements (temperature, pee)
- Agree on one type of solution to use among departments
- Phone calls are given priority over email (slating dept)
- Right-sized equipment (hemoglobin)

Inventory

- Updated supplies
- New computer, fax, copier

Motion

- Fax, Photocopies done in PAC, computer and printer needed as well.

Overproduction

- Consent forms done by OR, no Day Surgery
- Lab work results

General Concerns

- Communication between departments.
- Standardized anaesthesia practices, hydration of patients.
- Definition of roles and responsibilities (ex. Obtaining consent).
- Flexible work schedule based on slate. No need to have nurses on staff late in the evening when busy time is morning/early afternoon.
- Use of statistics in slating times, evidence-based
- Increased orientation/training for new technology

Summary of PACU Identified Potential Areas of Improvement

Correction/ Rework

- Incomplete orders-post-op orders, PCA admission orders
- Changing IV solutions prior to the child's transfer to Day Surgery-IV may be D/C within 30 minutes of arrival in Day Surgery-time involved in changing the IV solution and cost of IV solutions-Data will be collected on this issue- Data collected has indicated that IV solutions are changed 50 % of the time
- MRI orders are not ready –off service medical patients require orders
- PACU order Sheet –many residents write on the General Order Sheets vs. the PCA Order Sheets- PACU order sheets not viewed as user friendly

Waiting

- For the ward to be ready to accept the patient/ nurse on break/same nurse taking all of the admissions/report time 1900-2030-handover time/PACU staff numbers decrease @1930/ Day Surgery hours-works better if Day Surgery open until 2100
- Unplanned monitored bed requests
- The OR requests a bed for a specific patient, there is a delay in the transfer that may impact on other transfers from the OR
- Waiting for parents to come back from coffee-? Vending machine in the post-op waiting room
- For Day Surgery/Wards to be ready to accept the child
- For IMCN staff to come to transfer the infant back to IMCN resulting in a bottleneck
- Transfer of patients to the wards-no IV pole available, no water in the bottle, transfer the patient from the stretcher to the bed if the child is not on a ward
- Waiting for Anesthesia sign-out-will the new 2 nurse sign out process assist

Overprocessing

- Changing IV solutions prior to transfer

Summary of CK3 Identified Potential Areas of Improvement

Corrections

- Rework related to specimens that were not properly labelled-specimens need to be collected again-? Labels
- Gentamycin levels not being drawn at the appropriate time necessitating rework
- Children coming to the ward from the OR with IV tubing taped using an old practice method
- Changes of IV tubing sets- children being sent out with buretrols that are no longer used on the ward

Waiting

- Discharge Issues:
- • Plastic Surgeons to come to the ward to D/C their patients resulting in delays
- • ENT Service coming late to D/C their patients who are being monitored
- • Waiting for Discharge prescriptions
- • Wheelchairs required for a D/C not being available on weekends
- • Social Work not being available on weekends when there are financial issues that might impact on D/C's
- • Home care not being able to accommodate next day dressing changes-usually come back to the ward
- Delays re: transfers from PACU in the evening

Overprocessing

- Charting re: Short Stay patients ie orthopaedic patients on the weekend

Proposed OR Internal Communication Process

Draft #2

August 6, 2008

Guiding Principles:

The Porter, Anaesthesia Assistant and Multi-Skilled Workers (MSW) in the OR will each be given a cellular telephone corresponding to a particular speed-dial number when they are on staff.

- Each cellular telephone will be labeled with its corresponding speed-dial number.
- The Anaesthesia Assistant will always be given the cellular telephone corresponding to speed-dial # 1.

<u>Clean-Up of Rooms</u>

The MSWs are divided into two teams. Each team is assigned the day before to a group of OR theatres.

The nurse's slate in each OR theatre will have 2 speed-dial #'s written down:
MSW Team Members 1 and 2.

All speed-dial #'s and corresponding telephone #'s will be posted on the board in each OR Theatre.

The MSW staff will follow the progress of the surgery on the whiteboard.

At the completion of the surgery, the Designated Nurse in the OR shall:

- Speed-dial the cellular telephone number of MSW Staff Person #1 assigned to the specific OR.
- If the Nurse is able to connect with MSW Staff Person #1, the Nurse indicates that "OR Theatre # ______ is ready to be cleaned", providing any additional information if necessary.
- If the Nurse is unable to connect with MSW Staff Person #1, the Nurse will speed-dial MSW Staff Person # 2.
- Speed-dial # 11 (the cellular telephone belonging to the Anaesthesia Assistant)
- When the Nurse is speaking with a MSW Staff Person or the Anaesthesia Assistant, he/she will ask if that person is with the other people that still need to be contacted. If yes, the Nurse will not need to call those people.

The Designated Nurse in the OR shall:

- Call the Nurse-in-Charge at the Front Desk if unable to reach MSW Staff Person # 1 and # 2.

- Call the Nurse-in-Charge at the Front Desk if unable to reach the Anaesthesia Assistant.

The first MSW Staff Person contacted by the designated nurse in the OR shall:

- Speed-dial their MSW partner when he/she has been notified that one of their assigned OR theatres is ready to be cleaned.

<u>Clean-Up of Rooms - Evenings</u>

During the evening shifts, the two MSWs in the OR will be given the cellular telephones corresponding to speed-dial #'s 7 and 8.

<u>Clean-Up of Rooms - Weekends</u>

During the weekend shifts, the MSW in the OR will be given the cellular telephone corresponding to speed-dial # 7.

<u>Breaks</u>

When a MSW goes on break, he/she shall:

- Notify his/her team member that he/she is going on break.
- Call forward his/her cellular telephone to his/her team member.
- Notify the Nurse-in-Charge or Unit Clerk at the Front Desk.

