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Abstract

This thesis describes the use of operational research techniques to analyze the wait list for the division of general surgery at the Capital District Health Authority (CDHA) in Halifax, Nova Scotia, Canada. A comprehensive simulation model was developed to facilitate capacity planning decisions and to analyze the performance of the division.

At the time of the study the wait list for elective general surgery patients was observed to be growing by approximately 13.2 days per year with no concrete plan to address it. The analysis examined the consequences of redistributing beds between sites, assigning operating room time by surgeon demand, and achieving standard patient lengths of stay, while contrasting them to current and additional resource options. From the results, multiple independent and combined options for stabilizing and decreasing waits for elective procedures were proposed.

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1 Introduction

Studies have shown that the demand for health care service exceeding the supply of health care service is an issue faced by every industrialized nation (Veatch, 1976). “It is patently obvious that available monies will never be enough to meet all demands for health care, and that rationalization of resource allocation is necessary to obtain the best outcomes possible with that money” (Gross, 2004). Methods of rationing must therefore be implemented to maintain a sustainable health care system. “In Canada, as in many countries, the existence of a cash-limited, publicly funded health care system implies that queue-based rationing of services is a necessity” (Blake et al., 2004). In Canada access to health care services is not distributed on ability to pay and thus, is not rationed through price mechanisms, but rather by time. In Canada, citizens can expect to wait; those who feel that the inconvenience of waiting is greater than the potential gain for service will remove themselves from the queue accordingly.

It is thought that time based queue rationing is more equitable than market-driven rationing methods because time is more equally distributed than money. Problems arise with this logic as a strict first-come first-serve queue policy ignores the relative urgencies of a patient’s ailment. To combat the resulting absurd resource allocations, patients are often given priorities. Blake et al. (2004) summarize the problems associated with prioritization: “since individuals with greater wealth are able to lobby or exert influence, expert prioritization is known to exhibit inegalitarian tendencies. Despite these shortfalls, few alternatives to expert prioritization are available or practical in publicly funded health care systems.” Pitt et al. (2003) addressed preferential treatment as an ethical issue and recommends that “decision makers at all levels should deal with these ethical considerations as systematically and rigorously as they would management, political and legal considerations.”

“Canadians believe that access to essential health care services should be fair, and based on need and urgency” (HCFS, 2004). If we trust wait lists as an instrument to ration health care, we must ensure that the time a patient waits achieves this, without jeopardizing the benefit of the procedure or causing undue stress and anxiety on the patient. Achieving such a delicate balance requires proper resource allocation and sound capacity planning.

Efforts in wait list management in Canada have largely focused on documenting and standardizing the measurement of patient waits and surgeon prioritization techniques. Somewhat less effort has been spent quantifying and projecting expected patient waits through analytical decision support models.

2 Problem Statement

2.1 National Scene

There is a general consensus among Canadian politicians that wait times for health care services are too long and that now is the time to reverse this trend. The mechanics of the current policy to address wait times include three main players. The first, acting in part as the catalyst and policy designers, are the First Ministers of Canada. The others are the Federal government, which provides funding for such changes, and the district and provincial agencies, which lobby for funding and perform analysis to determine proper allocation of funds.

On September 16, 2004, the First Ministers' Health Care Accord released a 10-year plan aimed at strengthening health care in Canada. Although many aspects of health care improvement were discussed, "the First Ministers agreed that access to timely care across Canada is our biggest concern and a national priority" (First Ministers, 2004). They committed to enhancing access by improving the management of wait times and to measurably reduce the wait times in cases where they are longer than medically acceptable.

In accordance with the First Ministers' recommendations the Federal Government has committed to wait time reductions by implementing a national waiting times reduction strategy. The Federal government accepted the framework developed by the First Ministers and committed "an additional 41 billion dollars for the next ten years, including a 4.5 billion dollar Wait Time Reduction Fund that will be used for jurisdictional priorities" (First Ministers, 2004). In addition, the Federal government has committed to making changes in the following areas which should positively correlate with wait time reductions:

- Licensing of foreign-trained physicians and nurses
- Increasing availability of primary health care and home care support
- Implementing better electronic health records

- Investing in demand management (e.g. disease prevention) to reduce pressure on the health care system

In the 2005 Federal budget an additional $15 million was set aside as direct funding for wait time initiatives (Dosanjh, 2005).

Groups that receive these funds, and build cases for additional funding, can be found throughout Canada. On the east coast, the Orthopaedic Surgery Wait List Pilot Project in Nova Scotia determined that an additional 25 beds and an extra Operating Room (OR) was the minimum amount required to stop the wait time growth for Orthopaedic services (Dunbar et. al., 2004). Ontario's Cardiac Care Network is widely cited for best practice, and collects and analyzes various data related to their services (Dosanjh, 2004). Perhaps the most widely known project is the Western Canadian Waiting List Project (WCWL), which "has a mission to improve the fairness of the health care system so that Canadians' access to appropriate and effective medical services is prioritized on the basis of need and potential to benefit" (WCWL, 2006). The Health Quality Council, an independent agency, centred in Saskatoon, is a Canadian leader in measuring, reporting, and promoting quality health care (HQC, 2006). In Alberta, a $20 million pilot project aimed at reducing wait times by reorganizing its practices and eliminating disconnects between services has reduced wait times for hip and knee patients below the national standard (CBC, 2005). These are only a few of the various groups in Canada that are committed to projects funded by the National Waiting Times Strategy.

Legal concerns regarding who could be found negligent as a result of a patient's loss of function due to extended waiting times puts further pressure on the system. On June 9th, 2005 two plaintiffs successfully argued that a year long wait for surgery infringed on the charter's guarantee of the right to life, liberty, and security. As a result a decision by the Supreme Court of Canada (Chaoulli v. Quebec) overturned a Quebec law that prevented people from purchasing private health insurance to cover procedures offered by the public system (CBC, 2006).

Duty of care is the main contributing factor to negligence that relates to waiting times. With regards to the moment a physician's duty of care should begin, Pitt (2003) concludes that “the courts may decide that a duty of care exists when you become aware of a patient’s problem or when a patient is put on a waiting list and you know about it.” Hospitals also share this risk, and therefore “have a duty to provide adequate staff, adequate medical supplies and maintain equipment” (Pitt el al., 2003).

Developing policies to address wait times is becoming increasingly important as pressure from the public and legal authorities for improved access continuous to mount. The Federal government, together with the First Ministers, is committed to providing funding to improve access but is continuously battling pressures for more involvement of the private health care sector. As a result, there is a growing importance and need for regional level projects to determine ways to improve the efficiency of resource uses and translate that into shorter wait times.

2.2 Capital District Health Authority

The Capital District Health Authority is the largest integrated health district in Atlantic Canada. It provides both core health services to 395,000 Nova Scotia residents and tertiary and quaternary acute care services to all residents of Atlantic Canada (CDHA, 2004). A map of the region is available in Figure 1. As do most health authorities, Capital Health must deal with accessibility issues and strained resources.

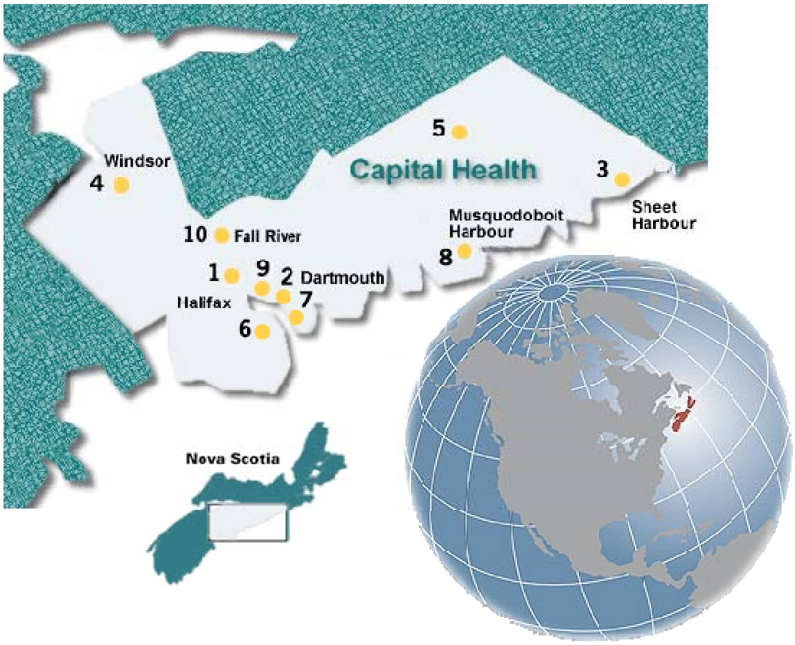


Figure 1: Capital Health District

In recent years, the waiting list in the Division of Orthopaedics in the department of surgery has been analyzed. This study resulted in a centralized database to track all requests for surgery, a visual analog scale to assist patient prioritization, and a simulation model to analyze the existing system and suggest alternative resource allocation (Blake et. al., 2004). This project resulted in a significant increase in resources for the division. This success was partially attributed to the simulation model's ability to quantify the bottlenecks and contrast the wait times of additional resources to the wait time of current resources.

The surgery division to be studied in this thesis is the General Surgery Division, within the Queen Elizabeth II Health Science Centre (QEII). The division consists of fifteen full time surgeons all with adjunct appointments at the Dalhousie University medical school in the Department of Surgery of the Faculty of Medicine. The QEII is a teaching hospital and has approximately thirty postgraduate general surgery residents (Dalgensurg, 2006). The division's surgeons currently provide surgical care for the local Halifax community and surrounding areas and tertiary care to a catchment population of 970,000 from Nova

Scotia, Prince Edward Island, and New Brunswick. Analysis have shown that the division has an aggregate capacity of approximately 4400 surgeries per year and, depending on patient urgency and responsible physician, elective waits range from one to 25 weeks.

In 2004, the division's surgeons believed that wait times had reached a critical point. To combat this growing problem, the division re-examined their booking process to ensure that the highest priority patients were seen as soon as possible. They also imposed a moratorium on less critical procedures to ensure patients with the highest need were seen as quickly as possible. Although this endeavour should have had an immediate, positive impact, it did little to curtail the long-term problem of timely access. Despite these efforts surgery cancellations continued and a rise in the wait lists for common malignancies such as breast and colorectal cancers was observed. In addition, recent data indicated that less than 30% of patients received treatment within the time criteria set forth by the Canadian Society of Oncology Specialties and the Canadian Society of Surgical Oncology.

Although the division had developed some sample patient flows, they were not able to examine the entire system. The division, accordingly, wanted a systematic review of the flow of patients through their ORs. The objectives of the review were to determine how to maximize throughput with current resources, determine the effects of process bottlenecks, and develop a plan to achieve the wait time standards set forth by professional health care societies. All factors hindering the flow of patients were to be studied. The division members had opinions on possible causes and possible cures, but were unable to substantiate their hypotheses. Accordingly, an instrument with which strategies could be tested and analyzed before implementation was required.

Addressing the wait times issue supports the guiding principles of the provincial Wait Time Advisory Committee. Generally stated, they ensure that current resources must be used efficiently and that the impact of any additional funds be quantified before new resources are provided (NSDH, 2006). The efficiency of the general surgery system will be examined to determine where flow bottlenecks exist. With the process bottlenecks as the focal point, this analysis will project the effect that system alterations, including policy changes and additional resources, will have on the wait for elective surgery.

3 Literature Review

Wait lists are an inescapable phenomenon associated with publicly funded health care and are often the metric used to describe the overall performance of the health care system. Managing wait lists in a way that rations services without eroding a patient's confidence in the system can be a challenging and tenuous task. Gibson et al. (2005) developed a framework to address wait list issues that ensures evidence, economics and ethics are all considered.

Vissers (2001) argues that given that a shortage of resources will always exist there is a need to determine acceptable wait times and to manage wait lists in such a way as to meet those targets. The Wait Time Alliance, a working group of the Canadian Medical Association, has identified evidence-based benchmarks for medically acceptable wait times in some of the major problem areas within Canada.

All queuing systems, whether real or theoretical, require queue policies to maintain their order. The goal of queue policies in health care is to balance equity and acuity, and as such many doctors prioritize patients based on urgency and arrival. Patients arriving first will receive service ahead of those who arrive after, except in cases where the late arriving patient shows more severe symptoms. The Western Canada Waiting List project defined a fair queue as one that prioritizes patients on the basis of need and potential to benefit (WCWL, 2001). Other social factors such as gender, martial status, education, or non-medical conditions should have no bearing on a patient's wait list position.

Prioritization of queues allows patients fair and transparent access to surgical care (Warnock, 2004). Duplicating the manner in which health care providers' prioritize queues can be a challenging process as procedures may vary from surgeon to surgeon. Due to their simplicity and efficiency, Visual Analog Scales (VAS) have been used to measure a surgeon's perception of patient urgency (Dunbar et al., 2004). Other studies have combined VAS, statistical analysis and simulated patient encounters to uncover surgeon driven queue policies (Taylor et al., 2002). The WCWL project has developed multiple tools to assess patient urgency including a VAS and a point-based surgeon questionnaire (WCWL, 2001). Although the public welcomed this method, its complexity limited its applicability (Dunbar et al., 2004).

Combining queues and switching from multiple-server multiple-queue systems to a single queue with multiple servers system is well known to improve the efficiency of a system. (Winston, 1993) In 1974 the College of Health, based on this queueing theory principle, recommended general practitioners 'shop around' for health services in order to find the shortest waiting list for their patients. Worthington (1987) tested this recommendation analytically and argued that this was not particularly well advised as the outcome of combining two differently managed queues will be unfair to patients and undermine what good management practices already exist.

Some argue that the addition of resources alone will not decrease wait time. Studies have shown that as resources are added, general practitioners will increase their referrals (Hindle, 1972; Cox, 1977). This phenomenon is often referred to as feedback or latent demand. Worthington (1987) performed a queueing analysis to test this theory and concluded that adding resources will indeed improve throughput but will do little to solve the wait list problem. Martin and Smith (1999) however, also studied the correlation between arrival rates and resource levels and concluded that increased resources may reduce waiting time without greatly stimulating utilization.

Other more focused studies examined wait lists for particular services with an emphasis on the number of people waiting and how waits vary based on severity of symptoms. Olson (2002) used actual patient data from an Edmonton hospital to perform statistical analysis to quantify the length of time a selected general surgery patient waits for treatment. He determined that non-cancer-related patients waited significantly longer for surgery than those patients who required procedures for cancer. Bailey (1954) applied statistical theory of queues to calculate the number of beds in a hospital, the number and length of clinical sessions and the appointment system to be adopted for each clinic session. Another method to address large wait lists is to add additional resources for a temporary period.

Within the scope of clinical practice, there are a number of active wait list initiatives in Canada and throughout the world. The UK, Norway, New Zealand and Sweden all have active wait list management programs. Within Canada, programs exist in British Columbia, Alberta (Romanchuk et al., 2002), Manitoba (Bellan and Mathen, 2001), Ontario (Rafferty, 2001), Saskatchewan (Glynn, 2002), and Nova Scotia. In general, these programs do not focus on the operational aspects of wait lists. Instead, the primary objective of these initiatives is to standardize the definition and collection of wait time data, provide prospective and longitudinal assessment of patient outcomes, and create a standardized mechanism for rationalizing patient queues.

3.1 Health Care Modelling

Models for resource planning described in the literature can be broadly categorized as analytical or simulation based. Since the complex nature of health care often makes analytical models intractable, researchers must decide between simple, but tractable models, or opt for complex, but realistic models. Harper (2002) argues that reducing the complexity of a problem to make solution methods tractable is less than ideal. Not surprisingly, the literature recommends simulations over analytical and deterministic approaches (Lowery, 1998). Everett (2002) notes that given the variety of objective functions that may be appropriate to the various stakeholders within a health care environment, 'optimality' is an ill-defined and unobtainable objective.

Simulation models have been used extensively to study health care operations. Lagergren (1998) notes that simulation models make it possible to study systems that do not exist, to predict complicated consequences of actions and developments and to do experiments that are impossible or too costly to perform in reality. Many of the simulation models in the literature can be defined as capacity planning models where the goal of the study is to match hospital resources to demand. Generalized capacity planning models often assume the current resources are achieving maximum capacity.

Many papers in the literature outline the appropriate use of simulation and present structured frameworks to help increase a project's success. Lowery (1998) argues for an approach in which simple models, without great detail, are developed quickly to engage decision makers. Lowery suggests that accurate documentation of assumptions and extensive sensitivity analysis allows modellers to increase success rates where quick and reasonably reliable results are required. For larger, more robust models, Harper (2002) suggests a framework that focuses on the importance of the creation of statistically and clinically meaningful patient groups, mathematically correct models, and outputs which provide the necessary information for end-users. De Angelis, et al. (2003) suggest determining the impact of each variable on the model's objective function and optimizing an extrapolated objective function. Everett (2002) argues that the function of a model is not simply to provide information to managers but rather to engage them in the development process so as to allow them to use the model independently as a decision support tool.

Even a cursory search of the literature reveals a plethora of models for resource capacity planning in health care. Preater (2002) divides the major areas for the application of simulation into outpatient clinics (including patient and staff scheduling systems), inpatient facilities, emergency services, and clinical and systems issues. Both Preater (2002) and Worthington (1987, 1991) provide rich bibliographic resources for readers interested in wait list management models.

Harper and Shahani (2002) describe a general surgery simulation designed to alter queue policies and day-to-day scheduling. Results indicate that a potential increase in throughput was possible without additional resources. Harper (2002) outlines a generic modelling approach including a system for extracting data and determining meaningful patient classifications (Classification and Regression Tree), a mechanism for using a simplex algorithm to estimate data parameters, and a generic tool for building hospital simulations. The framework is illustrated by cases drawn from a set of local hospitals. Harper and Gamlin (2003) show how visual interactive simulation can be used within a structured environment to address wait list issues and build acceptance of results amongst managers.

A number of simulation models have been designed to manage the wait list for critical resources, including organs for transplant. Ratcliffe et al. (2001) describe the use of simulation to model policies for allocating cadaveric livers to patients awaiting transplants. Wujciak and Oplez (1993) present a study aimed at analyzing policy options for allocating cadaveric kidneys. Davies and Davies (1987) develop a custom simulation model to evaluate treatment regimens and transplant protocols for patients with renal disease.

Simulation has been used extensively to model operations within surgical suites to improve efficiency and reduce wait times. Blake et al. (1991) describe a model simulating the flow of surgical patients that was used to test the impact of a master surgical schedule on inpatient nursing workload. Bowers and Mould (2004) describe a simulation model to test the potential for increasing OR utilization by scheduling deferrable elective patients into planned orthopaedics blocks. Dexter and Traub (2002) use a simulation methodology to suggest next case scheduling policies in theatres functioning in parallel with flexible end times.

Simulation has also been applied frequently in publicly financed health care systems to analyze wait lists for elective procedures. Everett (2002) develops a "what-if" simulation as a decision support tool to allow managers to experiment with different resources levels to determine their impact before implementation. Vasilakis and El-Darzi (2001) show that a lack of social services was to blame for a recurring winter bed crisis in a British hospital.

MacAulay and Blake (2002) use simulation to suggest reallocation of inpatient beds in a paediatrics hospital. Bagust et al. (1999) determined a relationship between average bed occupancy levels and expected bed shortage crises in a hypothetical emergency department. Vissers et al. (2001) describe a framework for examining wait list issues and provide an example by modelling regional demand for cataract surgery. Tuft and Gallivan (2001) describe a pilot application to determine the appropriateness of simulation for analysing ophthalmology surgery in the UK. They conclude that simulation is practical, but that detailed, accurate data are necessary to support modelling efforts. Davies (1994) develops a custom simulation model that identified bed shortages as the cause of a bottleneck in the treatment of cardiology patients at a London hospital.

Thus, we conclude that while simulation is a mature technology, with numerous applications in health care, its application to wait list management in the Canadian context is somewhat novel. Given the emphasis on wait list reduction in Canada and the preponderance of resources dedicated to clinical aspects of wait list management, it is critical that an operational approach to wait list management be developed. In addition, developing generalized simulations without the ability to test the organization of services of the mechanisms of its delivery is an incomplete method, as it is essential to ensure effective use of current resources before adding more.

The process of developing pertinent models for the Canadian system has been described as both time consuming and expensive. The time required to obtain, manage, analyze, and interpret sufficient data for such a model can be overwhelming and often prevents theoretical models from maturing into application. In addition the skill set required to design and build these simulation is often specialized and expensive (Blake, 2005). There is a need, at the local and national levels, to build and maintain a registry of data sources. From this data robust self-building models need to be developed with the ability address multiple objectives, yet portable enough to be applied in multiple settings.

4 Methodology

Due to the structure of health care funding, organization, and delivery in Canada, patients generally spend time in queues before, or between, services. Queues are caused by two factors, an imbalance between supply and demand and/or randomness in customer arrivals and customer throughput. Traditionally queueing theory has been used to study queues. But due to complexity, high variation, and the possibility of an imbalance between supply and demand, queueing theory it is not ideal in most health care settings. In place of queueing theory many researchers turn to computer simulation, which will model the system with greater accuracy and can more easily allow for variations in the processes and data. In the case of general surgery, the process variance between the division's surgeons and the belief that a resources shortage exists makes queuing theory infeasible, and modelling with simulation the logical alternative.

4.1 Simulation Requirements

To meet the objectives in the problem statement, the simulation must addresses model inadequacies exposed in the literature review. The model must be accurate from a patient flow and data analysis perspective, reproducible (allow examination of multiple scenarios), and relative (ensure a useable model that connects research and operational interests). Developing a model within these constraints is necessary for comprehensive wait list management analysis.

Consideration was given to the lessons learned from the Orthopaedic Wait List Management Pilot Project (OWLMPP) competed in the same department. The OWLMPP was successful in lobbying the provincial Department of Health for additional funding based on "the model's ability to quantify the bottleneck and clearly show the impact of both doing nothing and also adding additional resources" (Blake et al., 2005). Part of the OWLMPPs success was attributed to a broad multi-disciplinary research team consisting of "good technical, clinical and administrative representation. This afforded the team credibility amongst the many different decision making groups common in a health care environment" (Blake et al., 2005). For the general surgery project presented herein, a similar methodological approach was taken but with an emphasis on developing a more comprehensive model based on a broadened dataset.

Although the OWLMPP had a strong team and achieved significant results a number of shortcomings were identified that must be addressed in future models. The absence of a complete performance analysis of the current system was identified as a deficiency. The appropriateness of adding resources without ensuring the current resources are achieving optimal throughput is a fundamental requirement of this and future CDHA wait list management initiatives.

A second obstacle not addressed by the OWLMPP was the issue of data availability and integrity. The OWLMPP dataset lacked historical records summarizing the metric of interest, patient wait times. The absence of this information caused difficulties in validating the model, making it necessary to validate individual data elements in its place. Additionally the aggregation of the dataset did not allow for theoretical distributions to be fitted to the data, forcing the model to rely exclusively on empirical distributions. It was clear that future models would require a more comprehensive dataset, which included historical wait time data.

Linking the simulation to a central database was considered an integral step in developing a flexible model. All of the model parameters, ranging from surgeon schedules, queue policies, and resource quantities, to patient attributes, were stored in a central database, accessible to the model when needed. The model is self-building in that it can accommodate the parameters set in the central database or make model modifications without user input.

Maintaining the linkages between research and operational interests was less challenging than in the past, partially due to the success of the OWLMPP. Process stakeholders within general surgery were eager to have a model developed in their area so that they too could have additional insight into the factors hindering the flow of their patents.

4.2 Design Approach

A conceptual model was designed, through discussions with division surgeons, evaluation of similar models in the literature, and by analyzing the datasets available at Capital Health. From this, a computer simulation was developed in ARENA using data drawn from the Capital Health patient databases. The model was then tested and validated in a series of processes that include quantitative analysis, factor analysis, and a qualitative review by content experts.

The simulation was developed in ARENA and designed to simulate the flow of elective, and non-elective general surgery patients through the CDHA main OR and into recovery beds. Non-elective patients included emergency patients and inpatient (wait list patients). Thus, all consumers of the resources of interest were modelled. The starting point for patients in the model is when a surgeon decides that surgery is required. The patient exit point is when the patient is discharged from a general surgery recovery bed. All patient steps between including surgery, recovery and patient transfers, are modelled. The model is designed to replicate any given patient's wait for surgery, with the objective of determining which factors affect wait. The over-arching goals are to quantify the current wait for elective surgery, evaluate the performance of the general surgery system and its operational policies, and to gain insight into how to improve patient flow.

When developing the model it was important to ensure a complete and robust representation of general surgery. A generalized model lacking the ability to evaluate operational changes was not desirable, since ensuring effective use of current resources is as important as quantifying the effects of additional funding. The division of general surgery is perhaps more complex than other surgery divisions due to multiple sites, high occurrences of non-elective patients, patients with pre-operative lengths of stay (LOS), and the dependence of other divisions on general surgery. These features and more are modelled to a fine level of detail to ensure an adaptable simulation, robust enough to perform operational performance analysis of the current process.

5 Division Description

5.1 Patient Types and Flow

Patients of the General Surgery Division can be categorized into three types, each representing a different patient flow path. The first type, called elective patients, are patients requiring elective general surgery. The flow of elective patients begins with a surgeon consult resulting from a general practitioner's referral. Should surgery be necessary, the patient will be added to the surgeon's list of elective patients; if surgery is not required, the patient will be sent home. Patients requiring surgery wait on the surgeon's list until selected for surgery by the surgeon. Based on urgency and order of arrival, the surgeon determines the preference for surgery and selects the next patient. Once selected, patients come to the hospital, receive surgery and are admitted to a bed (should one be required). Patients who are not admitted to a bed will be discharged after surgery. Patients who were admitted remain in a bed until they are fit to be discharged home, they die, or are transferred.

All other patients who receive surgery are classified as non-elective patients. Non-elective surgery includes follow-up procedures for general surgery inpatients, urgent procedures for inpatients of other divisions, or emergency surgeries for emergency patients. These patients enter the general surgery system immediately and either go directly into surgery, or into a bed for diagnosis and a pre-operative LOS. After surgery, non-elective patients follow the same care path as elective patients.

The remaining group of patients does not enter the OR but consumes general surgery resources, and are classified as non-surgery patients. The flow of these patients is similar to that of non-elective patients. They enter the system by referral from other divisions. They differ from non-elective patients in that they are discharged from their bed without receiving surgery in the main OR. Patients are omitted from surgery for various reasons including, not being fit for surgery, substitution by a less invasive technique, or patient death. Regardless of the reasons for bypassing surgery these patients consume the same bed resources required by elective patients. A pictorial of the flow of each patient type and their originating source is shown in Figure 2.

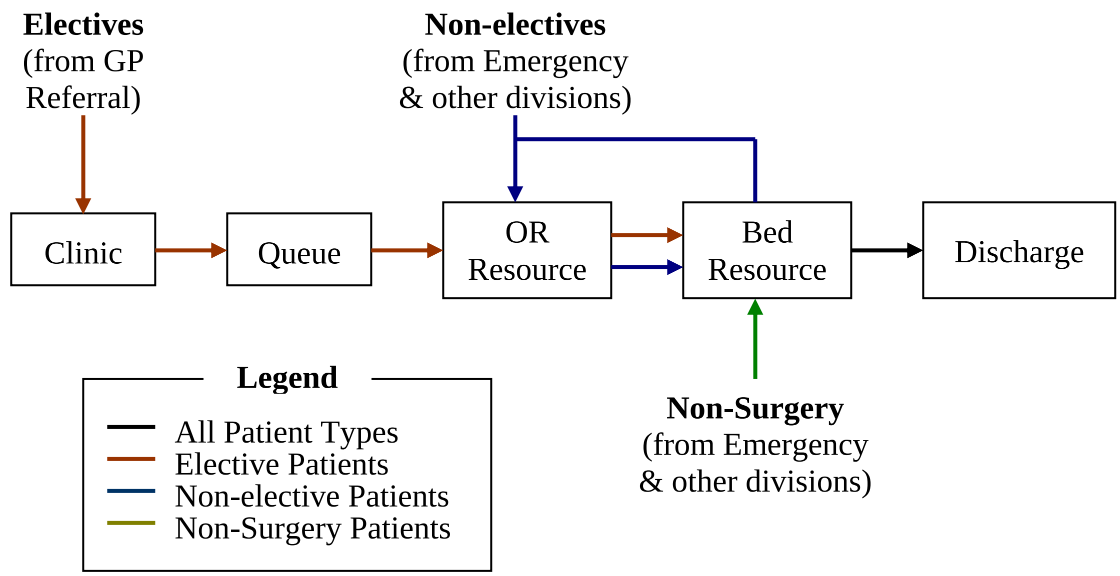


Figure 2: Patient Flow Scheme

5.2 Facilities and Resources

The division of general surgery operates at both of the QEII hospital. Since the emergency department for the QEII is located at the Halifax Infirmary (HI) site, the division is predominately dedicated to non-elective patient types at that site. In contrast the majority of elective patients receive surgery at the Victoria General (VG) site.

With an allotment of 14 dedicated beds and five OR slots of ten hours each week, the division completes approximately 900 non-elective surgeries each year at the HI site. Although the site's primary function is to manage non-elective patients, some OR time, and consequently some beds, are used for elective patients. The general rule followed in the division is to use weekday mornings for two to three short elective cases before switching priorities and completing all the non-elective cases for that day. Approximately 750 elective patients receive surgery at the HI site every year as a result of this arrangement. Finally, to ensure a sufficient number of beds are available at the HI site for new non-elective patients, all inpatients that have stayed longer than three day are transferred to the first available bed at the VG site.

At the VG site the division is allotted 14.5 OR slots of ten hours each week, solely dedicated to elective patients. All OR slots are ten hours long; there are no half or partial slots assigned. To utilize the 14.5 allotment of slots the weekly allocation of OR slots fluctuates between fourteen and fifteen slots. The division allots 42 of their 56 beds to the VG site, which services both patients receiving surgery at the VG and patients transferred from the HI site. A diagram of how each patient type flows through the division and their interaction with each site is shown in Figure 3. Approximately 2200 elective patients and 340 non-elective patients have general surgery operations at the VG site every year.

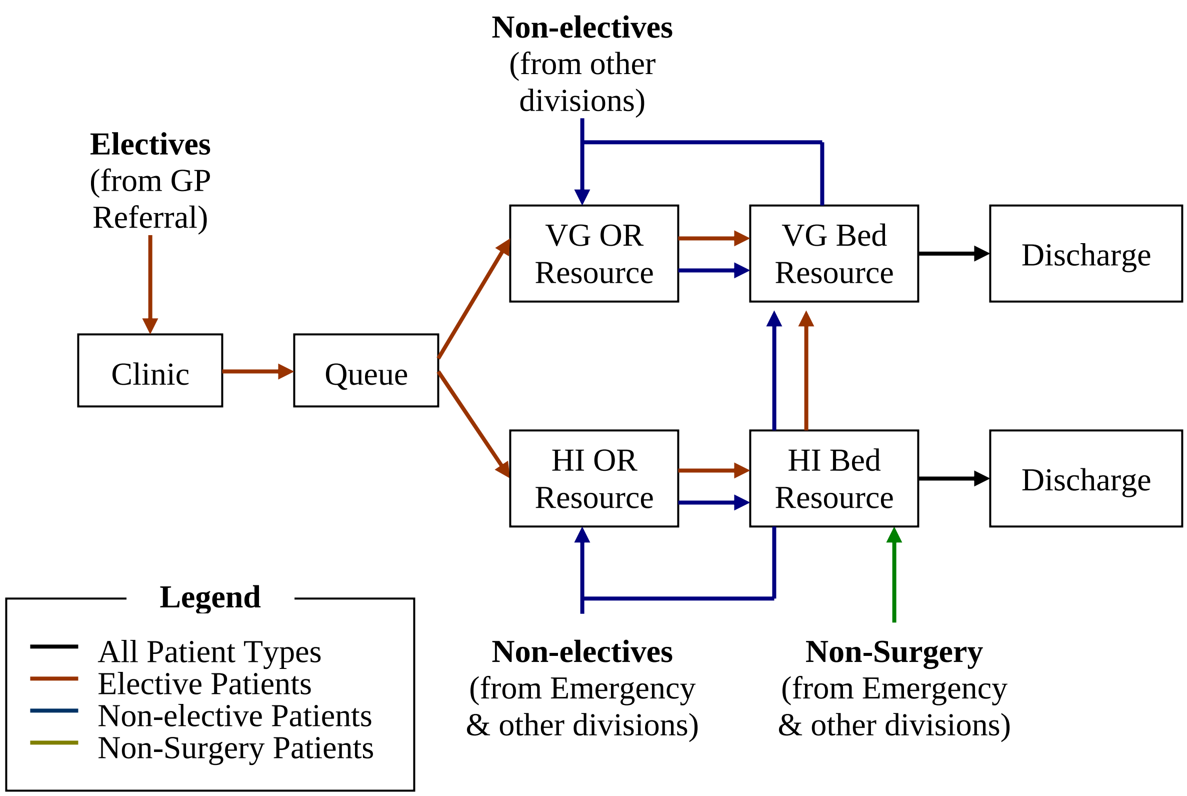


Figure 3: Site Specific Patient Flow

5.3 Diagnosis Classification

The available dataset for this project clearly defined patients by site and type. Information regarding a patient's diagnoses and consequent procedure where not however as readily available. The process of collecting and collating the data comprised in the dataset will be discussed in a later section.

Classifying patients by diagnosis or procedures in a General Surgery Division is challenging due to the variety in patient diagnoses and procedures. Over one calendar year the dataset indicates a total of 351 different procedure, 2700 different diagnoses, and 963 different intervention descriptions. To alleviate this issue, the division determined which patient diagnoses and procedures where of interest; all remaining patients were considered only in aggregate. The list and proportion of the total patient population that each procedure represents is shown in Figure 4.

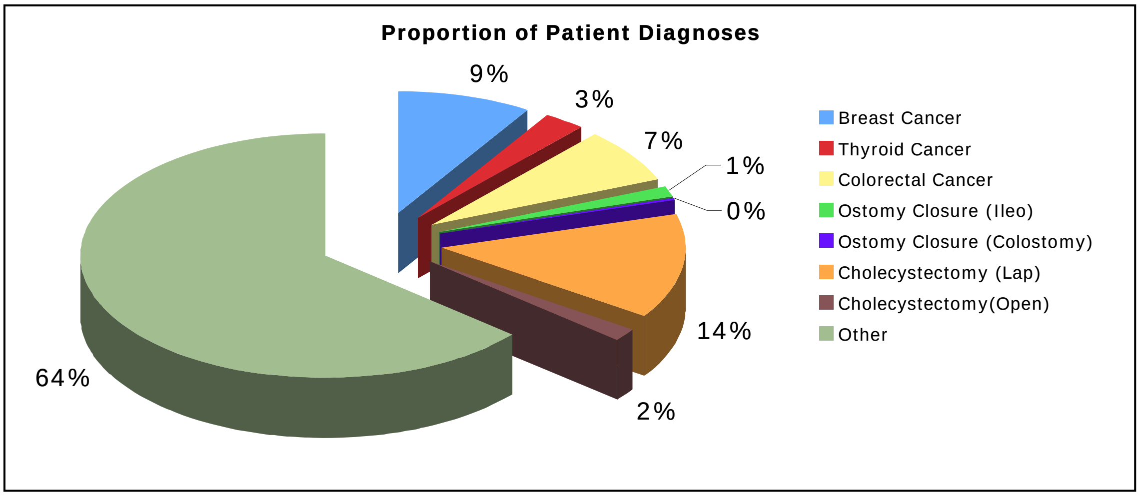


Figure 4: Proportion of Patient Diagnoses

As the categories were fairly specific and the dataset was broad, classifying patient records into each category proved to be a difficult task. Capital Health's patient management software did not specifically assign these groups to patients. The division head, as a content expert, volunteered to manually assign a category to each of the records. To make these classifications he required that the diagnosis field, the procedure field, and the intervention description field be available for each patient record. Once classified, the casemix for each surgeon and each patient type was available for modelling and future analysis.

6 Model Description

A simulation of the flow of patients through the General Surgery Division was developed in Rockwell's ARENA simulation package. The simulation was designed to evaluate the flow of elective patients and the resulting wait time. The use of resources by all patient types was included to ensure the impact of each on the wait for elective surgery was properly modelled.

6.1 Model Entities and Flow

The simulation models the three patient types: elective, non-elective, and non-surgery. Patient attributes needed for the model, such as diagnosis category, OR times, and LOS, are assigned based on historical data.