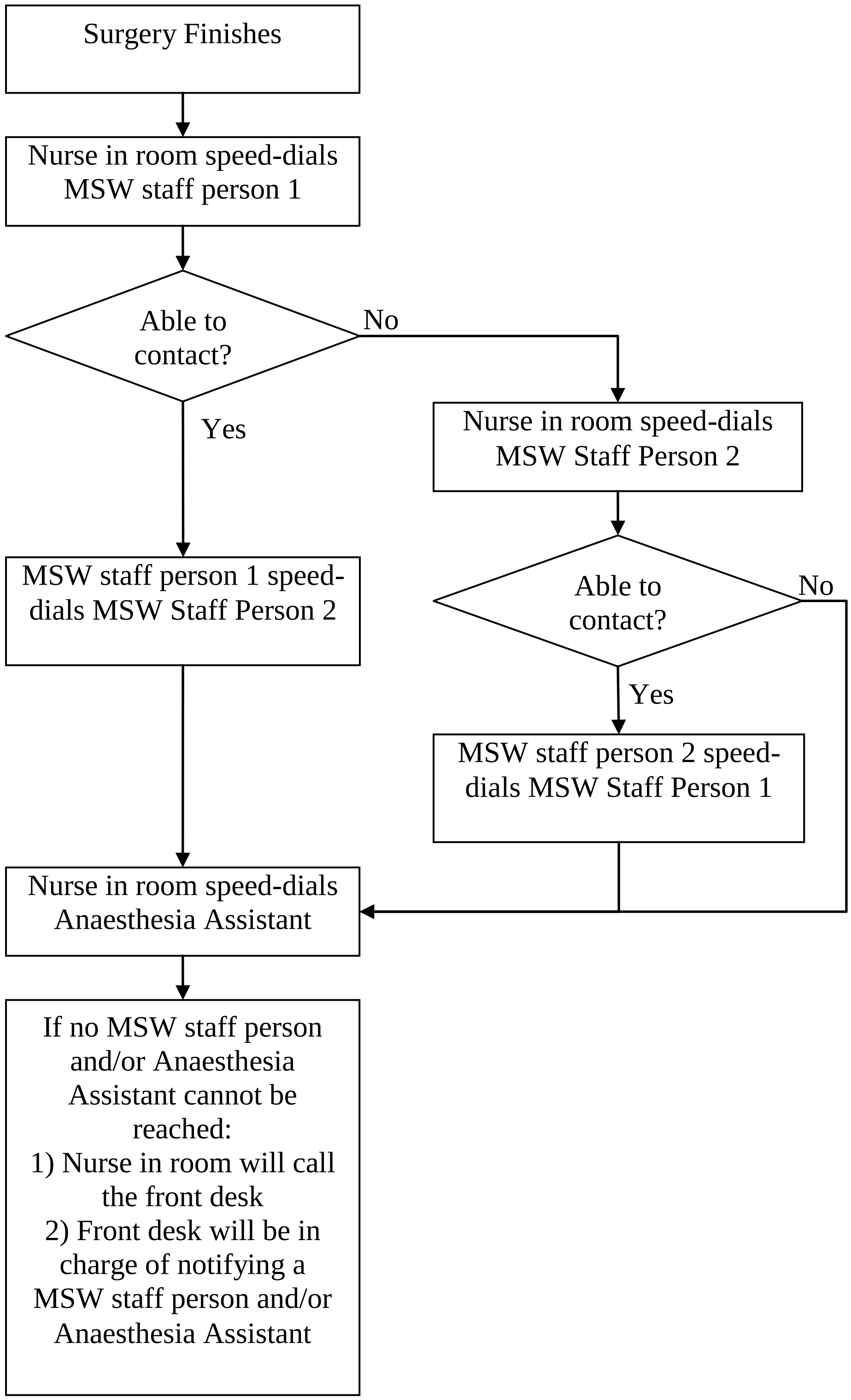
When the Anaesthesia Assistant goes on break, he/she shall:

- Notify an available MSW that he/she is going on break and will be call forwarding his/her cellular telephone to this person.
- Call forward his/her cellular telephone to the available MSW who will cover for the Anaesthesia Assistant.
- Notify the Nurse-in-Charge or Unit Clerk at the Front Desk.

When the Porter goes on break, he/she shall:

- Notify the Nurse-in-Charge or Unit Clerk at the Front Desk.
- Leave his/her cellular telephone at the Front Desk.
- If a patient needs to be picked up while the Porter is on break, the Nurse-in-Charge at the Front Desk shall:
  - Ask an available MSW to pick up the patient, including the necessary details
    - E.g. Where to pick up the patient, whether a bed or stretcher is required

Flowchart: Clean-Up of Rooms



Note: When the Nurse is speaking with a MSW Staff Person or the Anaesthesia Assistant, he/she will ask if that person is with the other people that still need to be contacted. If yes, the Nurse will not need to call those people.

Communication Between the OR and ED/Wards/Day Surgery Regarding Emergency Surgical Patients

Surgeon/Resident Shall:

Call Adult OR to book the surgery.

Adult OR Slating Clerk Shall:

Record the required information (i.e. fasting, surgeon availability etc.) on the Emergency Booking Slip and tube it to the OR.

Enter the data into SIMS.

Children's OR Clerk Shall:

Write down the case information on the OR whiteboard.

OR Charge Nurse Shall:

Discuss when to schedule the case with the Anaesthesia Floor Manager

(based on the Surgeon's availability).

• Receive call from the ED/Ward Designate (Phone Call #1) regarding the patient's OR time. If the time is unknown, the OR Charge Nurse will give the ED/Ward Designate an estimated range.

• Call the patient's Assigned Nurse (Phone Call #2) in the ED/Ward/Day Surgery **20 minutes** prior to the OR time and:

o Confirm the time that the MSW Staff Person will be coming to pick up the patient

o Clarify whether the MSW Staff Person should bring a wheelchair, stretcher or bed and ask if a second person is required for the transport, is a nurse required, and monitoring as per PPDM

• Call the MSW Staff Person and indicate when, and where, the patient is to be picked up, whether a wheelchair, stretcher, or bed is required and/or if a second person is required for the transport.

ED/Ward Designate Shall: (Phone Call #1)

• ED Charge Nurse/Designate shall (phone call #1)

o Call the OR Charge Nurse/Designate re: OR time; or estimated OR time once case is booked and scheduled.

o Leave a message on the answering machine if necessary.

• Provide the OR Charge Nurse with important information i.e. allergies (bananas, eggs, latex, etc.) and isolation requirements (e.g. MRSA, VRE, etc.).

• Inform the patient's Assigned Nurse about the plan and estimated surgical time.

• If patient is transferred from the ED to the ward or Day Surgery prior to surgery, ED notifies the OR when the patient transfer is made.

ED Unit Clerk (Designate) Shall:

• Days, Monday to Friday:

o Call the designated Manager of Patient Care who assigns and notifies the patient's post-operative unit
• Evenings / Nights / Weekends:
o Call the Nursing Supervisor who assigns and notifies the patient's post-operative unit

ED/Ward/Day Surgery Assigned Nurse Shall: (Phone Call #2)

Confirm with the OR Charge Nurse at the **20 minute call** that the patient (and his/her guardians) will be ready in 20 minutes.

Give report on the patient to the OR Charge Nurse including whether the patient has an IV, is on oxygen, is being monitored, requirement for VS (HR, RR) 15 minutes and pain and sedation scores 30 minutes post administration of narcotic per PPDM, confirm allergy status and any isolation requirements.

Confirm with the OR nurse if she/he or another nurse is required to accompany the patient to the OR.

Complete the OR Pre-op Checklist, ensuring all items are valid and notifying OR Charge Nurse if some requirements have not been met (e.g. patient fully clothed, is wearing jewellery, etc.)

Ensure all necessary information has been communicated as per transfer checklist.

MSW Staff Person and/or Nurse (if required) **Shall:**

Transport patient to the OR at the appropriate time.