6.1.1 Elective Patient Entities

Elective patients, the patient type of greatest interest, were modelled at the greatest level of detail. The flow of elective patients begins when the surgeon decides that surgery is required. At this point the simulation assigns the patient one of the eight diagnoses introduced in the preceding section. This assignment is proportional to the surgeon's historical patient casemix as shown in Table 1. The patient's LOS is also assigned before the patient is forwarded to the surgeon's queue where the wait for surgery begins.

Table 1: Elective Casemix Per Surgeon

	Surgeon														
Category	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1			3%	19%	50%			1%			18%	1%	40%		
2		12%		4%	26%										
3		1%	7%	5%		23%	23%	1%	18%		14%	2%	1%	2%	2%
4			2%	2%		6%	2%		4%		2%				
5			1%			1%	1%		1%			1%			
6		16%	15%	8%		20%	6%	21%	4%		6%	18%	17%	36%	14%
7		1%	1%	1%			3%	2%	2%		1%	1%	1%	3%	5%
8	100%	69%	71%	62%	23%	49%	65%	75%	71%	100%	58%	77%	41%	59%	78%

Each of the surgeons manage their own queue according to their own practice and preferences. Since no standard or measurable priority setting technique existed it was not possible to precisely define how patients were selected from the queue. To alleviate this problem a priority scheme was developed based on the observed wait time in each patient diagnosis category for each surgeon. The wait times for patients of each diagnoses group were computed for each surgeon as shown in Table 2. This was used to model how each surgeon priorities each diagnosis groups. The surgeon's group with the shortest wait was given the highest priority; the group with the longest wait was given the lowest priority; all groups in-between were assigned priorities accordingly.

Table 2: Average Wait in days for Elective Surgery

	Surgeon														
Category	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1			32.0	16.3	22.4						18.8	22.0	31.5		
2		58.6		43.2	86.2						3.0				
3		27.5	18.8	48.9		44.9	33.9	44.5	35.1		41.8	83.8		40.0	
4			32.0	57.0		72.0	42.0		113.7		24.3				
5			27.7			79.5	115.0		6.0			32.0	76.0		
6		78.0	19.9	33.0		47.9	10.5	32.5	116.3			57.4	52.5	60.3	38.1
7			32.7			22.0		59.5	43.0			91.5	57.0	89.8	40.3
8	59.8	113.0	43.7	35.1	42.8	65.1	42.4	58.7	120.5	81.2	48.8	73.0	79.0	85.1	35.6

Once a patient reaches the front of the queue they receive surgery as soon as all the necessary resources are available. Patients with a LOS of greater than 0 will become inpatients after surgery and thus require a bed and OR time before they may exit the queue. Patients with a LOS of 0 are outpatients and only require available OR time to exit the queue. Elective patients may receive surgery at either site. Thus, patients are sent to which ever site their surgeon is assigned to on their day of surgery.

Once removed from the queue, the OR time for surgery is immediately assigned to the patient. The patient maintains control of the surgeon and the OR for the total OR time and setup time. Once surgery is complete, the model checks the state of the beds and the amount of OR time the surgeon has remaining. If there are no beds available and the surgeon has time to complete another case the model reshuffles the queue to ensure the next patient will be an outpatient. Should no beds be available at the start of the day the model will also ensure that the surgeon starts with an elective outpatient, if one is available.

After surgery, the surgeon and the OR resource are released and made available for the next patient. Outpatients exit the simulation without any delay. Inpatients maintain control of their bed resources for their assigned LOS. Inpatients admitted to the VG site will occupy a VG bed for as many days as their assigned LOS. Inpatients at the HI site however, will be considered for transfer to the VG site after their third night in the hospital. This is modelled by removing all HI patients with a LOS of greater than three days from the normal exit path. These patients will occupy a HI bed for three days. On the morning of the fourth day, before surgeries begin at the VG site, they are transferred. If no VG beds are available they will remain at the HI site for another day. The following morning, if the patient's LOS has not expired, the process is repeated again. Figure 5 shows the flow of elective patients in the model.

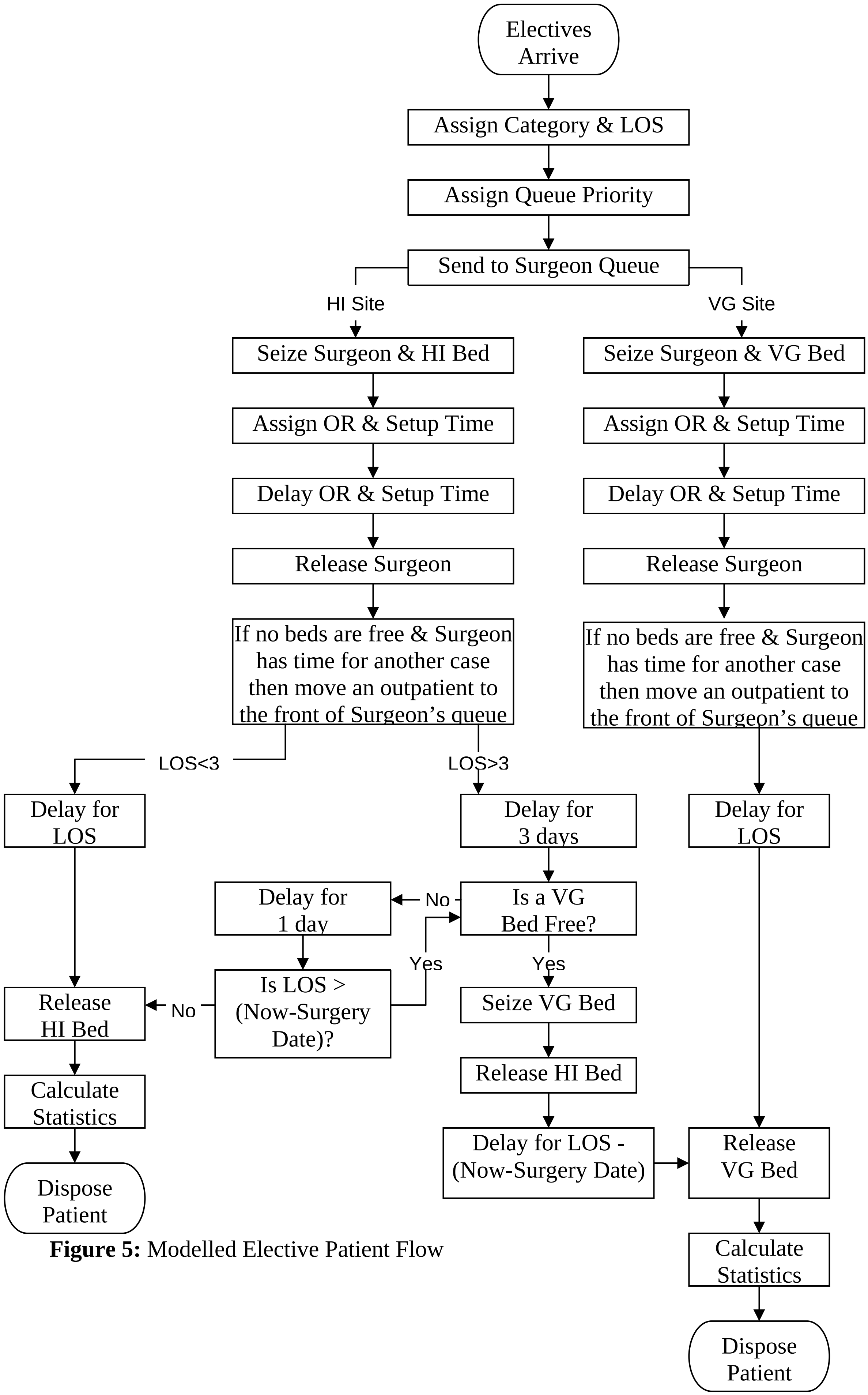


Figure 5: Modelled Elective Patient Flow

Although the LOS is assigned as an integer number of days, all patients are discharged at 06:30 before new elective cases begin for that day. This ensures that surgery cancellations do not occur due to a bed shortage one minute only to have a patient discharged the next. A revised LOS value, which expires at 06:30, is calculated when a patient exits surgery. The new LOS maintains the same number of midnights in the hospital but ensures the patient is discharged by 06:30. The formula used to calculate this is shown below in Equation 1.

Equation 1: Revised LOS

$$RevisedLOS = (LOS*24)-(ORExitTime - Int(ORExitTime / 24) * 24) + 6.5$$

where:

LOS is in days
RevisedLOS is in hours

6.1.2 Non-electives (HI site)

The division's primary responsibility at the HI site is to provide general surgery services to the emergency department and to patients transferred from other divisions. Non-elective patients are modelled when they are transferred to the General Surgery Division. They are immediately assigned one of the eight diagnoses proportional to the historical casemix for non-elective patients, as shown in Table 3. Based on distributions built from historical data and specific to the assigned diagnosis, they are given an OR time, a preoperative LOS and a postoperative LOS.

Table 3: Non-elective Patient Casemix

		Casemix
Breast Cancer	1	1.1%
Thyroid Cancer	2	0.1%
Colorectal Cancer	3	4.7%
Ostomy Closure (Ileostomy)	4	0.3%
Ostomy Closure (Colostomy)	5	0.0%
Cholecystectomy (Laparoscopic)	6	15.9%
Cholecystectomy(Open)	7	3.6%
Other	8	74.3%

After all patient attributes are assigned; non-elective patients at the HI site immediately seize the first available bed for their preoperative LOS. Upon completion of their pre-operative LOS they maintain control of their bed resource and seize the first available surgeon. This ensures patients do not lose their bed when they are undergoing surgery. Similar to the elective patients, non-elective patients need a surgeon with available OR time to exit the queue. Non-elective patients, however, are not assigned specific surgeons and may receive surgery from any surgeon assigned to the HI site.

Non-elective patients compete with elective patients for OR time at the HI site. Surgeons generally spend the first 60% of their day at the HI site performing elective surgeries. Surgeons finish their scheduled elective cases on average at 13:30 and begin selecting patients from the non-elective queue. (A surgeon specific breakdown of the exact timing of this switch is shown in Figure 6.) Surgeons then complete all of the day's non-elective patients before stopping. To model this, elective patients are given a higher priority for surgery but require an additional resource to enter the OR. This additional resource acts as an elective patient door, which closes to ensure the last patient exits at the average time shown in Figure 6. The process used to select the time to close the door is discussed in the validation section. As shown in the figure not all surgeons are assigned OR time at the HI site; surgeons one and ten only do surgeries at the VG site.

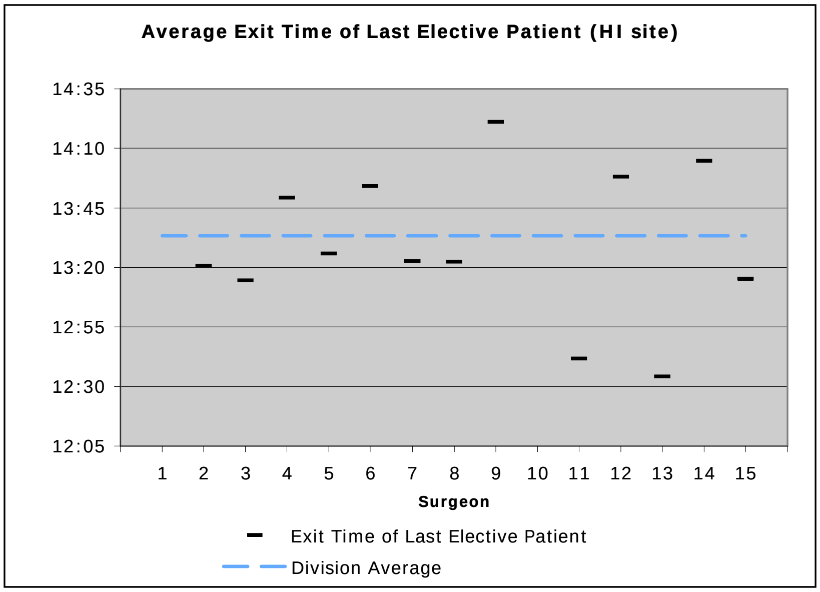


Figure 6: Average Exit Time of Last Elective Patient (HI Site)

Once non-elective patients are selected for surgery their post surgery flow is identical to elective patients that receive surgery at the HI site.

6.1.3 Non-electives (VG Site)

Non-elective patients at the VG site flow through the model in a similar manner to their counterparts at the HI site. The difference is that at the VG site, non-elective patients do not consume elective OR time. Upon arrival to the model, these non-elective patients are assigned a diagnosis and a LOS. They seize the first available bed and control it until the LOS has expired and then exit the model. The time these patients spend in an OR is not modelled as non-elective patients at the VG site do not consume OR time allotted to elective patients. Figure 7 shows how non-elective patients flow through the simulation.

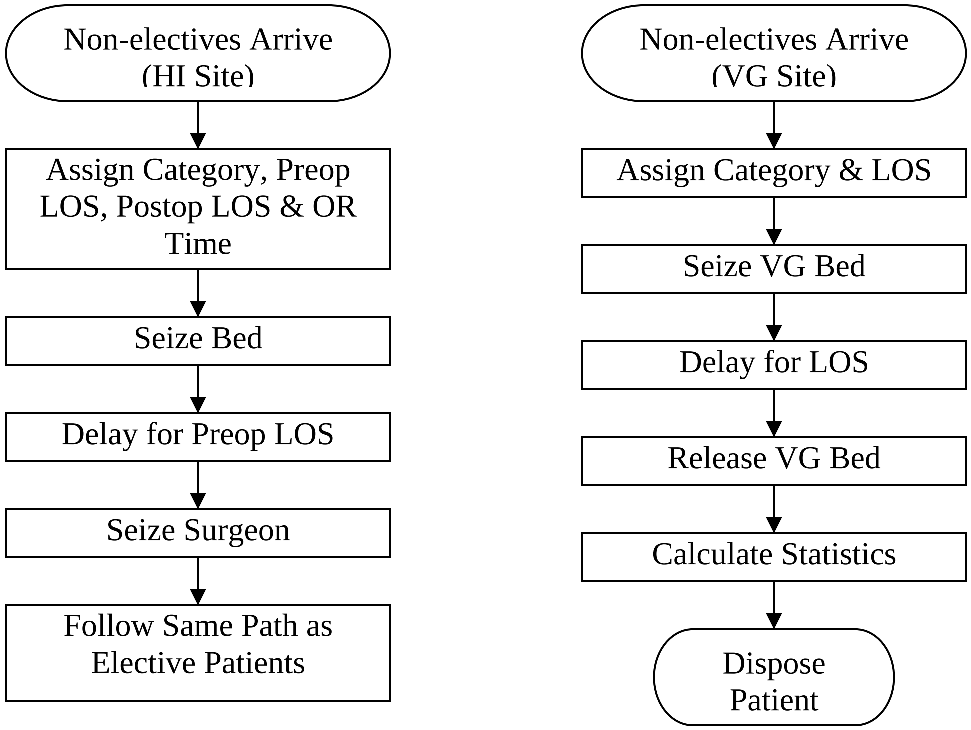


Figure 7: Modelled Non-elective Patient Flow

6.1.4 Non-surgery Patient Entities

The final patient type included in the model is the non-surgery patient type. These patients are only present at the HI site and consume only bed resources. As explained earlier, these patients do not undergo surgery but spend time in a bed prior to being discharged. They arrive in the model at a rate consistent with historical records and are immediately assigned a LOS and seize the first available bed. They remain in the bed for their LOS and then are discharged. Figure 8 shows how these patients flow through the simulation.

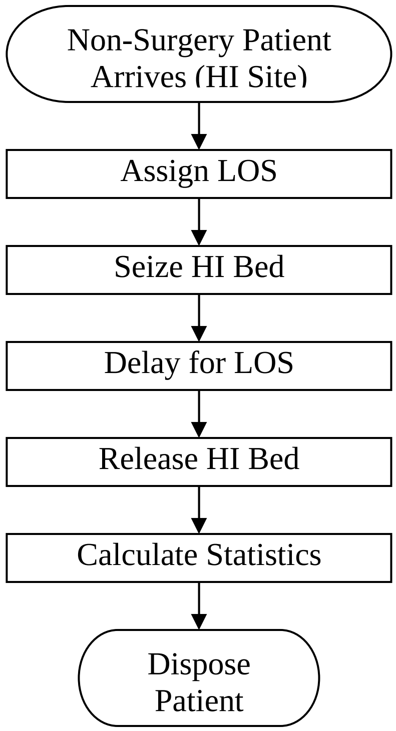


Figure 8: Modelled Non-surgery Patient Flow

6.2 Modelled Resources

The simulation models the two main resources needed by elective patients. The first resource beds, is modelled by two bed pools: one for each of the sites. The other major resource is OR time. This section will discuss how the OR time is modelled and how it is distributed amongst the surgeons.

6.2.1 Operating Rooms

The division of OR time among the 15 surgeons is done as equitably as possible given their different roles. Of the 15 surgeons, 13 rotate through weekly assignments at the HI site and subsequently forego all OR time at the VG site for that week. The remaining two surgeons only operate at the VG site. One of the fifteen surgeons splits his time between divisions and operates as a 0.75 FTE surgeon within the General Surgery Division. The surgeons and their obligations are shown below in Table 4. The assignment of the variable *VG Surgery day* is based on each surgeon's preferred operating day where possible.

Table 4: Surgeon Schedule

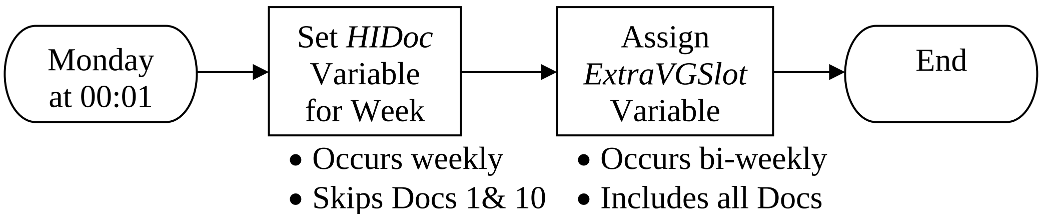
Surgeon	% FTE	VG Surgery Day (Sat =1)	HI?
1	1	6	No
2	1	6	Yes
3	1	4	Yes
4	1	6	Yes
5	1	2	Yes
6	1	4	Yes
7	1	2	Yes
8	1	4	Yes
9	1	3	Yes
10	1	3	No
11	1	5	Yes
12	1	5	Yes
13	0.75	2	Yes
14	1	3	Yes
15	1	5	Yes

6.2.1.1 Modelling Surgeon Schedules

The OR time resource was modelled by creating 15 surgeon resources, each with a specific daily schedule. Every surgeon is assigned a weekday that they use to operate at the VG site. Their capacity for that day can either be one or zero: one, meaning a regular OR slot and zero meaning they forego their OR slot. The capacity is reduced to zero only if they are assigned to the HI site for that week. The assignment of the HI surgeon is set every Monday morning and rotates through those surgeons who have committed to that site. When a surgeon is assigned to the HI site, their capacity at the HI site is set to one for each weekday.