Communication Between the OR and ED/Wards/Day Surgery Regarding Emergency Surgical Patients

NEW

Phone Call #1

ED Charge Nurse/Designate:

- Calls OR Designate re: OR time; or estimated OR time
- Leaves a message on the OR answering machine if necessary

ED/Unit Designate:

- Provides information that affects OR set up NB. Allergies (latex, eggs) Isolation requirements (MRSA, VRE)

↓

ED/Unit Designate informs patient's Assigned Nurse re: OR time

↓

NEW

Days Mon-Fri:

ED Unit Clerk (Designate):

- Calls designated Manager of Patient Care who assigns and notifies the patient's post-op unit

Evenings / Nights / Weekends:

ED Unit Clerk (Designate):

- Calls Nursing Supervisor who assigns and notifies the patient's post-op unit

↓

NEW

ED Unit Clerk (Designate):

- ED notifies Ward/Day Surgery of admission and arranges time of transfer.
- ED notifies OR when transfer is made.

↓

NEW

Assigned Nurse:

- Then expects Phone Call #2 from OR Charge Nurse

↓

Phone Call #2: 20 minutes prior to the OR time

OR Charge Nurse:

- Calls Assigned Nurse & confirms the patient (& guardians) will be ready to go in 20 min.

Assigned Nurse:

- Gives a report
- Clarifies how to transport
- Confirms that post narcotic monitoring requirements can be met in the OR
- Completes chart as per transfer checklist

↓

OR Charge Nurse:

- Informs MSW about where and when patient is to be picked up and transport needs

↓

MSW Staff Person and/or Nurse (if required):

- Transport patient to the OR at the appropriate time

Appendix B - Surgeon Interview Transcripts

What are the current needs for monitored beds in your sub-specialty program, i.e.T+A patients, ie other patient populations?

Can we better predict which children require monitoring?

What does monitoring mean? Is it the same for all groups of children?

Do you have some thoughts on future monitored bed requirements?

Ideas for improvement?

- Dr. Leitao

Tonsillectomy patients requiring post-operative monitoring have the longest waiting list.

Children having airway surgery may require monitoring, i.e.neonates requiring sub-glottic airway management, airway reconstruction

Children at high-risk for post-operative complications should be monitored post-operatively. However, the criteria for ICU/monitored bed may differ according to the surgeon.

There are 9-10 pediatric ENT surgeons.

Reason for Surgery may define the need for post-operative monitoring:

Obstructive Sleep Apnea (OSA)-the child needs to be monitored

Recurrent Tonsillitis-child does not require monitoring and may not need admission depending on the child's age.

A child who is a restless sleeper, snores, gasps for air, has choking spells-may have sleep disordered breathing. Approximately 10% of this group of children will have OSA.A tonsillectomy may help this group of children.

These criteria are based on the AAP 2002 Clinical Practice Guideline: Diagnosis and Management of Childhood Obstructive Sleep Apnea Syndrome.

For tonsillectomies, the decision may be based on one or more of the following conditions:

Age (e.g. <3 years should be monitored)

Growth (e.g. 95th percentile should be monitored)

Craniofacial anomalies, Cardiac co-morbidities, Neurological problems, children with syndromes.

Developmental Delay

Patients with obstructive sleep apnea (OSA).

There is no objective test for OSA and its diagnosis may differ according to surgeon, based on one or more of the following:

Clinical history

Parental diagnosis

Sleep study results

Pediatrician’s opinion

This poses a challenge because the respirologists may differ in their views of the criteria for a positive sleep study.

In adults, < 5 apnea hypopnea events/hour is normal. It is uncertain if this type of measure exists for children.

1 study cited greater than 1 apnea hypopnea episode per hour as abnormal.

Note that adult patients require positive sleep study results in order to have a monitored bed

In 2005, Dr. J McKenna undertook a study: “The incidence of respiratory complications in patients admitted post-tonsillectomy: A review of the 2005 tonsil care map”.

208 patients admitted and 24% had an intervention.

Respiratory complications requiring intervention beyond supplemental oxygen in post-tonsillectomy patients are rare (1/208)

Supplemental oxygen usage beyond 5h in patients without an identifiable risk factor in post-tonsillectomy patients is rare (5/208)

When post-operative monitoring is requested, the main concern post T+A is significant edema in the upper airway.

This may require interventions such as jaw thrusts, intubation, etc.

These patients primarily need respiratory monitoring.

Oxygen saturation (O2 sat) monitoring is not really useful.

Supplemental oxygen does not improve upper airway condition.

Pulmonary problems usually cause oxygenation problems, but that usually occurs when a patient has received a general anaesthetic.

Cardiac monitoring is not really required.

Real requirement-close monitoring, 02 sat monitoring, and a nurse to observe.

It is normal for these children requiring post-operative monitoring to be cancelled > once. There are only 2 monitored beds.

In the San Francisco facility where Dr. Leitao previously worked, the ward had telemetry. Allowed central monitoring of patients so monitored bed availability was not really an issue.

Future Need: Four bed monitored unit.

- Dr. Ross

Dr. Ross currently performs around per year:

15-20 children requiring craniosynostosis repair

35 children requiring cleft palate repairs

20 children requiring complex craniofacial surgery

30 children requiring pharyngoplasties

In general, conservative protocols are used at HSC regarding which patients need monitoring.

These patients may include those undergoing:

Revisions of palates

Pharyngoplasty

Surgery on clefts, splits

Syndromic children requiring mandible/jaw surgery

Tracheostomies.

Surgery on palates

25-40 palates per year.

For Dr. Ross's patients, he has two requirements:

Tongue stitch

This allows nurses to easily respond to certain problems (e.g. tongue falling backwards and causing an obstruction) Tongue stitch can beremoved

Oximetry monitoring overnight

The wards may convert this need into a monitored bed need so that there is more nursing available to deal with patient needs.

Most non-syndromic patients probably will not need monitoring.

However, very little documentation/literature regarding this issue exists for these children

The #'s of patients in this group is small.

Some children requiring palate revisions may require an ICU bed.

Most post-operative events (e.g. massive bleed, swelling) happen in the first 24 hours.

Some patients may need to be placed in an ICU setting post-operatively for various reason:

Palate revisions

Severe Craniofacial anomalies

History of sleep apnea

Intubation

Children post pharyngoplasty, children who have a syndrome involving their mandibles/jaw may be in a gray area. Trialed pagers with this group of children-false alarms-workload issue.

Children post choanal atresia repair require a controlled extubation. Child is narcotized for the first 24 hours. May need to stay longer related to feeding issues.

Children post tracheostomy may need a monitored bed if not going to PICU.In the past children did not require monitoring post craniosynostosis repair. Dr Ross indicated that management of this group of children changed when he became an attending. The children are admitted to PICU post-operatively.This decision was made to ensure patient safety and good patient outcomes. Should this be evaluated based on outcomes over the past 5 years?

There has only been one post-op bleed in the past 5 years.

Collect data that can be used to prove which group of patients need monitoring. Provide useful data to surgeons, which may encourage them to adjust their practice accordingly.

Plastics block time is on Wednesday AM-OR starts @ 0900.Delays in deciding if the surgery can move forward may impact on the # of cases that can be done.

Future Need: Four Bed Monitored Unit

- Dr. McDonald

Dr. McDonald’s patients who need monitoring/critical care beds are emergent/trauma cases.

Children with ignificant head injuries who are intubated, may require ICP monitoring.

Infants post-myelomeningocele procedures:

Traditionally these children have been cared for in NICU. This group of children was being transferred to different units in the hospital. Given the low patient volume it was believed that it was important for their care to be provided on one nursing unit in order to build nursing expertise. This group of children is now cared for on CK3.

These children need to be watched to avoid wound breakdown due to soiling from stool.

Constant care attendants are used.

Only a few of these procedures are performed every year, therefore Dr. McDonald would prefer to send this group of children to CK3 in order to develop/concentrate the nursing expertise..

IMCN is not an option due to the physical distance from Children’s Hospital.

O2 sat and cardiac monitoring are only required during the first week of life.

If the child has no pulmonary issues, they are usually extubated quickly, and can go to PACU followed by a monitored bed on the ward post-operatively.

However, some anaesthetists will not perform surgery unless an ICU bed is available.

Elective patients who need post-operative monitoring are usually those undergoing craniotomy procedures

Tumours, Chiari Malformations, Craniofacial, etc.-a minority of children in these groups will require ventilation post-operatively.

Children with suspected but not confirmed VP Shunt malfunction-in this group of children bradycardia is an ominous sign. If there was increased access to monitored beds –a monitored bed would be requested for this group of children.

Future Needs:

Epilepsy monitoring unit if epilepsy surgery starts in the Child Health Program- would likely involve < 10 children/year.

In the current process, staff work hard to accommodate children who require a critical care/monitored bed as much as possible. However, the current process is likely unsustainable.

Improvement Ideas:

Earlier notification either the day prior to surgery or as early in the AM as possible regarding whether a case requiring post-operative monitoring can proceed.

This will help reduce cancellations due to lack of OR time.

Explore ways to improve the physical layout. For example:

Have telemetry on the wards.

Amalgamate rooms so the nursing to patient ratio is reduced (e.g. Rooms that can hold 4 patients, allowing a 1:4 nurse to patient ratio rather than 1:2).

Locate the nursing station in an area where the nurses can have a view of more patients.

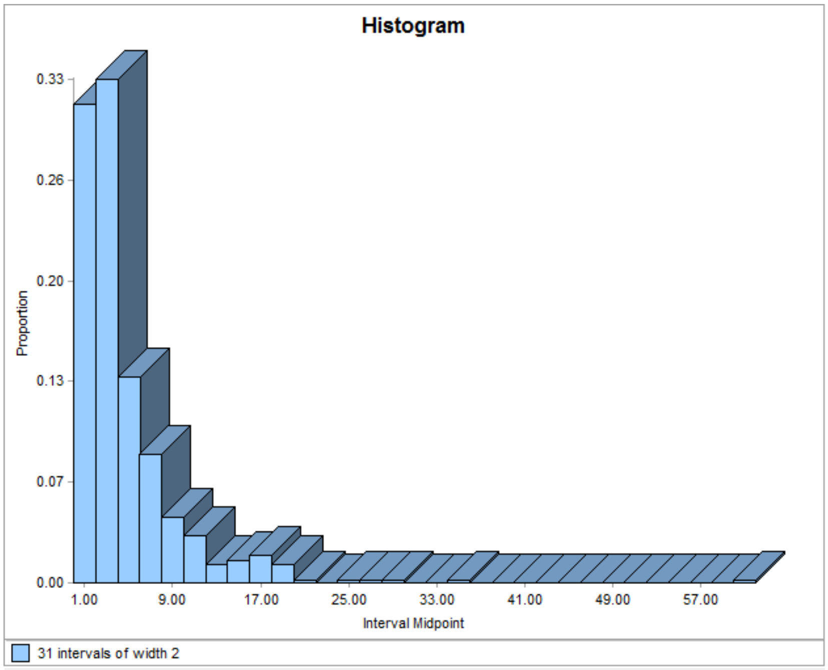
Separate resource allocations for emergent and elective patients. For example:

Have a surgical step-down unit with more than 2 beds. Most patients are not ventilated unless they have extensive trauma, and therefore a surgical step-down unit is sufficient for their needs (as opposed to the PICU).

Perhaps some of the unfunded PICU beds can be used as step-down beds.

Having this unit collocated in PICU has the advantage of having built in mentors for the step-down nurses.

Appendix C - Pediatric Intensive Care Unit Simulation



Data Characteristic	Value
Source file	<edited>
Observation type	Real valued
Number of observations	491
Minimum observation	1
Maximum observation	61
Mean	4.14868
Median	2.00000
Variance	26.53499
Coefficient of variation	1.24165
Skewness	4.39855

Figure C.1 Preliminary Simulation Flexsim Data Import

Relative Evaluation of Candidate Models

Model	Relative Score	Parameters	
1 - Gamma(E)	87.50	Location	0.98276
		Scale	8.11354
		Shape	0.39020
2 - Lognormal	81.25	Location	0.00000
		Scale	2.66379
		Shape	0.88321
3 - Inverse Gaussian	80.00	Location	0.00000
		Scale	4.14868
		Shape	3.64490

21 models are defined with scores between 1.25 and 87.50

Absolute Evaluation of Model 1 - Gamma(E)

Evaluation: Bad
Suggestion: Use an empirical distribution.

Additional Information about Model 1 - Gamma(E)

"Error" in the model mean
relative to the sample mean 0

Flexsim Representation

Use:

When using a pickoption:
Select "By Percentage (table)"
Change "mytable" to the correct table name

When using code:
empirical("MyTable")

Where:

MyTable is a user-defined global table with the following values:

Percentage (Column 1)	X value (Column 2)
31.020	1.000000
22.857	2.000000
10.000	3.000000

Figure C.2 Preliminary Simulation Flexsim Distribution Fitting

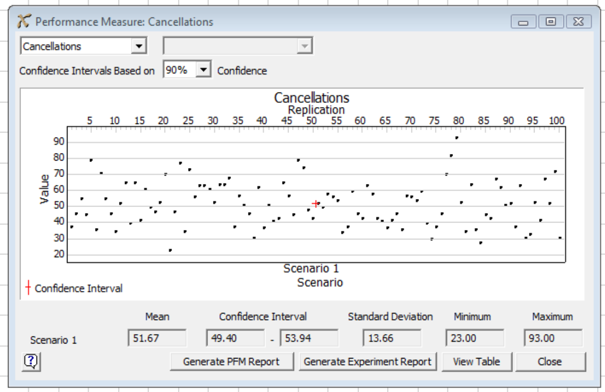


Figure C.3 Preliminary Simulation Results (90% Confidence Interval)