Since one surgeon is assigned to the HI site every week, only one of the 15 surgeons foregoes a slot. This leaves 14 surgeons with slots available to operate at the VG site. As discussed earlier, the allotment of OR slots at the VG site switches from 14 to 15 weekly. The additional bi-weekly slot is modelled by assigning one of the VG site surgeons an extra slot every second week. This extra slot rotates among all 15 surgeons to ensure OR time is distributed equitably.

Finally surgeon 13 works as a 0.75 FTE meaning he is assigned only three slots for every other surgeon's four. In the model, every time surgeon 13 is assigned an OR slot there is a 25% chance that he will forego it and give it to the next available surgeon. This method does not reduce the total amount of OR time assigned to the division but does ensure surgeon 13 is assigned 25% less OR time than the other surgeons. Figure 9 shows an example schedule and how the variables are set.



Variables:
HIDoc = Doc3
ExtraVGSlot = Doc1

Sample Schedule

Surgeon	Mon	Tue	Wed	Thu	Fri
1				VG	VG
2					VG
3	HI	HI	HI	HI	HI
4					VG
5	VG				
6			VG		
7	VG				
8			VG		
9		VG			
10		VG			
11				VG	
12				VG	
13	VG				
14		VG			
15				VG	

Figure 9: Sample OR Time Schedule

7 Model Data

In a recent paper, Blake et al. (2005) state, "One of the primary concerns with many surgical wait list studies in Canada is the lack of a central data registry to track all patients requiring surgery. In the absence of such systems, researchers typically rely on survey methods to determine the volume of patients awaiting surgery. These methods are known to be unreliable, since they rely on self-reporting from physicians. Furthermore, given that a standard definition of wait time cannot usually be applied to data derived from survey methods, it is often difficult to compare wait list statistics provided by different surgeons or collected through different studies. Finally, the lack of an overall patient registry usually implies a number of counting errors: patients may be double counted on more than one provider's list, patients may have died, moved, or may no longer require the surgery."

7.1 Data Sources

This study is unique in that the data issues created by disparate individually held data sources are not an issue. Although the Capital Health IT systems were not purposely designed to track patients waiting for surgery, they do capture and time stamp most steps in the patient flow process. Although challenging to access, there is significant data available to track patients and to indicate their resource use at process milestones.

7.1.1 Corporate Systems

Capital Health's peri-operative management system, Surgi-Server, proved to a good source for data. The system maintains an extensive database of information regarding every surgery performed in the OR at both sites. The patient's Hospital Unit Number (HUN), combined with the surgery date, acted as the primary key to sort records in the database. The entrance and exit time for all surgeries is recorded, giving sufficient information to calculate each patient's total surgery time. In addition to site, this information can also be sorted by patient type and surgeon. Diagnosis and procedure description are also captured, but in a free-text format, making querying by these fields problematic. The sample of records the was obtained, contained all surgeries performed by general surgeons between April 2003 and June 2005

Capital Health's Discharge Abstract Database (DAD) is used to summarize a patient's visit and provide data to national organizations. The data captured in this system provides details regarding pre-operative and post-operative LOS for all the division's patients. However, details regarding a patient's surgery are incomplete, since only the primary intervention is recorded. A sample from the same time frame as the surgi-server data was obtained for all discharged general surgery patients.

The final corporate system used to gather data about the division is the patient registration and scheduling system (STAR/PHS). The data from this system was used to determine when patients see their surgeon in a pre-surgery clinic. The system could not, however, distinguish between patients that received surgery and those that did not. A dataset representing all clinic visits between January 2003 and June 2005 was captured.

Figure 10 displays the time lines covered by each dataset in addition to the history each surgeon has with the division.

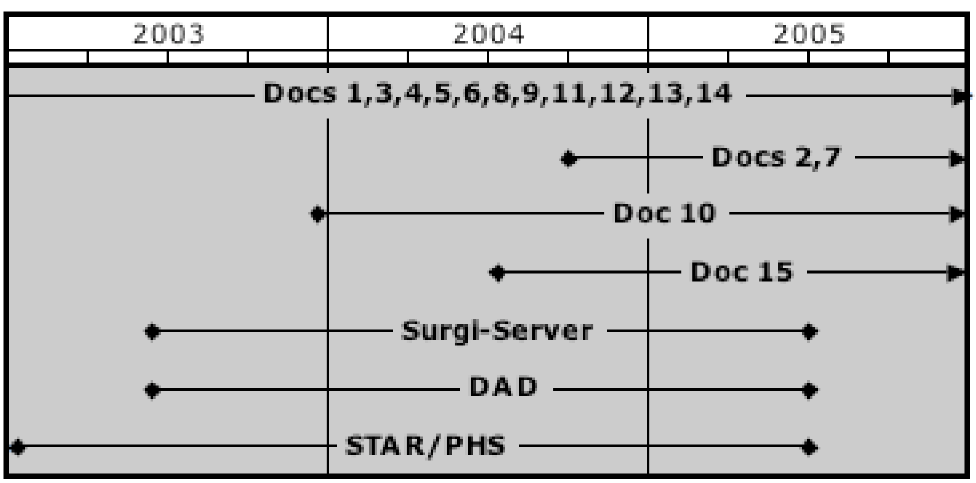


Figure 10: Time line for Surgeons and Datasets

7.2 Division Dataset

Each corporate system provided only a piece of the data required for the model. Combined, however, they provide a comprehensive dataset. Combining Surgi-Server with the DAD was the logical starting point, as both detailed resource use and could be sorted by the HUN and surgery date. Some problems arose when linking the system, because patient information entered into the DAD by stenographers was not always done in a consistent manner. This resulted in approximately one hundred DAD surgery dates being "off" by one day. This problem was brought to the attention of the database administrator who retrieved the charts corresponding to all the problem records to correct the surgery date. Despite the inconvenience, it was possible by inspection to manually link these anomalous records with the Surgi-Server data.

Once combined, Surgi-Server and the DAD provided a comprehensive picture of all patients who received surgery from the division of General Surgery. Combining Surgi-Server's OR time use data with the DAD's LOS information provided a thorough description of resource use by the division. Linking the free text diagnosis and procedure description fields from Surgi-Server with the DAD's intervention description revealed enough information about the patient's malady to have them classified into one of the eight categories. With the information from Surgi-Server and the DAD it was possible to determine the capacity of the division with the current resource level and use.

The dataset consisting of the Surgi-Server and DAD data did not provide sufficient information to compute the demand by elective patients. To capture this it was necessary to determine when the decision for surgery was made for each elective patient. Generally, the physician makes the decision for surgery with the patient during a clinic visit. The STAR/PHS data captures all clinic visits, but does not clearly indicate when the decision for surgery is made. To cope with this, it was assumed the last clinic visit prior to surgery was the point where the decision was made and when the patient began their wait for surgery. This assumption is consistent with the common practice of the division's members and with the way wait times are reported by the Nova Scotia Department of Health (NSDH, 2006).

The final step in developing a single comprehensive dataset involved linking the STAR/PHS clinic visit data with the Surgi-Server surgery date data. The STAR/PHS dataset extended four months further into the past to ensure that clinic visits were captured for surgeries happening at the start of the Surgi-Server data. Creating the relationship between the two datasets involved combining –not linking- the records from both tables. Since the STAR/PHS table did not include a surgery date, it was not possible to link the tables as one patient may have had multiple surgeries over the two-year time frame. The new table contained the patient information and an event field which consisted of either the surgery date field or the clinic date field. (See Figure 11) The table was then sorted by the HUN and Date fields. From this table it was possible to determine the rate at which patients join each surgeon's queue and their associated wait time as shown in Figure 11.

HUN	Surgeon	Date	Event	Surgery Decision?	Wait Time
1234	1	4-Sep-03	Clinic		
1234	1	25-Sep-03	Clinic		
1234	1	1-Oct-03	Clinic	Pnt Joined Queue	
1234	1	17-Nov-03	Surgery		47
2345	2	15-Oct-03	Clinic	Pnt Joined Queue	
2345	2	29-Oct-03	Surgery		14
3456	1	11-Oct-03	Clinic	Pnt Joined Queue	
3456	1	4-Dec-03	Surgery		54
4567	1	9-Oct-03	Surgery	Unknown	Unknown

Figure 11: Calculating Elective Patient Demand and Wait Time

Unfortunately when combining these tables it became apparent that some clinic data was missing. (As an example see Figure 11, HUN 4567) The percentage of surgery records missing a corresponding clinic record was calculated for each surgeon and ranged from 1% to 45% with a mean of 15%. The figures for each surgeon are shown in Table 5. How these inconsistencies are coped with will be discussed in a later section.

Table 5: Percentage of Surgery Records Missing Clinic Records

Surgeon	% of Surgery Records Missing Clinic Records
1	17%
2	13%
3	13%
4	11%
5	1%
6	21%
7	8%
8	6%
9	45%
10	35%
11	22%
12	5%
13	4%
14	15%
15	12%

A summary of the information available from the three corporate databases and how they were combined in available in Figure 12

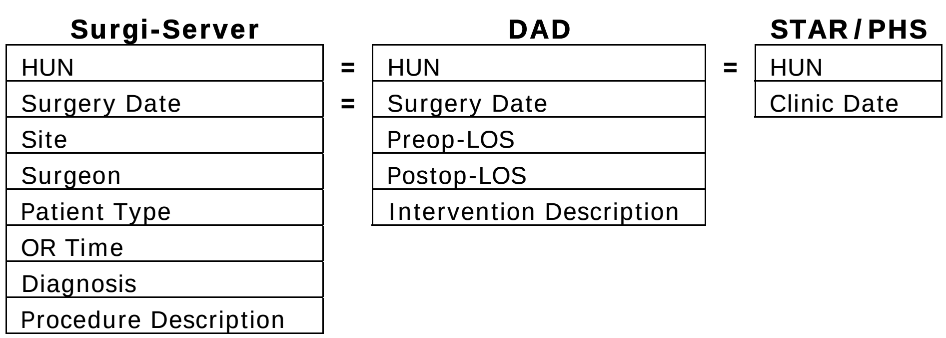


Figure 12: Combining Datasets

After combining all the information from the three sources, one comprehensive dataset existed for the General Surgery Division. Figure 13 shows the information available from this cumulative table.

Division Dataset
HUN
Surgery Date
Surgeon
Site
Patient Type
OR Time
Diagnosis[1]
Procedure Discription[1]
Preoperative-LOS
Postoperative-LOS
Intervention Description[1]
Clinic Date[2]
Wait Time[2]
Diagnosis Category

1: Needed to Categorize Patients
2: Only for 85% of Elective Case

Figure 13: Division Dataset

7.3 Random Input Variables

From the composite dataset, the parameters for the simulation's main random input variables can be computed. The main input variables for the model are OR time, LOS and arrival rates. Using only average values in a simulation is not advised, as it does not account for system variability. Thus, the distribution of each of these variables must be calculated.

There are three common approaches used to specify the distribution of random data. The first, and least desirable, is to use the data values themselves directly in the simulation. The second is to use the data to define empirical distributions functions for each for each random input variable. The final and most desired is to use standard techniques of statistical inference to fit a theoretical distribution form to the data and to use hypothesis tests to determine the goodness of fit (Law and Kelton, 2000). In this model, wherever possible, the third technique, of fitting theoretical distribution to each of the random input variables, was used.

7.3.1 Fitting Distributions

This process used to fit the data to distributions started with drawing a histogram of the data to give some insight as to which distribution family the data belonged. The challenge with this method is determining which range of data should be included in a given bar column or the number of histogram cells. The goal of this decision is to select the smallest range, which gives a "smooth" histogram without causing it to look "ragged". (Kelton et al., 2002) After hypothesizing to which family the data belongs, estimators can be used to determine the parameters that scale the distribution to fit the histogram. As a visual check of goodness of fit the distribution's density function can be plotted over top of the histogram as shown in Figure 14. The statistical metrics used to determine the goodness of fit include the chi-squared test, the mean squared error, and the Kolmogorov-Sirnov(K-S) goodness-of-fit hypothesis test. This process was followed with the assistance of the Rockwell software package named Input Analyzer. Input Analyzer was used to measure and determine the acceptability of a distributions fit with the K-S goodness-of-fit hypothesis test and the chi-squared test.

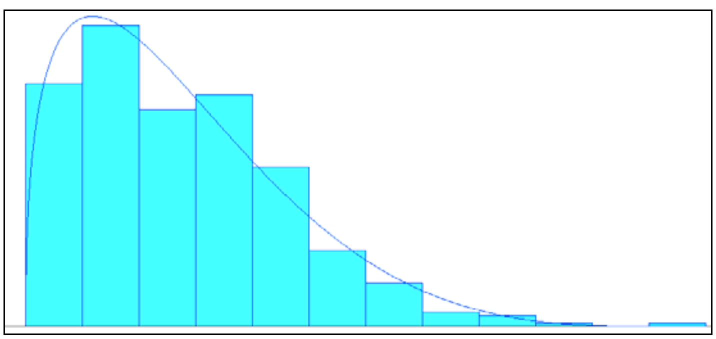


Figure 14: Fitted Theoretical Distribution

Dividing the data by factors allows for different patient populations to be separated, which leads to better distribution fits. For example, the OR time for one diagnosis category may be significantly higher than that of a different category. This effect of dividing the dataset by three main factors was computed before distribution fits were estimated. The first factor was site, either the VG site or the HI site. Next was patient type, elective, non-elective, or non-surgery patient type. The final factor was the eight diagnosis categories.

7.3.2 Operating Room Time

The OR time for all the patients was examined to determine if the data should be disaggregated to allow for a better fit. The records were divided by site and a 95% confidence interval was computed for their OR time. As Figure 15 shows, a statistical difference between the OR Time at each site was observed. Figure 15 also shows the results of dividing the data by patient type (Non-surgery patients are not graphed as they do not receive surgery thus do not have OR time) and diagnosis category. It was clear that the OR Time required for surgery is not statistically different between elective and non-elective patients. It was also observed that the OR Time difference between some categories is statistical different. Thus distributions were fit to OR time data that was divided by site and by diagnosis category.

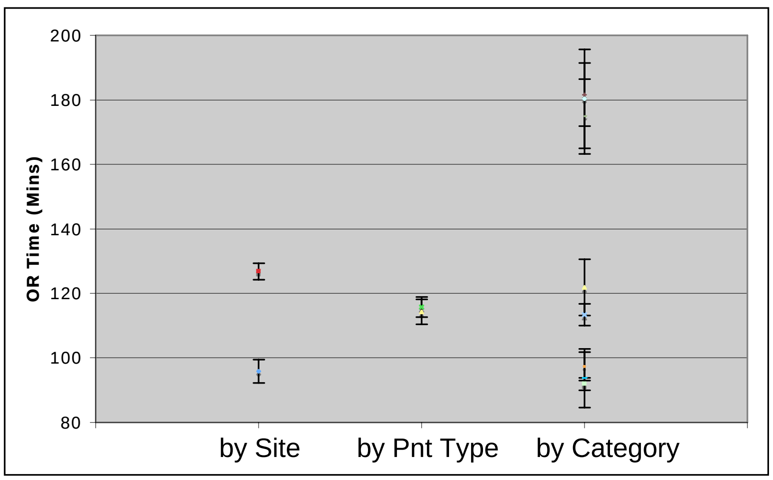


Figure 15: 95% Confidence Intervals for OR Time

The distribution families and parameters computed for the OR time datasets is displayed below in Table 6. Input Analyzer was again used to compute these parameters and to evaluate the goodness-of-fit. Input Analyzer reports the probability values differently than other statistical software packages, as such a minimum probability of 0.05 is recommended by Kelton et al. (2002) to claim the distribution is a good fit. All of the distributions shown in table 6 had probability values of greater than 0.05.

Table 6: OR Time Distributions

Site	Category Name	#	Distribution
HI	Breast Cancer	1	40 + 200 * BETA(0.748, 1.87)
HI	Thyroid Cancer	2	NORM(160, 41.3)
HI	Colorectal Cancer	3	29 + 349 * BETA(1.83, 3.01)
HI	Ostomy Closure (Ileo)	4	54 + WEIB(38.6, 1.24)
HI	Ostomy Closure (Colostomy)	5	NORM(180, 30.3)
HI	Cholecystectomy (Lap)	6	48 + GAMM(13.3, 3.42)
HI	Cholecystectomy(Open)	7	60 + 144 * BETA(1.34, 1.63)
HI	Other	8	18 + ERLA(35.6, 2)
VG	Breast Cancer	1	35 + 273 * BETA(1.45, 4.89)
VG	Thyroid Cancer	2	115 + WEIB(76.7, 1.3)
VG	Colorectal Cancer	3	31 + ERLA(49.4, 3)
VG	Ostomy Closure (Ileo)	4	55 + EXPO(39.8)
VG	Ostomy Closure (Colostomy)	5	NORM(180, 30.3)
VG	Cholecystectomy (Lap)	6	48 + ERLA(14, 3)
VG	Cholecystectomy(Open)	7	78 + EXPO(38.3)
VG	Other	8	20 + LOGN(113, 128)

7.3.3 Length of Stay

A similar analysis was performed on the LOS random input variable. The LOS data was divided by site and 95% confidence interval was computed for patients who received surgery at each site. The intervals overlapped, proving that there is no statistical difference between them. A division by patient type clearly indicated that there is a statistical difference between elective patients, non-elective patients, and non-surgery patients. Finally, the data was separated by diagnosis category. Again it was clear that LOS was statistically different for some categories. These confidence intervals for the three factors are shown below in Figure 16. Thus, the LOS data was divided by patient type and diagnosis category before fitting it to distributions.