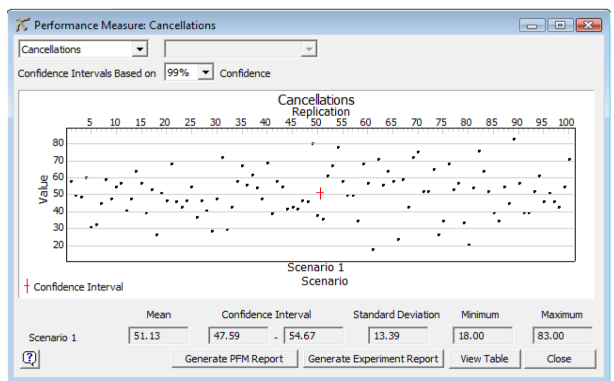


Figure C.4 Preliminary Simulation Results (99% Confidence Interval)

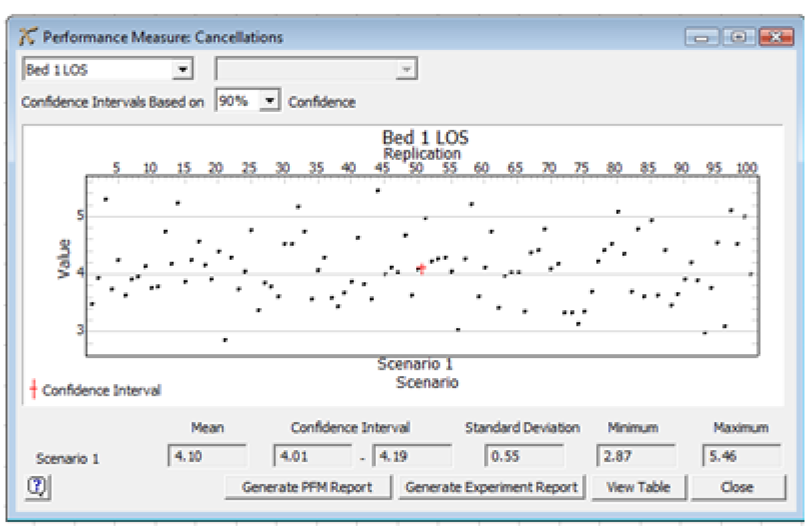


Figure C.5 Average Patient Length of Stay

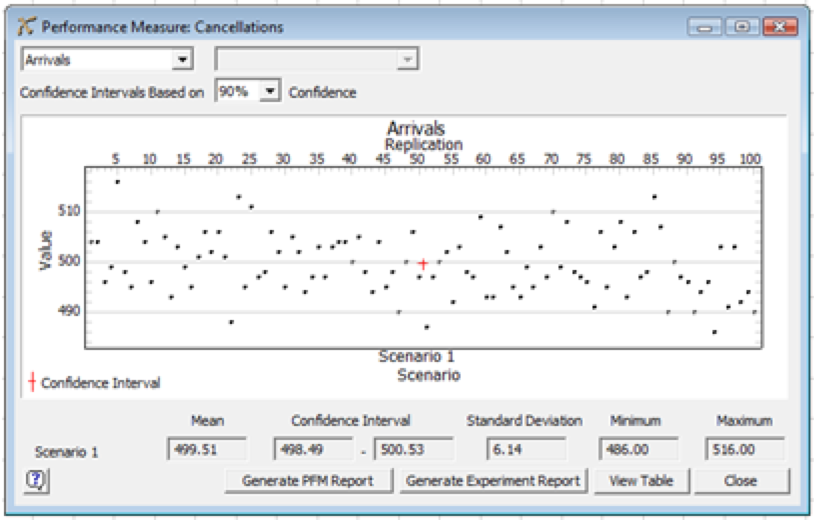


Figure C.6 Average Number of Patient Arrivals

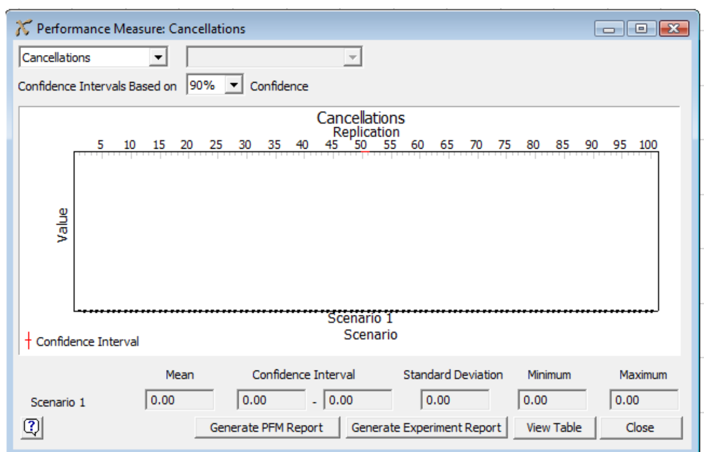


Figure C.7 Average Patient Cancellations After Additional Bed

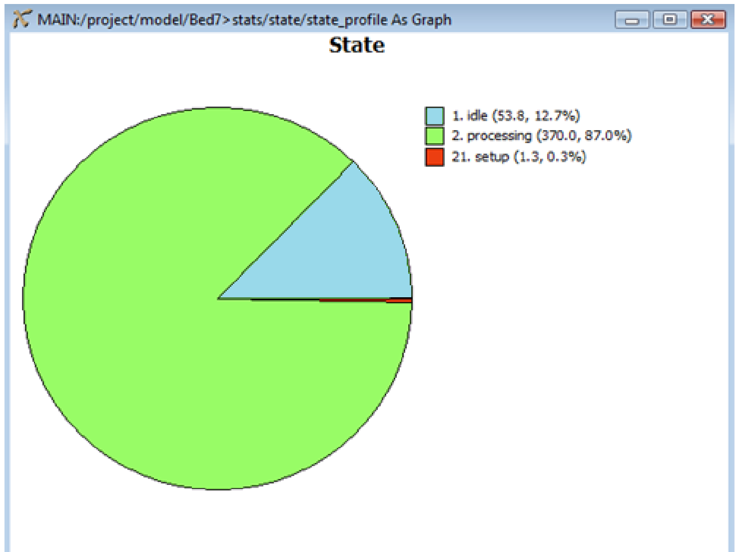


Figure C.8 Additional Bed Utilization

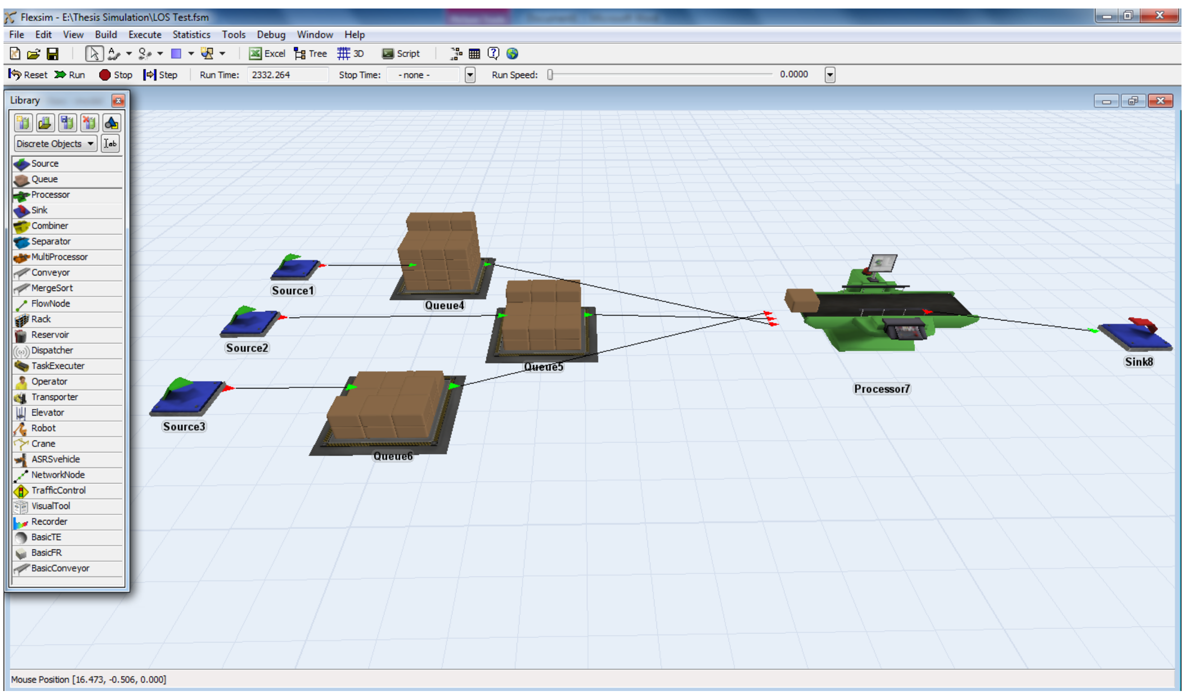


Figure C.9 Patient Length of Stay Test Simulation

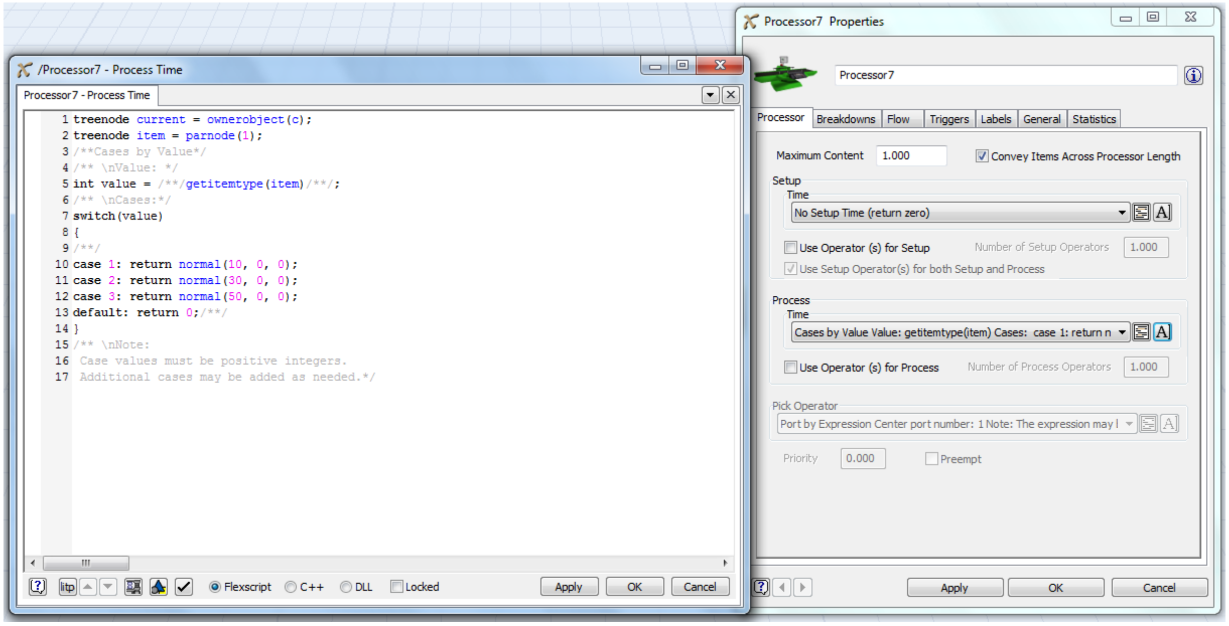


Figure C.10 Patient Length of Stay Case by Value

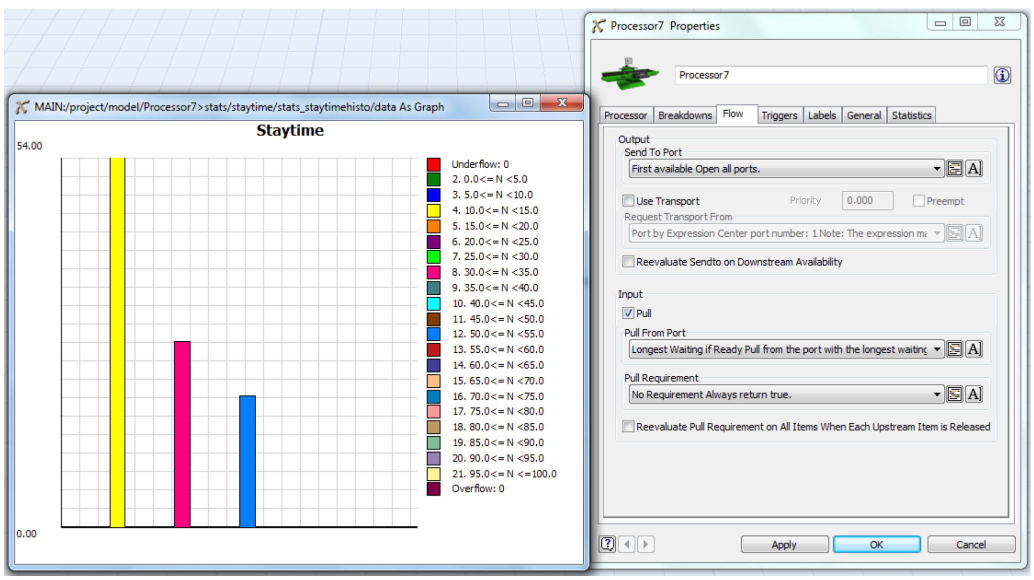