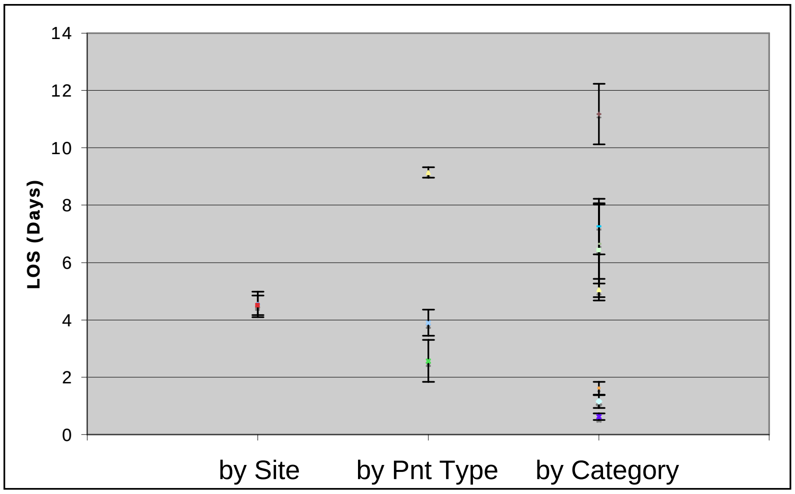


Figure 16: 95% Confidence Intervals for LOS

The distributions and their parameters used for the random input variable LOS are displayed below in Table 7. Before fitting distribution the outpatients were removed. In the case of the LOS, not all the data could be fit to theoretical distributions. In cases where good fits were not possible an empirical distribution was used.

Table 7: LOS Distribution

Patient Type	Category Name	#	Probability LOS = 0	Distribution
Elective	Breast Cancer	1	55%	0.5 + EXPO(0.759)
Elective	Thyroid Cancer	2	0%	0.5 + EXPO(1.11)
Elective	Colorectal Cancer	3	2%	3.5 + LOGN(6.24, 5.36)
Elective	Ostomy Closure (Ileo)	4	0%	(-0.5) + LOGN(6.53, 3.71)
Elective	Ostomy Closure (Colostomy)	5	0%	Empirical
Elective	Cholecystectomy (Lap)	6	92%	0.5 + EXPO(1.13)
Elective	Cholecystectomy(Open)	7	60%	Empirical
Elective	Other	8	64%	Empirical
Non-elective	Breast Cancer	1	55%	0.5 + EXPO(0.759)
Non-elective	Thyroid Cancer	2	0%	0.5 + EXPO(1.11)
Non-elective	Colorectal Cancer	3	0%	(-0.5) + WEIB(17.9, 1.76)
Non-elective	Ostomy Closure (Ileo)	4	0%	1.5 + LOGN(4.28, 2.87)
Non-elective	Ostomy Closure (Colostomy)	5	0%	Empirical
Non-elective	Cholecystectomy (Lap)	6	5%	0.5 + EXPO(2.97)
Non-elective	Cholecystectomy(Open)	7	9%	1.5 + LOGN(8.22, 8.32)
Non-elective	Other	8	34%	Empirical
Pre-Op	All	All	62%	0.5 + 13 * BETA(0.566, 2.3)
Non-Surgery	All	All	0%	0.5 + GAMM(2.01, 1.59)

7.3.4 Patient Arrivals

The rate at which patients join a surgeon's queue is considered the patient's arrival rate in the simulation. Each of the three patient types enters at a different rate and flow differently through the system. The data needed to calculate the flow rates was available in division's dataset.

7.3.4.1 Elective Patients

As discussed earlier, while the dataset included fields for clinic and surgery dates, only 85% of the surgery dates had matching clinic visit dates. These 15% of clinic visit records were missing because the STAR/PHS database administrator was unable to determine all the cut codes required to query them. Cut codes are used in the STAR/PHS system to identify why patients are in the hospital. All patients arriving at the hospital are entered into the STAR/PHS system with a cut code. Unfortunately, over the years the meaning of these cut codes has become vague making their interpretation difficult. Separating a clinic visit from other visits is challenging as the cut codes can vary by division and even by clerk. After running an exhausting number of queries with multiple cut code combination it was conceded that 85% was the best outcome achievable.

The missing records were originally ignored and the number of new patients joining each surgeon's queue per day was computed. The distribution was on average a 15% underestimate of the actual demand. This problem was fixed by decreasing the number of days with 0 arrivals by the percentage of missing clinic visits. The number of new patients per day was then increased by this percentage. The resulting distribution represents an estimate of the complete demand of new patients on each surgeon.

As an example, see Figure 17 where 83% of the surgeries had a matching clinic record. Alternatively this means 17% of new patients are not accounted for in the demand. To accommodate for this, the occurrences in the zero column are decreased by 17% and redistributed proportionally among the non-zero bins. The mean arrival rate per day with 83% conformance was 0.3789, after it was adjusted to accommodate 100% of the surgeries the mean daily arrival rate was 0.3789/0.83 or 0.4566.

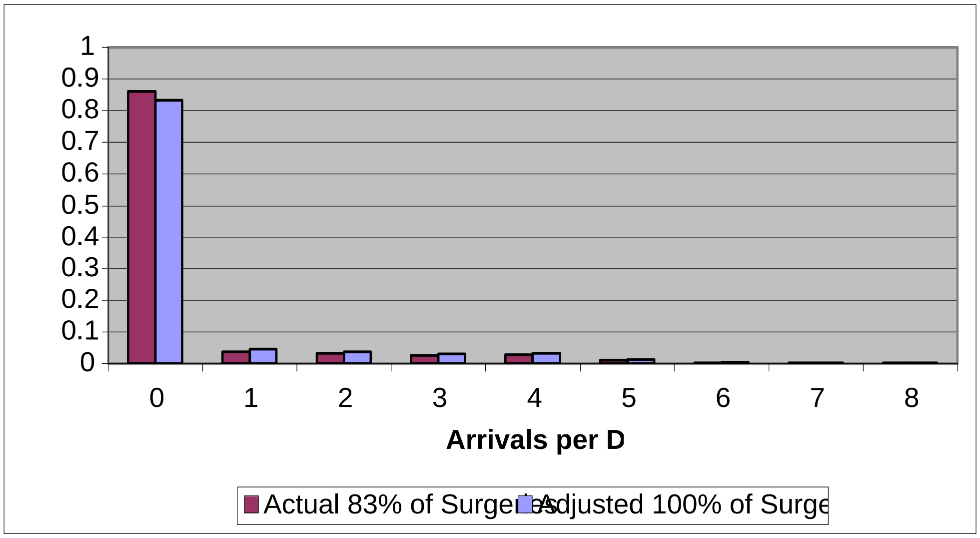


Figure 17: Example Arrival Rate Distribution

The arrival rate distribution for elective patients was computed in this manner for all surgeons. Tests were performed to fit this data to theoretical distributions to no avail. It was hypothesize that the arrival rates fail to meet the test for Poisson arrival rates due to the collection process. Surgeons generally only have clinics once or twice a week resulting in batch arrivals on those days and no arrivals on other days. In place of theoretical distributions, empirical distributions were used.

7.3.4.2 Non-elective Patients & Non-Surgery Patients

Computing the distribution for the rate of new non-elective and non-surgery patients entering the system was a much more straightforward process. These patients do not wait before entering the system and thus their arrivals are captured by corporate systems. The number of new patients per day entering the division for each patient type was fit to a Poisson distribution with the same level of confidence required for the OR Time distribution. The Poisson arrival rate distribution for these patient types is shown in Table 8.

Table 8: Non-elective and Non-surgery Patient Arrival Rates

Site	Distribution
Non-elective Patients (HI Site)	POIS(2.48)
Non-elective Patients (VG Site)	POIS(0.923)
Non-Surgery Patients	POIS(1.54)

7.4 Summary Statistics

Surgeons were concerned about wait times, but had very little quantitative data to justify their concerns. From this new dataset, comprised of data from the three corporate systems, it was possible to provide information on wait times as well as demand, average case time per patient, and LOS values. Surgeons are able to use these statistics to benchmark their practices with their colleagues and other General Surgery Division. Surgeon specific statistics are shown in Table 9.

Wait time is defined as the time between the decision for an elective surgery and the time surgery is completed. The wait time is measured in days, and was calculated by using the STAR database to determine when the last patient-surgeon clinic visit was held prior to surgery and then subtracting that date from the surgery date.

The variable *new pts / week* represents the number of new elective patients entering the general surgery system on a weekly basis. This was calculated by combining the data from the surgery scheduling system and the STAR patient registration system. The surgery system was used to identify patients that had undergone surgery and the STAR system was used to determine when the decision for surgery was made, hence when the patient joined the queue.

The *ORT* column represents the average time a surgeon spends operating on a patient. This information was derived from the surgery scheduling system by subtracting the time a patient enters a room from the time the patient exits the room. This information includes both elective and non-elective patients

The *LOS* column represents the average number of days a patient spends in a general surgery recovery bed post-surgery. This information was derived from the Discharge

Abstract Database (DAD), which tracks, among other things, the LOS for inpatients and outpatients. This information includes both elective and non-elective patients

Table 9: Surgeon Specific Statistics

	Overall Averages			
Surgeon	**Wait Time (days)**	**New Pts / week**	**ORT (mins)**	**LOS (days)**
1	59.84	3.1962	98.77	0.01
2	83.49	1.3714	104.78	3.84
3	37.90	4.8631	93.45	1.99
4	31.50	3.6980	169.23	6.24
5	43.86	4.5498	128.05	1.71
6	56.47	4.9893	110.09	5.36
7	39.97	3.4450	137.97	6.98
8	50.66	3.0320	126.48	3.99
9	105.49	4.7531	113.10	7.90
10	81.20	0.4447	169.16	1.23
11	34.74	3.5335	122.66	6.01
12	69.60	6.6510	74.45	1.71
13	49.32	4.0060	84.81	1.50
14	73.02	4.0782	121.83	7.13
15	36.44	2.3787	143.21	7.54

Similar calculations categorized by surgery type are shown below in Table 10. The surgery types were determined by the head of general surgery and based on the diagnosis and procedure descriptions available from the surgery scheduling system and the DAD.

Table 10: Category Specific Statistics

		Overall Averages			
Category Name	**#**	**Wait Time (days)**	**New Pts / week**	**ORT (mins)**	**LOS (days)**
Breast Cancer	1	23.99	4.96	97.36	0.62
Thyroid Cancer	2	74.45	1.43	181.62	1.61
Colorectal Cancer	3	39.52	3.99	174.87	11.18
Ostomy Closure (Ileostomy)	4	71.27	0.78	93.68	6.64
Ostomy Closure (Colostomy)	5	52.60	0.21	180.31	7.25
Cholecystectomy (Laparoscopic)	6	48.49	7.62	91.90	1.15
Cholecystectomy(Open)	7	59.45	0.83	121.83	6.43
Other	8	64.77	35.16	113.38	5.06

Of greater significance than average wait times is the change over time and the trends observed in this data. This change in elective wait times for each category is shown below in Figure 18. The wait time for elective surgeries computed monthly from historical records between January 2003 and July 2005 is shown below in Figure 19.

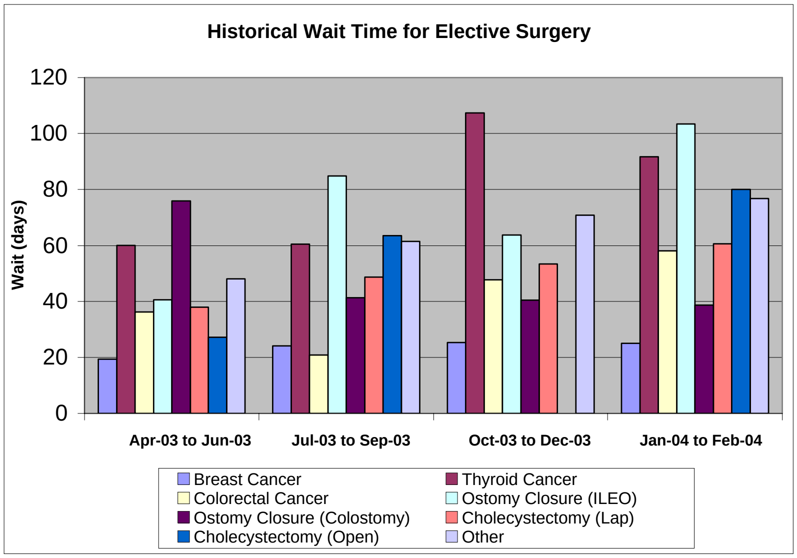


Figure 18: Historic Wait Times by Category for Elective Surgery

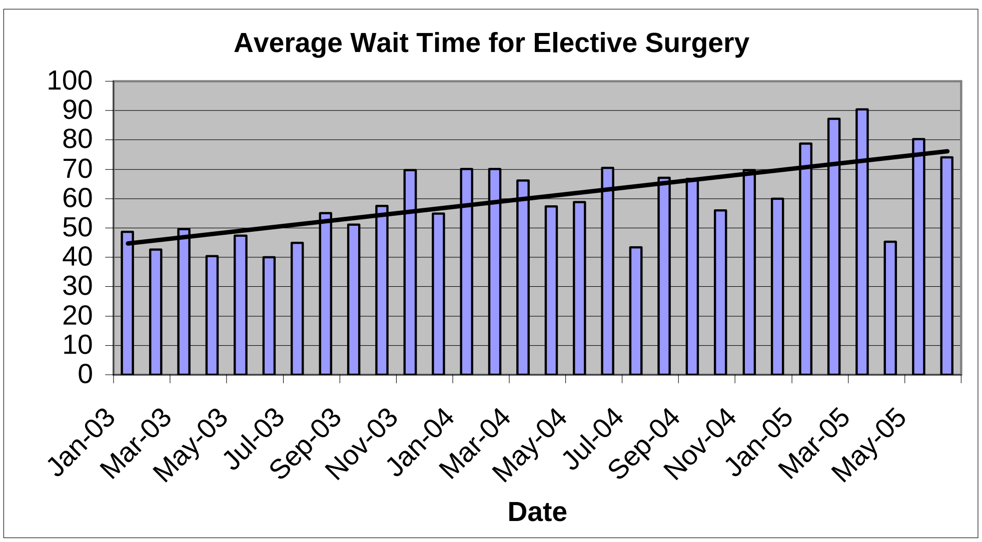


Figure 19: Trend in Average Wait Time for Elective Surgery

It appears obvious from the graph that the wait times for elective general surgery have grown over the past two and a half years. The regression analysis (Figure 20) proves this claim, as the 95% confidence interval for the slope does not include zero. Furthermore the analysis demonstrates that the wait time has grown on average by 1.08 days per month during this time frame.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.6843
R Square	0.4683
Adjusted R Square	0.4493
Standard Error	10.3193
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2625.9184	2625.9184	24.6594	0.0000
Residual	28	2981.6492	106.4875		
Total	29	5607.5676			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	43.7242	3.8643	11.3149	0.0000	35.8086	51.6398
Slope	1.0809	0.2177	4.9658	0.0000	0.6350	1.5268

Figure 20: Wait Time Data Regression Analysis

7.4.1 OR Turn Around Time Per Site

An additional investigation into operational performances between the two sites revealed different turnaround times between cases. Due to the patient population, operations performed at the VG site tend to be more invasive and require more OR time. (This will be further investigated in the validation section.) It is of interest to note, however, that the turn around time in the OR for these longer cases is on average shorter than that seen at the HI site, as summarized in Table 11. The 95% confidence intervals for each of these times are shown in Figure 21 and Figure 22. It is clear form the confidence intervals that the turn around times and case times are significantly different between the two sites. Further investigation may be required to confirm that there is a significant performance differences between the two sites.

Table 11: Average OR Turn Around Time Performance

Site	**OR Time (Minutes)**	**Turn Around Time (Minutes)**
HI	93.3	57
VG	119.2	32.9

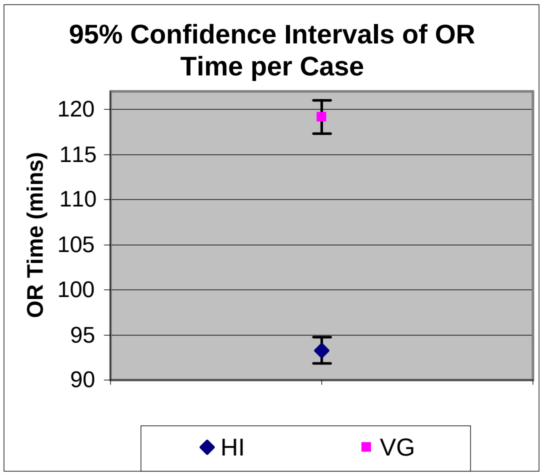


Figure 21: 95% CIs for OR Time

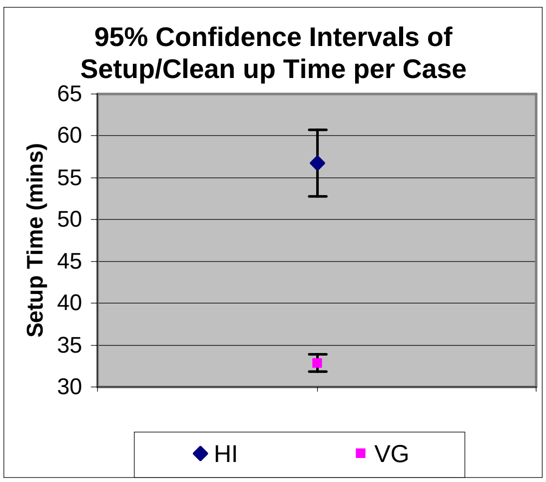


Figure 22: 95% CIs for Turn Around Time

7.4.2 Resource Distribution Among Surgeons

A cursory review of the surgeon specific arrival rates and service rates indicates that an equitable distribution of OR resources among the surgeons may result in unused OR time. Examining how well the supply matches the demand on a surgeon specific level will provide insight into the appropriateness of current allotments of OR time amongst the surgeons. As discussed earlier, not all the surgeons use the HI site to perform non-elective surgeries. In addition, one of the surgeons is a 0.75 FTE. The average number of elective cases a surgeon can complete in a week was subtracted from the average number of new elective patients joining a surgeon queue each week. If the difference is negative it means the surgeon has an insufficient amount of OR time. As is shown in Figure 23 some surgeons have an abundance of OR time while others experience a shortage.

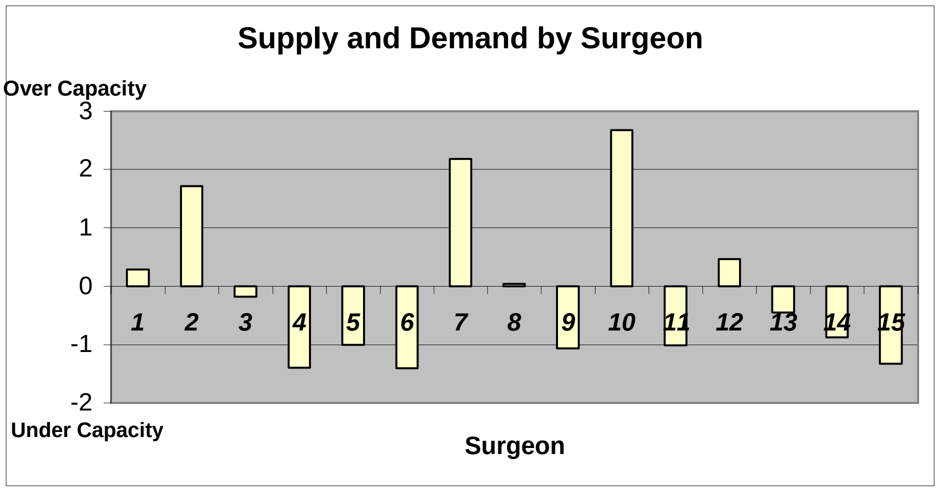


Figure 23: Supply and Demand by Surgeon

8 Simulation Self-Development

All the model data and parameters are stored in a central database for the simulation to access. The simulation examines the database and builds itself to reflect the data in three phases. In the first phase, the model exists as a template without defined resources or capacity. The second phase adds resources based on the parameters defined in the Excel spreadsheet. The final phase adds the patients to the model and extracts their attributes from the Excel file. Visual Basic Macros (VBM) programmed in ARENA transform the model through the three phases. These VBMs access the Excel spreadsheet and manipulate the simulation accordingly.

The first phase consists of a template simulation developed as a shell that all subsequent models build on. The template incorporates the structure of the division, which includes the two sites, and the path of the three patient types. It is essentially an empty hospital without defined capacity or demand. Policies to manage patient transfers and to cope with patient types competing for resources are defined here. When the simulation is opened the first VBM runs, which deletes any previous changes and restores this template.

Once the template is restored a second VBM immediately runs, which transforms the simulation. Phase two is used to make the simulation specific to the division. The number of surgeons and information regarding their patient population, such as arrival rates and queue priorities are added. The algorithm used to schedule the ORs at both sites is defined for each of the surgeons. And finally the number of beds available in the wards at each site is defined. All of these parameter values are stored in an Excel worksheet and can be easily changed. Once changed, the next time the model is opened the simulation will be rebuilt to represent those changes.

The final alteration of the original template occurs during the simulation run. Once the runs begin, patient entities will request attributes such as, OR time and LOS. The first time an attribute is requested by an entity a VBM will retrieve the distributions for that parameter from the Excel worksheet. The distribution and its parameters are then stored in local memory and subsequent requests for that attribute can be assigned without accessing Excel. This process is completed for each of the attributes. When all of the attributes have been assigned, the simulation no longer needs to access Excel. This improves the speed of the model.

As a result of building the model in three phases changes in the division's capacity, patient population, and demand can be changed in Excel by non-simulation experts. The original template model is specific to the General Surgery Division at the QEII, but not constrained by their current resource levels or surgeon specific practices. A valuable extension of this model would be to remove the policy components from the template phase to allow the model to be more easily transferred to other divisions. A scheme of the three phases of the simulation's self-development is available in Figure 24.

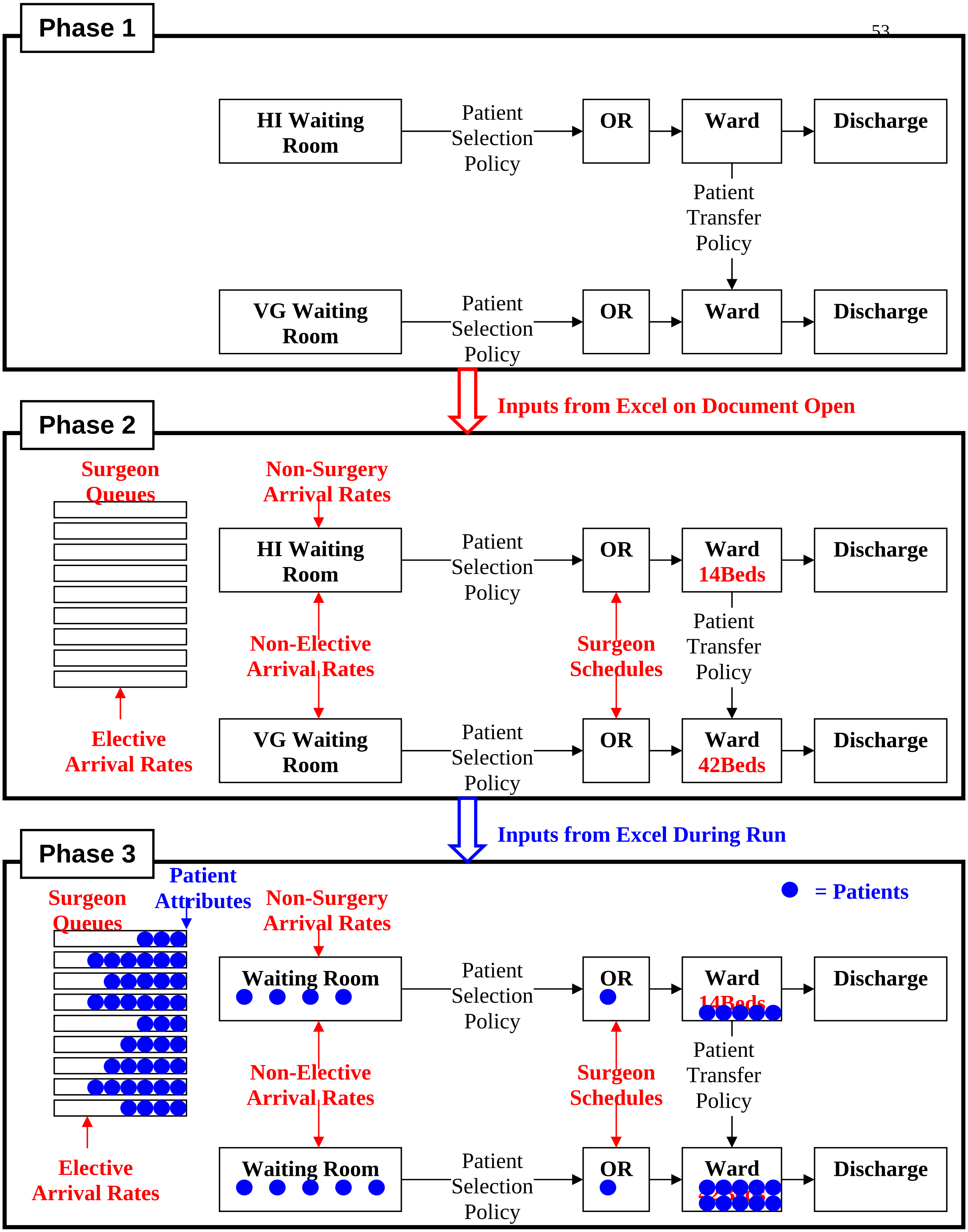


Figure 24: Three Simulation Self-Development Phases

9 Model Validation

To ensure that the model is an accurate representation of general surgery, the Schellenberger (1974) framework was used to validate the model. Initial testing focused on ensuring the model was performing as designed by investigating individual data elements. This included computing 95% confidence intervals for patient LOS, OR time, and arrival rates for both simulation output and historical data. Overlapping confidence intervals ensured that the model data were being interpreted correctly from the database. As an example the 95% confidence intervals for OR time are shown in Figure 25 and Figure 26. By ensuring the confidence intervals, from both the simulation and historical data, overlap it was concluded that the model was indeed performing as it had been designed.

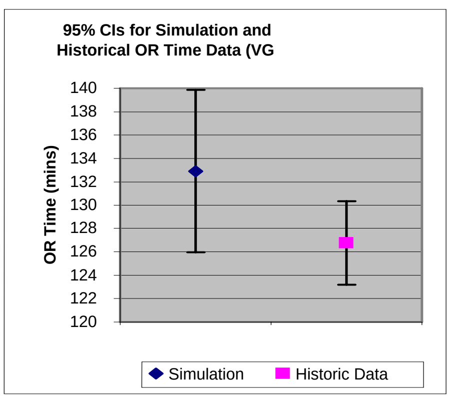


Figure 25: 95% CI for Simulation and Historical OR Time Data (VG Site)

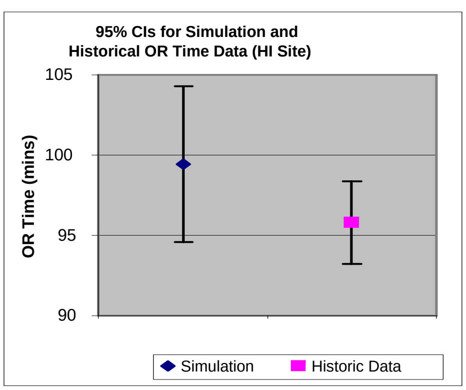


Figure 26: 95% CI for Simulation and Historical OR Time Data (HI Site)

The next subsections explain how the overall performance of the system was tested to ensure the designed model was an accurate depiction of the general surgery system. The overall performance was tested using three metrics. The first two, effective use of OR time and bed utilization, correspond to patient throughput and ensures patients are utilizing resources and are being serviced as would be expected from the historical data. As a final test the wait time for patients at a department level was studied to determine the average wait and the current trends. This was then compared to wait time levels achieved by the model.

9.1 Patient Flow and Service Rates

Patients are restricted from flowing through the system by the availability of needed resources. In this model the two resources needed by the patients are OR time and beds. To prove the model is valid, it must be ensured that modelled patients consume these resources in the same manner as in the real system. The effective use of each resource by the division was analyzed and the model was designed to do the same.

9.1.1 Effective Use of OR Time

A direct determination of the utilization of the OR was not readily available from the corporate systems. As an alternative to an OR utilization metric the OR throughput was used to determine the effective use of the OR. Over a two year period, the number of elective patients seen in one ten hour OR slot at each site by each physician, was computed. The results of this analysis are shown in Table 12.

Table 12: Historical Patient Throughput

Surgeon	Avg VG Cases / OR Slot	Avg HI Cases / OR Slot
1	3.36	
2	3.16	2.53
3	4.32	2.55
4	3.02	1.97
5	3.46	2.38
6	3.58	3.37
7	2.72	2.25
8	2.82	2.14
9	3.15	3.33
10	2.17	

11	2.99	2.08
12	5.24	3.13
13	4.51	1.97
14	2.98	3.35
15	2.19	2.12
Average	**3.58**	**2.51**

To ensure the patients in the model are flowing through this process as efficiently as the actual system, the model outputs were compared to the historical records. The results from the model are shown in Figure 27.

Figure 27: Modelled Throughput

	VG Site	**HI Site**
Cases/Slot (Avg)	3.15	2.37
Cases/Slot (Stdev)	1.11	1.09

The 95% confidence intervals for the historical data were computed to ensure the differences in the modelled results were not statistically significant. The statistical analysis, shown below in Figure 28, proves with 95% confidence that the throughput seen in the model cannot be considered different from the actual system. Although, the throughput and variance of the model was slightly less than was expected, we concluded that it was caused in part by the number of replications in the model run and that its effect on the model would be minimal.

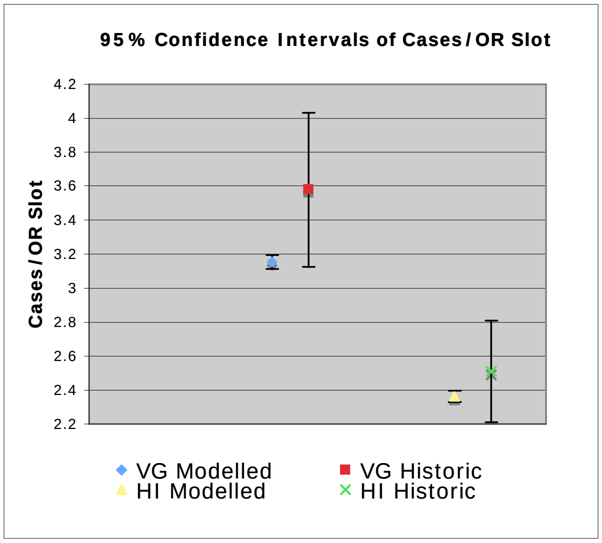


Figure 28: CI for Cases per OR Slot

As discussed earlier the OR time at the HI site is split between elective and non-elective patients. The first part of the OR slot is spent with elective patients and the second half with non-electives. The average time of day when surgeons finish their elective cases and switch to non-elective cases is approximately 13:30. To ensure the model was dividing the HI OR slots up in the same manner as the actual system, 95% confidence intervals of the modelled and actual switch times were computed. As shown in Figure 29, the confidence intervals overlap proving that the model is performing as desired.

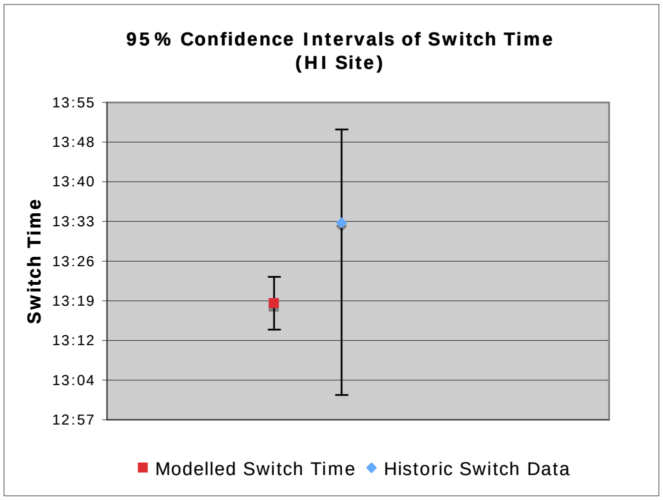


Figure 29: CI for HI OR Switch time

9.1.2 Effective Use of Recovery Beds

After surgery, all inpatients remain in the system and are transferred to a bed for recovery. The General Surgery Division has an allotment of 56 beds and allocates 14 to the HI site and 42 to the VG site. Although there are a fixed number of beds assigned to each service, divisions often share beds with other services. This allows the division to have flexible bed boundaries and the ability to use more beds than they are allotted. A study of the nightly bed census over a 13-month period was completed to determine the actual use and availability of beds and the corresponding utilization. The results of this study are shown in Table 13.

Table 13: Historical Bed Utilization

	VG Site			HI Site		
Month	Available Beds	Beds Used	Utilization	Available Beds	Beds Used	Utilization
September-04	42.8	40.4	94.4%	21.6	15.4	71.3%
October-04	43	42.7	99.3%	17	19.7	115.9%
November-04	43	39.2	91.2%	17	16.9	99.4%
December-04	37.6	37.3	99.2%	16.5	16.2	98.2%
January-05	42.2	38.4	91.0%	16.8	15.7	93.5%
February-05	43.4	46	106.0%	17	16.4	96.5%

March-05	43.8	40.2	91.8%	17	15.9	93.5%
April-05	44	41.2	93.6%	17	13	76.5%
May-05	44	41.9	95.2%	17	15.2	89.4%
June-05	43.8	42	95.9%	16.9	11.7	69.2%
July-05	33.3	31.7	95.2%	16.1	15.5	96.3%
August-05	32.9	36.6	111.2%	15	17.2	114.7%
September-05	40.5	42.6	105.2%	15	17.2	114.7%
Average	**41.1**	**40**	**97.6%**	**16.9**	**15.8**	**94.5%**

The actual number of beds used was then modelled to determine how they would be utilized. The average bed utilization at each site from the simulation is shown in Table 14. Again, 95% confidence intervals were computed for both the model and historic data to ensure the differences in the modelled results were not statistically significant. The results of the statistical analysis, as shown below in Figure 30, indicate that they are not statistically different.

Table 14: Modelled Bed Utilization

Site	Bed Utilization
VG	97.9%
HI	94.7%

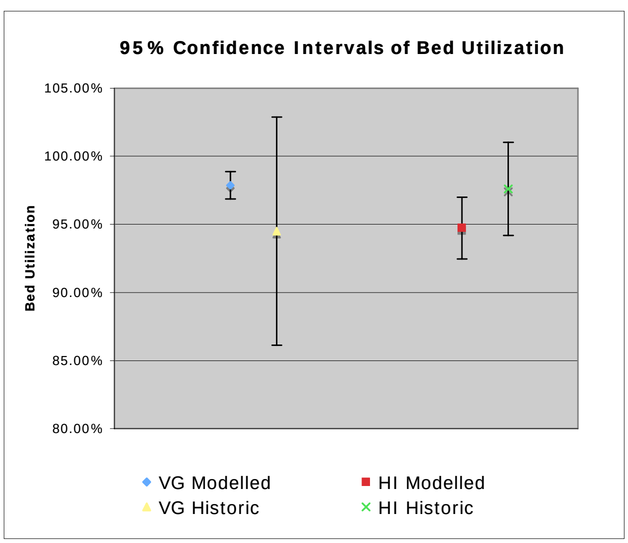


Figure 30: CI for Bed Utilization

By ensuring these two resources are modelled effectively it can be concluded that the service rate achieved by the General Surgery Division is accurately represented in the model. This ensures that patients in the model flow through at the same rate as patients in the actual general surgery system.

9.2 Waiting Time

The effective use of OR time and the utilization of beds are both independent metrics of the metric of interest, waiting time. Waiting time is a function of both the arrival rate and the service rate. The trend computed from historical data was shown previously in Figure 19. The plot of both the actual and modelled wait time is shown below in Figure 31.