Figure C.11 Distinct Length of Stay Times Based on Itemtype

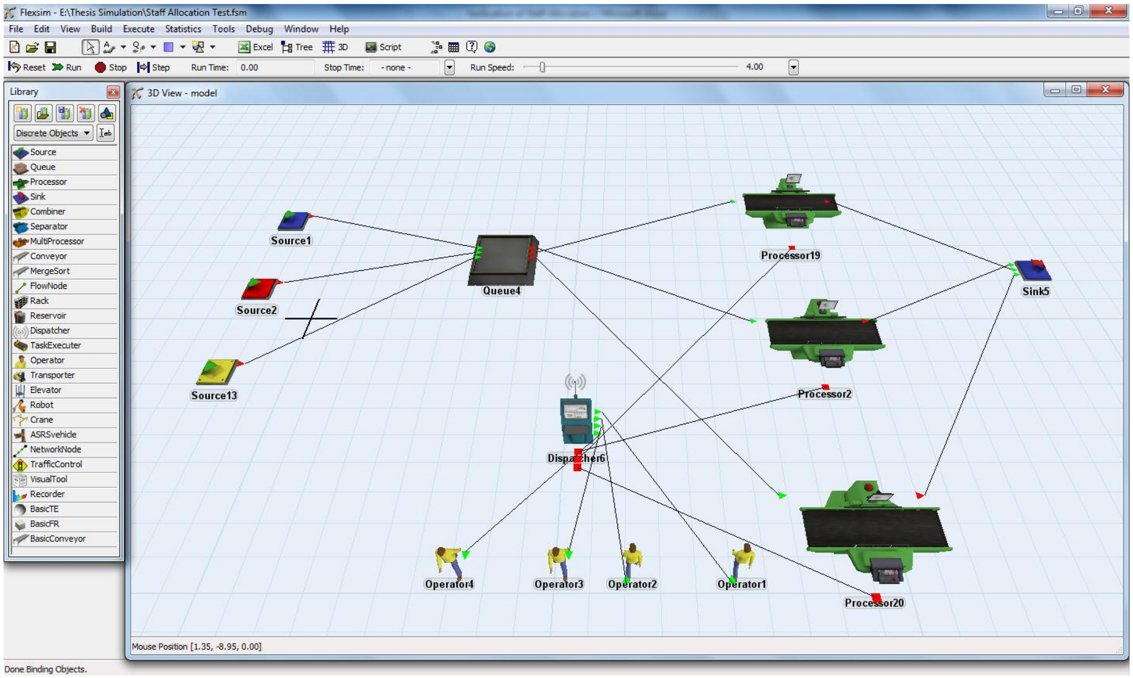


Figure C.12 Staff Allocation Test Model

Staff Allocation Flexsim Code

```
string tablename = /**/"NoProcessOps"/**/;
/** \nRow: */
int row = /**/getitemtype(item)/**/;
/** \nColumn: */
int col = /**/1/**/;

setvarnum(current, "nrofprocessoperators", gettablenum(tablename,row,col));
//Set the number of process operators variable

return value;
```

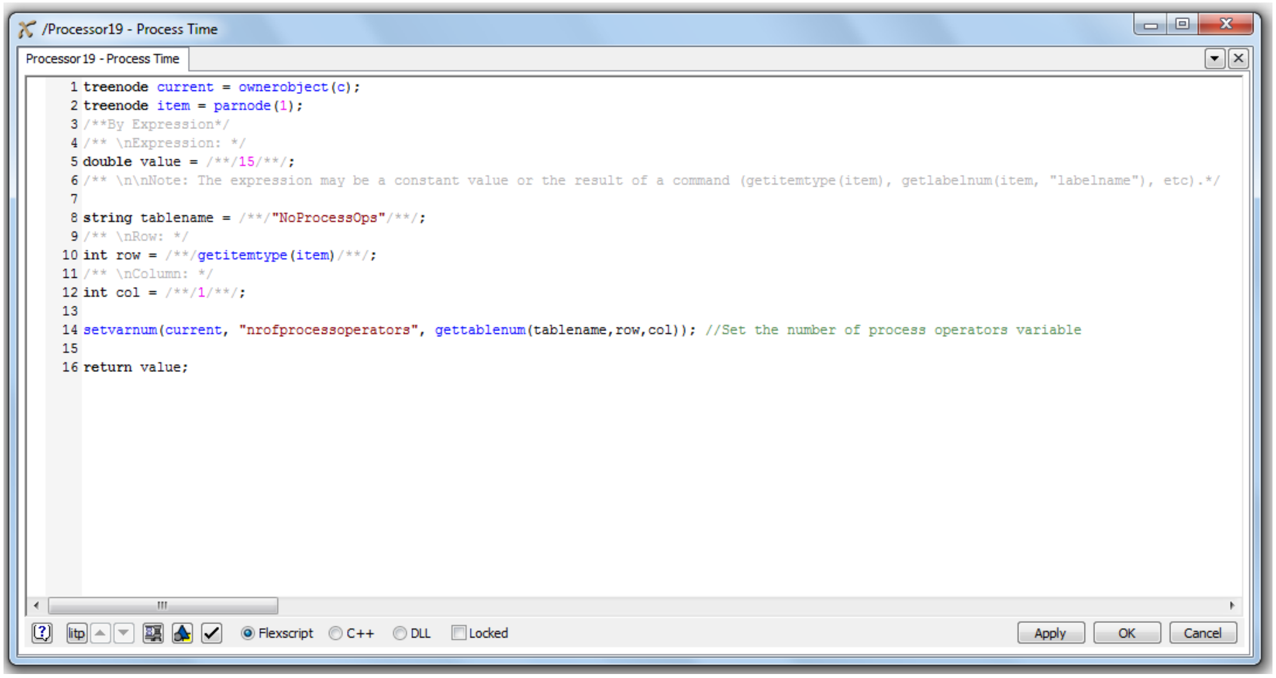


Figure C.13 Staff Allocation Code

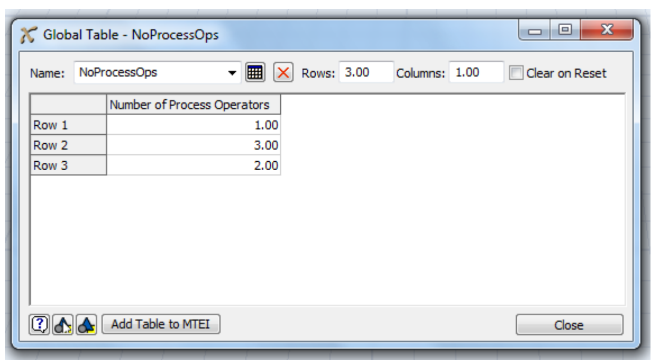


Figure C.14 Global Table for Assigning Staff

Delay Queue FlexSim Code

- Triggers On Exit from the Queue

```
treenode item = parnode(1);
treenode current = ownerobject(c);
int rownumber = parval(2);  //row number of the schedule/sequence table

{ //************* PickOption Start *************\\
```

```
/**Create and Initialize Label*/
/** \nObject: */
treenode involved = /**/item/**/;
/** \nLabel: */
string labelname = /**/"release_time"/**/;
/** \nValue: */
double newvalue = /**/time()+4/**/;  //current time + wait time (in hours)
/**\n\n*/
addlabel(involved,labelname);
setlabelnum(involved, labelname,  newvalue);

} //******* PickOption End *******\\


treenode item = parnode(1);
treenode current = ownerobject(c);
int port = parval(2);

/** pd(getlabelnum(item, "release_time")) */
pt("Entry:");
pd(getlabelnum(item, "release_time"));
pr();
```