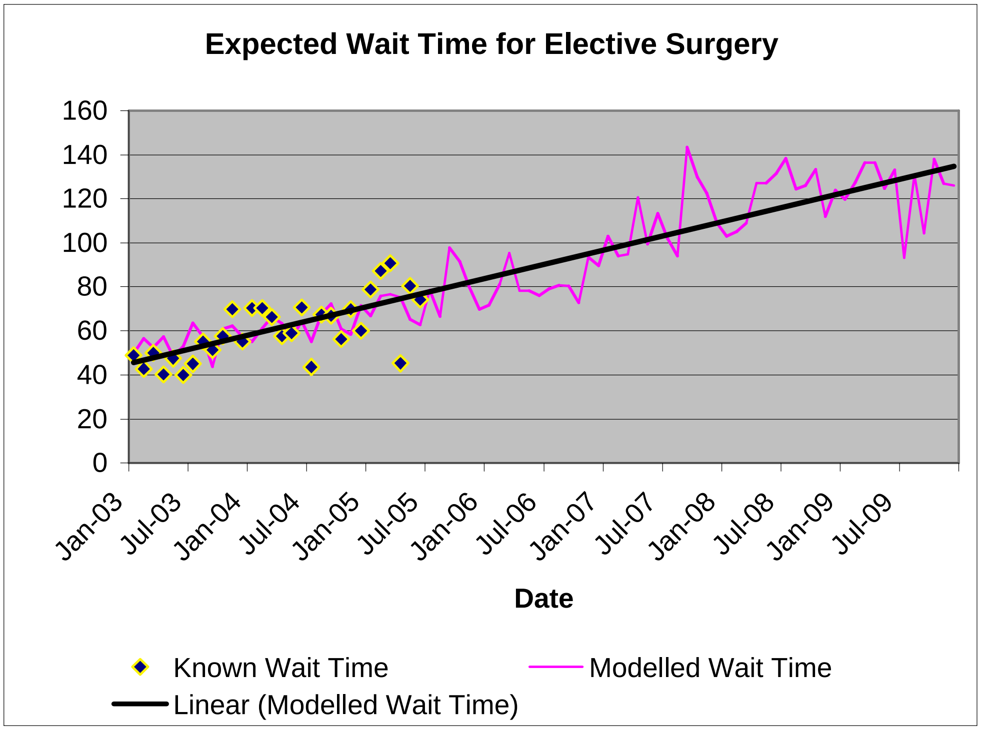


Figure 31: Modelled Average Wait time for Elective Surgery

Again a linear regression analysis was completed and shows the trend in wait time growth seen by the model. The model sees an average growth wait time of 1.08 days per month, which is the same as was observed in the historical data.

The model wait time and the historical wait time were compared to ensure they were not statistically different. Thirty points between January 2003 and June 2005 were selected and the difference between the modelled and actual wait times was computed. A 95% confidence interval for these thirty differences was computed revealing an upper bound of 4.91 and a lower bound of -3.68. (See Table 15 for calculation details) Since the confidence interval contains zero it was concluded that there is no significant difference between the historical mean wait times and the modelled mean wait times.

Table 15: CIs for Actual Wait Time and Modelled Wait Time Difference

Standard Deviation	11.24
Data Points	30
Mean	0.6185
Upper 95% CI	4.914
Lower 95% CI	-3.677

The model successfully passed these three types of testing. This first set of tests ensured that it was correctly interpreting and accessing the model data stored in the Excel database. Next, it was confirmed that the service rate in the model matched the actual system by ensuring resources were being used as the historical data indicated. Finally, the main metric of interest, wait time, was proved consistent in the simulation. Thus, it can conclude that the model is indeed performing as designed and that the design is an accurate depiction of the general surgery system.

10 Model Results

With confidence that the simulation is an accurate depiction of the general surgery system it is possible to use it to address the concerns of the division. The following sections report the insights derived from the model. The first set of runs, reported in the general insights section, were used to analyze the system in its current state to determine resource use by patient types and process bottlenecks. The performance of the system with regards to the effective use and distribution of resources was next examined. Finally the results of improved resource use, additional resources, and a “do nothing” option were compared and contrasted. The section will conclude with recommendations for reducing the wait of elective patients.

10.1 General Insights

10.1.1 Resource Use among Patient Types

The VG site, which is allotted 42 beds, services all patients who receive surgery at the VG site and all patients transferred from the HI site. As a rule, all patients who receive surgery at the HI site and require more than three days to recover are considered for transfer. This helps ensure beds are available for incoming non-elective patients. As a result, on average, patients who received surgery at the HI site occupy 29% of the beds at the VG site. A further breakdown of bed utilization at the VG site is available in Figure 32.

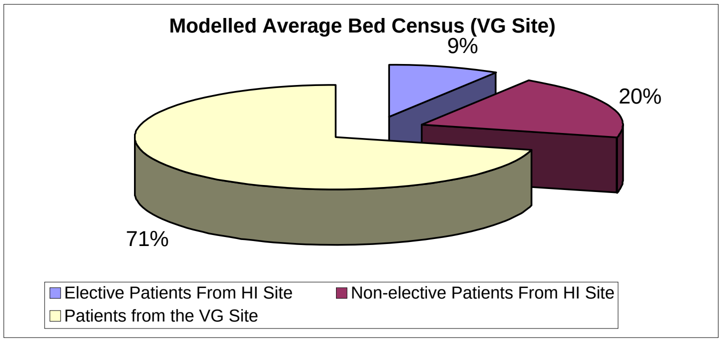


Figure 32: Modelled Average Bed Census (VG Site)

A third category of patients that occupy beds at the HI site, are inpatients undergoing diagnosis but who do not go on to have surgery in the main OR. These patients, on average, use 37% of the 14 beds available at the HI site. Non-elective patients utilize the majority of beds and elective patients absorb the remaining 10%. This information is shown in Figure 33.

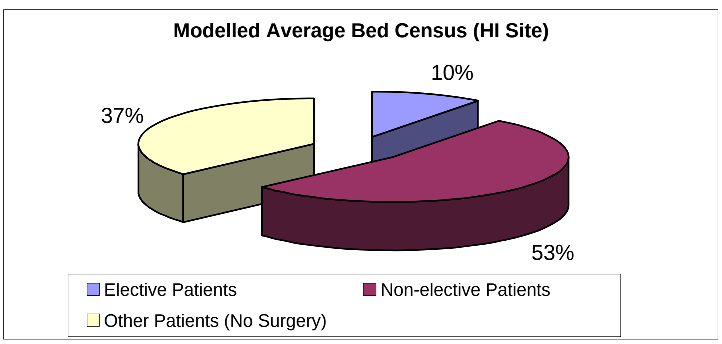


Figure 33: Modelled Average Bed Census (HI Site)

Finally, the aggregate wait time shown earlier was broken down according to surgeon to determine which surgeons bore the brunt of the wait time issue. In the interest of clarity, the ten surgeons that are not experiencing a significant increase in wait times for elective patients have been excluded from figure below. Figure 34 shows surgeon specific expected wait times as function of time. It is clear that the wait times for these surgeons are increasing.

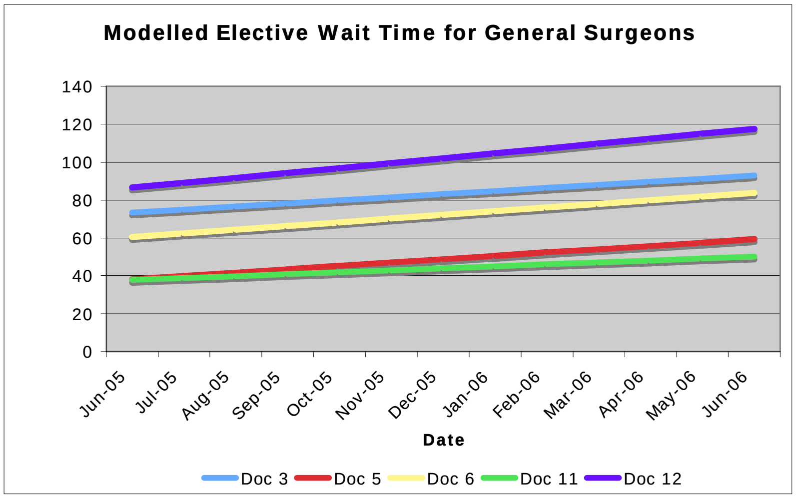


Figure 34: Modelled Surgeon Specific Elective Wait Time

10.1.2 Bottleneck Analysis

To draw insights into the effect that the model's two main resources have on the throughput of elective patients, a sensitivity analysis was performed. With the current resource level of 41 VG beds and 14.5 OR slots/week an average of 226 elective patients undergo surgery per month. If 15% more OR time were made available for surgeons at the VG site the throughput would rise slightly to an average of 228 patients per month. A 95% confidence interval was computed for the difference between the throughput with 15% extra OR Time and the throughput with the current OR time allotment. The confidence interval contained zero and thus it can be concluded that there is no statistically significant improvement as the result of adding 15% more OR Time. See Table 16 for a summary of the calculations.

In contrast, when four extra beds are added the throughput per month rises to 234 patients per month. Again a 95% confidence interval was computed for the difference between the throughput with four extra beds and with the current number of beds. This time however, the confidence interval did not contain zero and it was concluded that a statistically significant improvement in throughput was achieved by adding four VG beds. (See Table 16 for a summary of the calculations) The bottleneck analysis is continued by decreasing OR time and adding more VG beds to further gauge how sensitive throughput is to resource levels. The results are shown below in Figure 35.

Table 16: CIs for Bottleneck Analysis

	Extra OR Time	Extra Beds
Standard Deviation	9.58	8.61
Data Points	43	43
Mean	2.05	7.36
Upper 95% CI	4.92	9.94
Lower 95% CI	-0.80	4.79

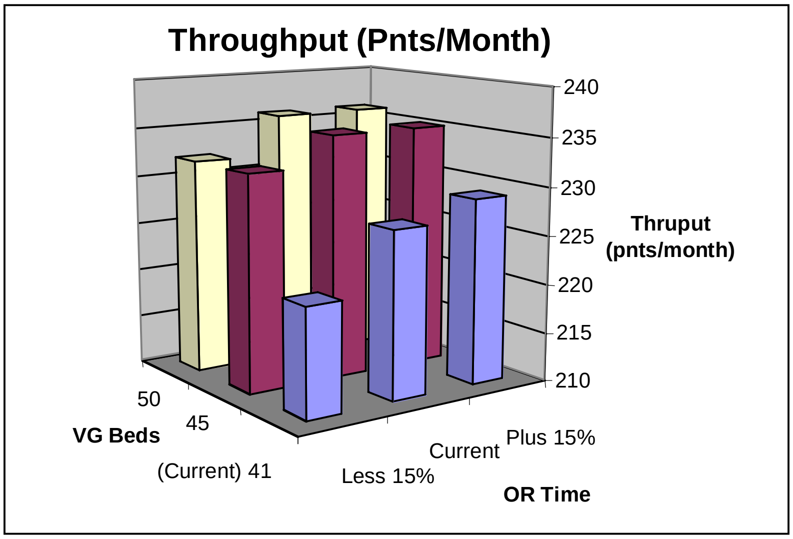


Figure 35: Bottleneck Analysis (Throughput)

Patient wait time, a second metric used to evaluate the sensitivity of the model, yields the same conclusion as above: the model is more sensitive to the availability of VG beds than the availability of VG OR Time. The sensitivity of wait time as a function of these resources is shown below in Figure 36.

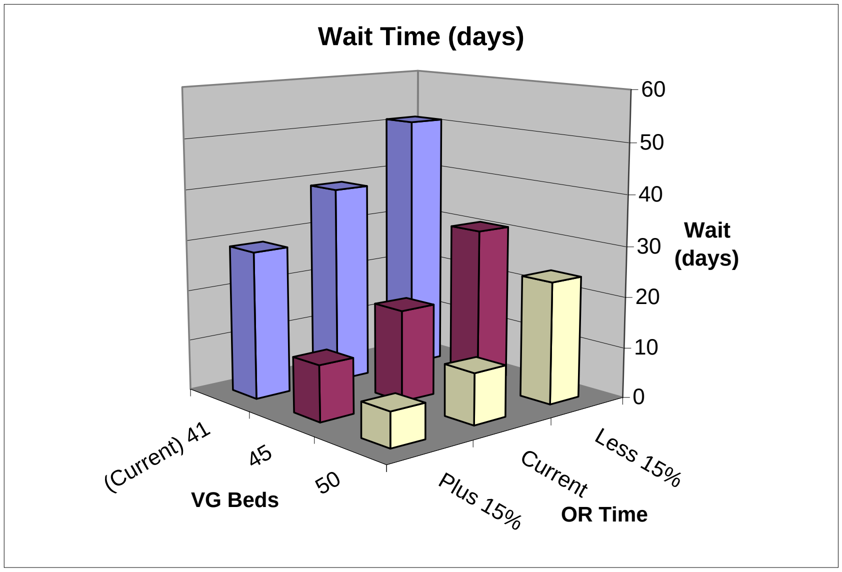


Figure 36: Bottleneck Analysis (Wait Time)

10.2 Use of Current Resources

From the bottleneck analysis it was concluded that the availability of beds hinders the throughput of patients and causes wait times to increase. To minimize the bottleneck caused by VG beds, how they are being used must be examined to determine if operational changes could reduce this bottleneck. Initially, the bed availability by day of the week was examined to determine which days would have a higher probability of a shortage. The next analysis looks at the number of beds assigned to each site and considers the advantages and disadvantages of changing this assignment. The historical patient LOS was examined and compare that to national standards for patients of the same age and same complexity to determine if the need for beds can be reduced.

10.2.1 Throughput by Day of the Week

As noted earlier, the throughput of patients is hindered by the availability of beds. It was of interest to see how the availability of beds changed by day of the week and to determine if there is a preferred day for operating. The model was rerun and an available bed count was completed in the morning after patients were discharged, but before new patients entered for surgery. The results were as expected with the greatest availability on Mondays due to weekend discharges with no new elective cases completed. The result of this analysis, as shown in Figure 37, is that operating earlier in the week reduces the chance of cancellation due to bed shortages.

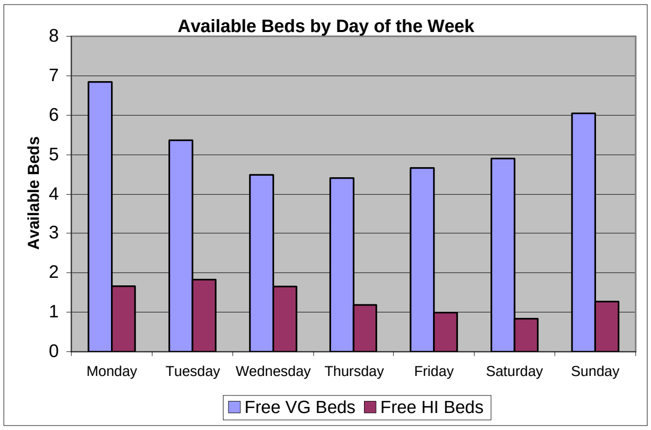


Figure 37: Daily Bed Availability

10.2.2 Bed Placement

The current distribution of beds within general surgery allots 14 beds to HI site and 42 beds to the VG site. In practice however, the general surgery division uses an average of 16 at the HI site and 41 at the VG site since they often loan and borrow beds to and from other divisions. A sensitivity analysis was performed on dispersion of beds between sites while maintaining a total of 56 for the division. A total of seven allotments were considered with each evaluated by three different metrics. The allotments used for each test are shown in Figure 38. The yellow line indicates the number of VG beds assigned for different allotments of HI beds. The red “X” shows the current bed use level.

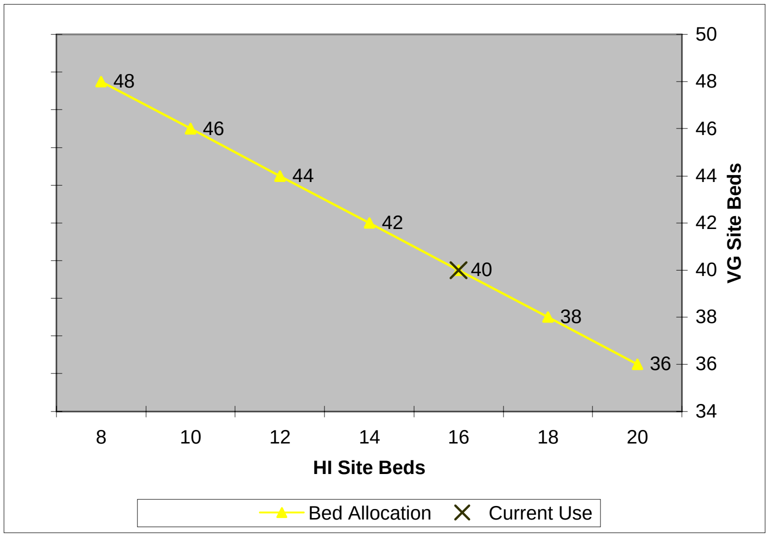


Figure 38: Bed Distribution Between Sites

The first metric used to evaluate the bed allocations is the bed utilization for each site as shown in Figure 39. Currently the division is averaging about 97% and 93% utilization at the VG site and the HI site respectively. It is clear that the HI site is very sensitive to the number of beds it is allocated. A reduction of two beds to 14 (the current allocation) would cause utilization to increase to 98%. This would no doubt lead to a bed shortage and extended waits for non-elective patients.

The VG site, which is less sensitive to adjustments in bed levels, is currently operating at 97% utilization and reacts less significantly to changes in beds levels. As the number of beds at the VG site decreases, the utilization increases. It is not possible to decisively conclude the proper allocation by this metric alone. However this metric does suggest that a reduction in HI beds will lead to high utilization.

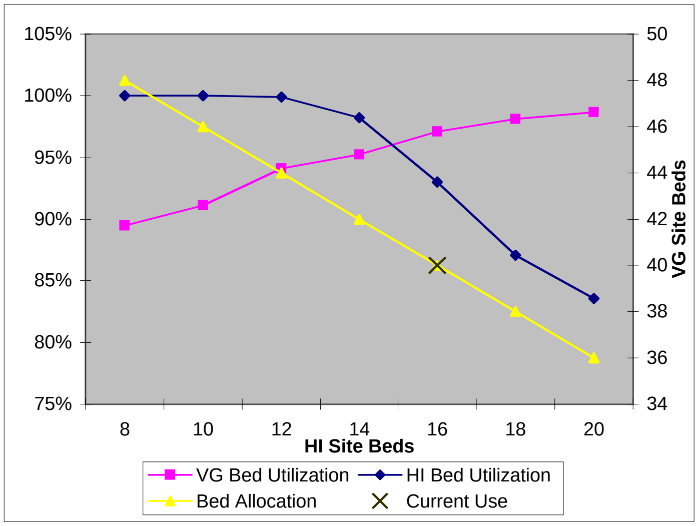


Figure 39: Bed Utilization as a Function of Beds per Site

As indicated by the utilization metric it is expected the wait time for non-elective patients will rise if some of the beds are moved to the VG site. The next metric, used to evaluate the bed dispersion, will quantify this concern. The average wait for non-elective patients to receive a bed is less than five hours with the current use of 16 beds. As the number of available beds is decreased, the wait time grows significantly. This wait time is quite sensitive to number of beds available, as shown in Figure 40. This supports the conclusion of the utilization metric that 16 beds is the minimum required to meet the demands of the patients at the HI site.

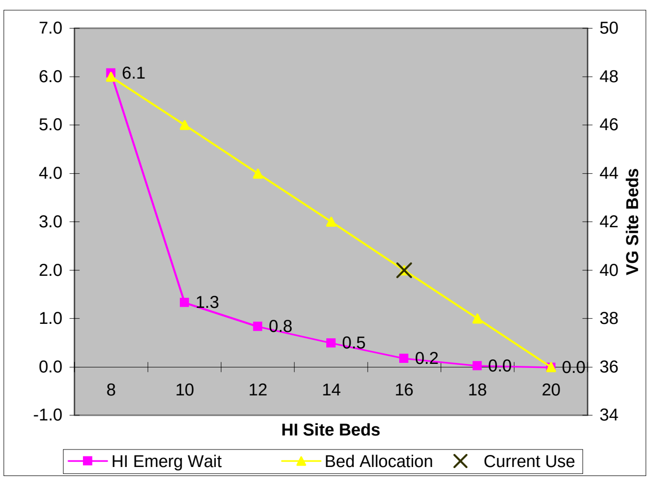


Figure 40: Non-elective Patient Waits as a Function of Beds per Site

The previous two metrics indicate that HI beds should not be relocated to the VG site; next the alternative, relocating VG beds to the HI site, is considered. As expected, the throughput of elective patient is especially sensitive to the number of VG beds available, as shown in Figure 41. The cause is twofold: first as the number of beds at the HI increases so to does the number of transfers to the VG site, leaving fewer beds available for new elective patients. It can be concluded that if the number of beds at the HI site is increased dramatically, a decision rule of transferring patients after three days into recovery should be revisited. The second cause of decreased elective patient throughput is simply the overall reduction in VG beds, which is consistent with the finding of the bottleneck analysis. It was concluded from this analysis that if the number of VG beds is reduced, the throughput of elective patients will be greatly affected.

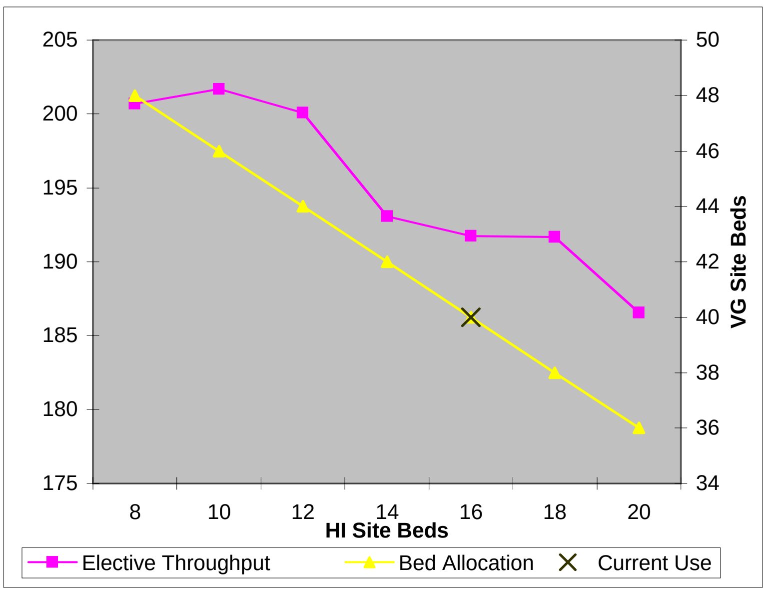


Figure 41: Patient Throughput as a Function of Beds per Site

It is clear from elective patient throughput that decreasing the number of VG beds will have a significant negative effect on throughput. However, it is also apparent from the wait time for non-elective patients, that a decrease in beds at the HI site will results in a significantly longer wait for non-elective surgery. It was concluded that both sites are operating with the minimum number of beds and that shuffling beds between sites is not a viable option.

10.2.3 Expected LOS Analysis

As was shown, bed availability is the major cause of extensive wait times for patients of general surgery. The next information examined was the effective use of the beds, namely the appropriateness of the LOS for each patient. The Canadian Institute for Health Information (CIHI) provides an expected LOS (ELOS) for each patient based on data estimates from four complexity levels and three age groups. This metric was used to determine the appropriateness of patient LOS times for each surgeon. The average and standard deviation of the difference between a patient ELOS and actual LOS was calculated for each surgeon as is shown in Table 17.

Table 17: Expected LOS Analysis

Surgeon	Average of (LOS-ELOS)	Standard deviation of (LOS-ELOS)
1	1.64	5.89
2	1.02	6.33
3	1.36	6.31
4	1.35	11.46
5	-0.03	3.89
6	-1.26	5.56
7	-0.65	7.20
8	0.48	6.75
9	0.98	9.22
10	2.99	6.63
11	0.71	4.86
12	-0.64	3.74
13	-1.00	4.41
14	1.99	9.45
15	0.95	8.56
Average	0.55	7.55

On average, surgeons are keeping their patients in beds for 0.55 days longer than would be expected from the CIHI data, suggesting that there is some room to conserve bed-days. The model was rerun to determine how the wait time for surgery would be affected if all surgeons were obtaining the standard LOS set by CIHI. The result of this scenario contrasted to the current situation is shown in Figure 42.

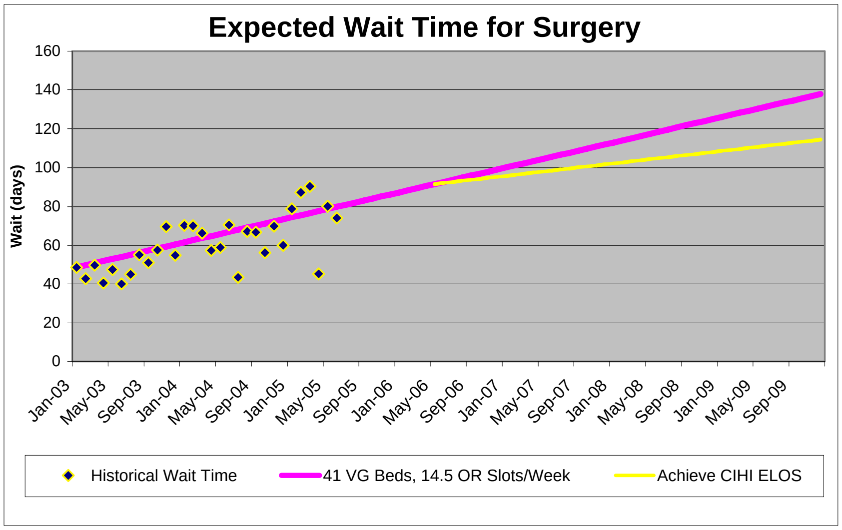


Figure 42: Projected Wait with ELOS

10.2.4 Anesthesiologist Shortage

A shortage of anesthesiologists within Capital Health has been a major dilemma for all divisions in the department of surgery. The shortage caused ORs at the QEII to operate at 92% capacity in January 2005 (CDHA, 2005). As a result, the General Surgery Division has seen a reduction in approximately one elective OR slot per week at the VG site. The model was rerun with the scenario of 41 VG Beds and 13.5 OR slots/week (a reduction of one slots/week) to quantify the impact that a long term anesthesiologist shortage will have on patients waiting for elective general surgery. The result of this analysis is shown in Figure 43 where the growth rate of wait time for elective patients has more than doubled to 27.8 days per year.

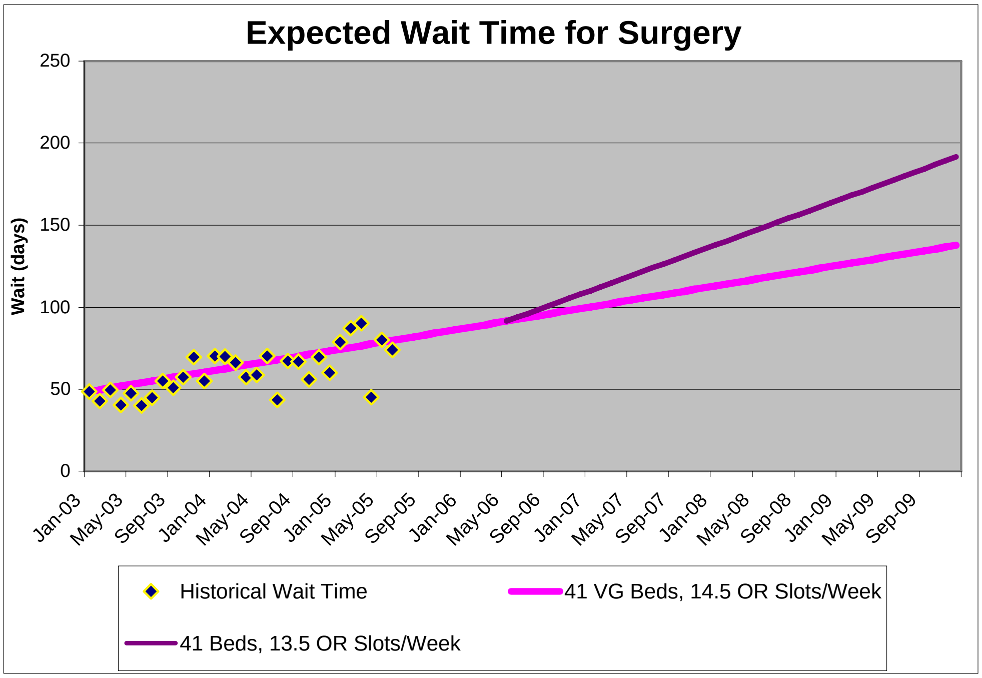


Figure 43: Wait time due to Anesthesiologist Shortage

10.3 Scenario Analysis

Multiple operational scenarios have been discussed so far in this paper. Some of which offer potential to reduce the wait time for elective surgeries. The “bed shuffling” analysis demonstrated that the HI site’s current resource use of 16 beds and five OR slots per week must be maintained at the current level to ensure non-elective patients receive surgery in an acceptable time frame. In addition, because the HI site is not the primary site for elective patients, adding resources there will be less effective in reducing the wait time for elective patients than adding them to the VG site. The impact of other scenarios such as achieving CIHI ELOS, anesthesia cutbacks, adding VG beds, and adding VG OR time will be examined in this section.

Figure 44 displays the results of multiple scenarios used to gauge the impact of operational and resource changes. It is clear that the reductions in the number of OR slots/week will accelerate the rate of growth in wait time for elective surgery. Additionally, adding more VG beds or reducing the LOS to standard set by CIHI will decelerate the growing wait time. Adding four VG beds and one extra VG OR slot/week is the only scenario that will eliminate the wait time growth and cause a substantial decrease in wait times. Four new VG beds and one extra VG OR slot/week represents a scenario of over capacity and should only be used temporarily to decrease wait times to an acceptable level.

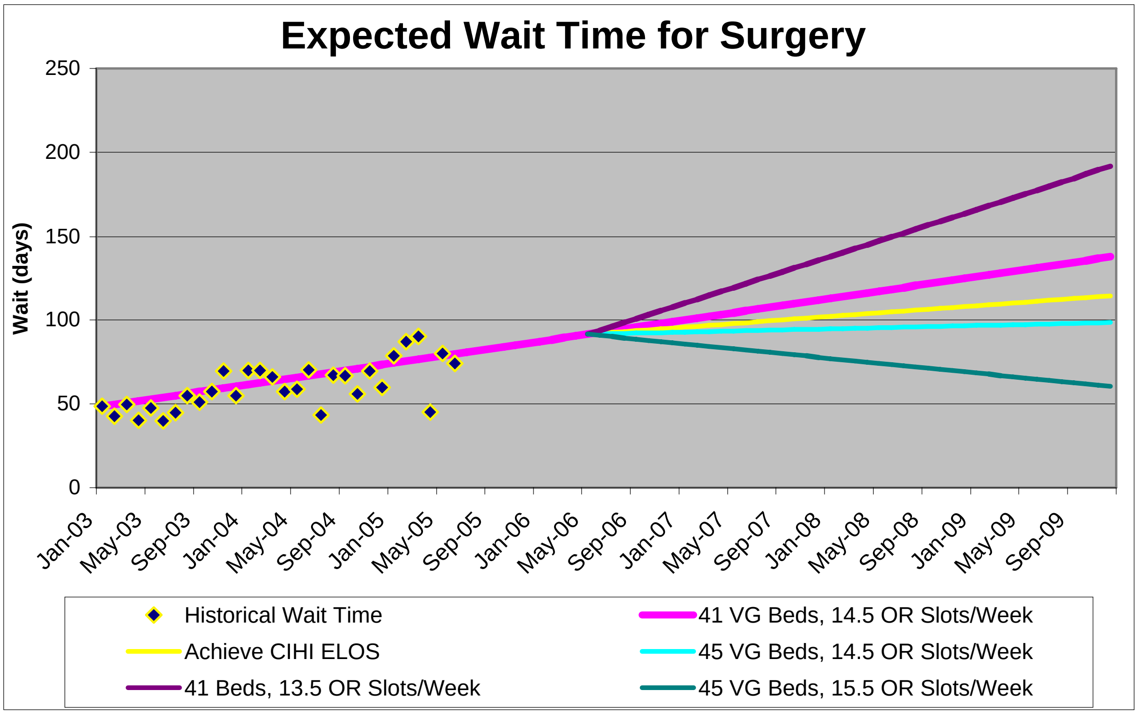


Figure 44: Multiple Scenario Wait Time Projections

10.4 Recommendations

It has been shown through analysis of historical data and computer modelling that the wait time for patients in the division of general surgery is increasing. With the current use and allotment of resources, the rate of change has been held relatively constant at about 13.2 days per year since the beginning of 2003. If this trend is allowed to continue it is projected that the expected aggregate wait for patients in the division of general surgery will reach 100 days by the beginning of 2007. The effect of several independently implemented operational and resource allotment alternatives have been presented, although combining them may be most practical. A responsible and effective solution should contain commitments for addition beds and OR time in combination with more stringent use of both resources. If implemented, the following recommendations will reverse growing wait list trend, while improving the patient throughput to resource ratio.

- The minimum number of beds that should be allocated to the HI site is 16, which is two more than the current allotment, and also the current average being utilized. The division needs to be allotted 16 beds at the HI site, any less will cause excessive waits for non-elective patients.
- At the VG site, beds are currently utilized at approximately 97%, which leads to cancelled elective surgeries, underutilized OR time, and long waits for elective patients. To improve upon this:
  - Surgeons should make an effort to decrease their bed use to the levels suggested by CIHI.
  - The allotment of 42 beds to the VG site is inadequate to meet the demand of elective patients in the division of general surgery and a minimum of three should be added to address the shortage.
- Although OR time is not currently the process bottleneck at the VG site, wait times for elective patients is still sensitive to any reduction. With respect to the OR resource the following can be concluded.
  - Even a single slot cutback in OR time per week to the division will cause the rate of growth of wait times for elective patients to double.
  - OR time is currently distributed equitably among the division's surgeons even though there is significant variation is demand among them. OR slots should be allotted based on surgeon demand.
  - It is suspected that the turn around time in the OR at the HI site is high relative to the casemix. A performance review should be initiated to see if best practices at the VG site could be implemented at the HI site.
  - Adding three VG beds will almost stop the wait time growth but by adding three beds and one extra OR slot per week at the VG site, the wait time will begin to decrease.

11 Conclusions

To understand and quantify the wait for health care services one must consider all factors causing that wait. Examining the system as a capacity-planning problem is a significant step, but alone may do little to evaluate the performance of the current resources. Adding money alone will not solve the problem of long waits, (Esmail, 2003); ensuring effective use of current funds should be a fundamental process step when requesting more resources. In this project, options to improve the use of the current resources were examined in addition to increased capacity considerations.

A structured sensitivity analysis proved that long wait times are more dependent on beds than available OR time. This conclusion provided direction to focus on alternatives that free beds to reduce the effect of the bottleneck. By considering the redistribution of beds between sites it was proved both are achieving their emergency operational requirements with the minimum number of beds possible. Overuse of beds proved to be an issue, as the ELOS from national standards was exceeded by many of the division’s patients. The potential gains of maintaining this national standard is contrasted with options to add resources.

Although OR time was not the process bottleneck, changes in the amount and its distribution should be considered. It was observed that OR time could be better utilized if allotment was made based on surgeon demand instead of by historical means of equality among surgeons. This transformation may be facilitated by Capital Health’s Alternative Funding Plan, which eliminates fee-for-service and financial penalties for giving up OR time. Additionally reductions in the current allotment of OR time were examined as an anesthesia shortage at Capital Health threatens the division. The effect of reductions and addition of OR time were contrasted with a do nothing approach and proposed changes in bed use and numbers.

11.1 Lessons learned

The success of this model and others that aim to be more than capacity-planning models depends on a detailed replication of the actual system built on a foundation of complete and accurate data. Although this may be the developer's ambition, most quickly realized that it is easier said than done. Blake (2005) when "describing application within the Canadian system notes that Operational Research models are time consuming and expensive to build. Specialist skills needed to build and develop models in the existing simulation environments makes Operational Research modelling expensive, while the time required to obtain and analyze sufficient data to build, test, and validate a simulation model is posited as being the limiting step in most studies." Several observations from this study that could increase the success of building accurate simulation models in health care will be highlighted in this section.

Being embedded within Capital Health and developing working relationships with database administrators proved a tremendous asset. The value of their expertise in accessing data coupled with their understanding and interpretation of its meaning is irreplaceable. Correctly interpreting data is as essential as the raw data itself. Often many data query iterations were necessary before the required information was obtained. Having unrestricted access to database administrators is essential to understanding the data and the timelines associated with patient flow.

Understanding policies and decision rules that cause intricacies in patient flow requires continuous consulting with both surgeons and staff. Selecting a process expert who can validate system presumptions is essential to developing an accurate model. In this project the division head acted as the process expert and corrected or approved all inferences about process components from patient flow assertions and data sources.

With the merging of health care providers, to achieve economies of scale, it is becoming common for division to operate out of more than one location. It is important to include such details in a model, as multiple sites cause additional constraints. Once included in the model, scenarios such as amalgamation of the two sites or redistribution of resources between the two sites, can be evaluated to demonstrate the importance and difficulty of managing multiple sites optimally.

A simulation should be both robust and accurate to ensure as many scenarios as possible can be precisely evaluated. When designing the model one must considered the flexibility required and develop it in such a way that manipulation can be made with as little reprogramming as possible. The general surgery simulation was developed to be self-building such that at run time it would extract the resource quantities and patient attributes from a central databases. Automatic model alterations allow for multiple scenarios to be run quickly with little manual manipulation.

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