- Triggers On Entry In Delay Queue

```
/**Sends a delayed message to releas an item*/

treenode item = parnode(1);
treenode current = ownerobject(c);
int port = parval(2);

// Calculte when this item should be released
double rel_time=getlabelnum(item,"release_time")-time();

// If rel_time is equal or less then 0, send message direct
// Otherwise send a delayed message
if (rel_time<=0)
        senddelayedmessage(current,0,item);
else
        senddelayedmessage(current,rel_time,item);
```

- Triggers On Message In Delay Queue

```
/**Release item*/
treenode current = ownerobject(c);

// Get a reference to the sending item
treenode item=msgsendingobject();

// Release item through port 1

releaseitem(item,1);
```

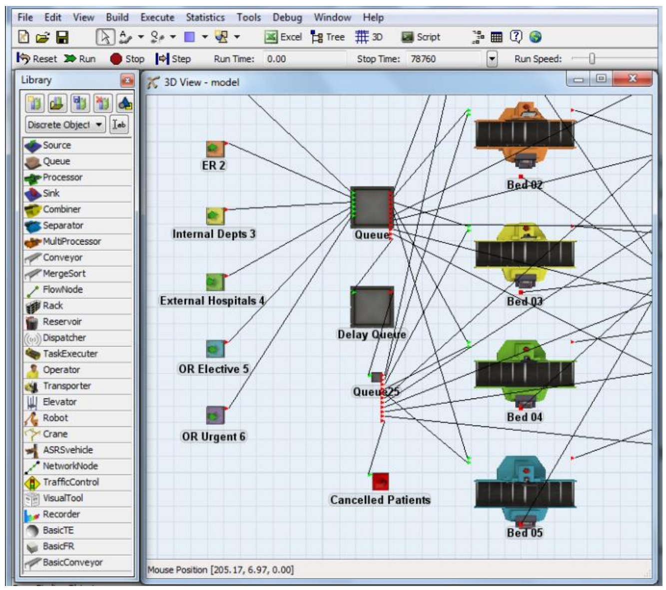


Figure C.15 Delay Queue Test Model

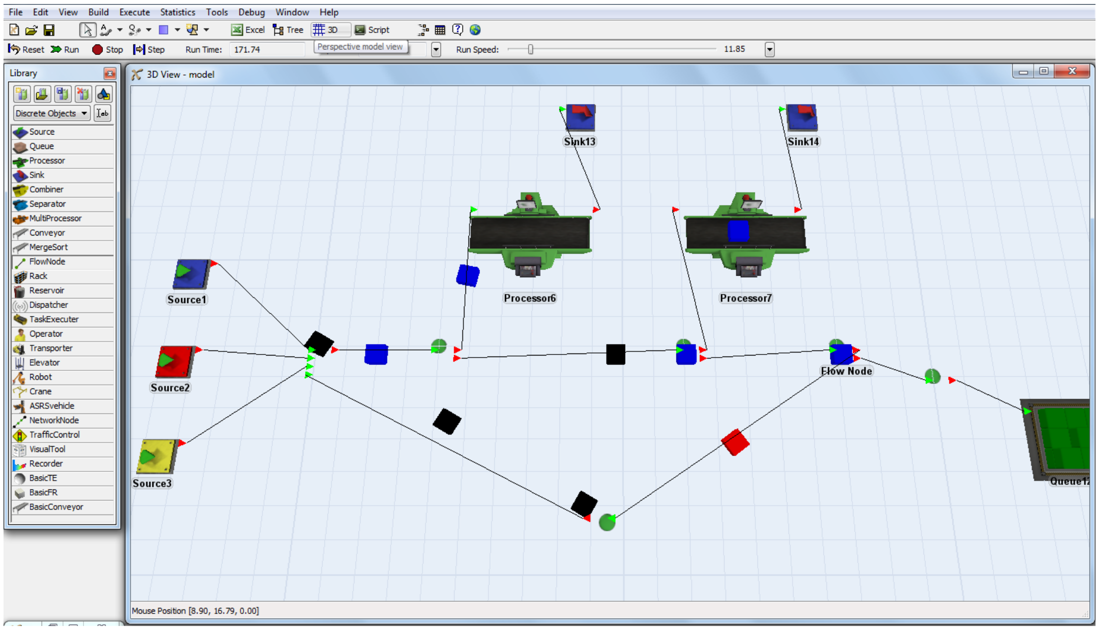


Figure C.16 Patient Delay Loop

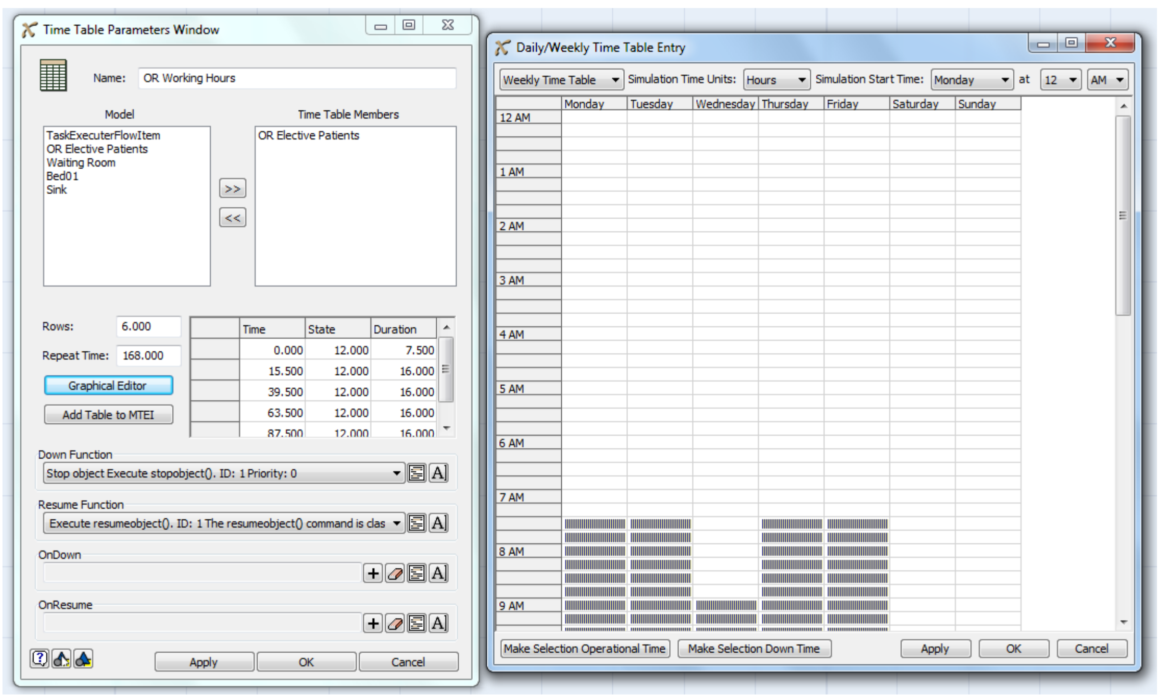


Figure C.17 OR Working Hours Time Table