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A comprehensive simulation for wait time reduction and capacity planning applied in general surgery

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Abstract This paper describes the use of operational research techniques to analyze the wait list for the Division of General Surgery at the Capital District Health Authority in Halifax, Nova Scotia, Canada. A discrete event simulation model was developed to aid capacity planning decisions and to analyze the performance of the division. The analysis examined the consequences of redistributing beds between sites, 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.

Keywords Simulation · General surgery · Capacity planning · Wait list management · Access to medical care

1 Introduction

Studies have shown that the demand for health care service exceeding supply is an issue faced by every industrialized nation [1]. "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" [2]. 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" [3]. 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. [3] 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. [4] 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" [5]. 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 measure-

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ment of patient waits and surgeon prioritization techniques. Somewhat less effort has been spent quantifying and projecting expected patient waits through analytical decision support models.

The surgery division to be studied in this paper is the General Surgery Division, within the Queen Elizabeth II Health Science Centre (QEII), located in Halifax, Nova Scotia, Canada. The division consists of 15 full time surgeons. The QEII is a teaching hospital and has approximately 30 postgraduate general surgery residents [6]. As part of the Capital District Health Authority (CDHA) the division's surgeons provide surgical care for the 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. Their beliefs were supported by data that 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. The division members had opinions on possible causes and possible cures, but were unable to substantiate their hypotheses. It was felt that a systematic review of the flow of patients through their Operating Rooms (ORs) was needed. 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. Accordingly, an instrument with which strategies could be tested and analyzed before implementation was required.

2 Literature review

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 and Shahani [7] argue 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 [8]. Everett [9] 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 [10] 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 [8] 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 [11] 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. [12] suggest determining the impact of each variable on the model's objective function and optimizing an extrapolated objective function. Everett [9] 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 [13] 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. England and Roberts [14], Preater [13] and Worthington [15, 16] provide rich bibliographic resources for readers interested in wait list management models and health care simulation.

Harper and Shahani [7] 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 [7] 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 [17] 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. [18] describe the use of simulation to model policies for allocating cadaveric livers to patients awaiting transplants. Wujciak and Oplez [19] present a study aimed at analyzing policy options for allocating cadaveric kidneys. Davies and Davies [20] 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. [21] 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 [22] describe a simulation model to test the potential for increasing OR utilization by scheduling deferrable elective patients into planned orthopaedics blocks. Dexter and Traub [23] use a simulation methodology to suggest next case scheduling policies in theatres functioning in parallel with flexible end times.

Simulation has also been frequently applied in publicly financed health care systems to analyze wait lists for elective procedures. Everett [9] 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 [24] show that a lack of social services was to blame for a recurring winter bed crisis in a British hospital.

MacAulay and Blake [25] use simulation to suggest reallocation of inpatient beds in a paediatrics hospital. Bagust et al. [26] determined a relationship between average bed occupancy levels and expected bed shortage crises in a hypothetical emergency department. Vissers et al. [27] describe a framework for examining wait list issues and provide an example by modelling regional demand for cataract surgery. Tuft and Gallivan [28] 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 [29] 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. Martin et al. [30] use a simulation methodology to analyze the function of a geriatric service in a Norwegian hospital and use their model to suggest improvements to patient flow. Cahill and Render [31] evaluate a series of bed allocation policies for ICU beds at a VA hospital in Ohio.

Simulation methodologies have been extensively applied in privately financed health care systems, though resource allocation policies in this area are less focused on reducing wait times than increasing throughput or revenue. For example, Isken, Ward, and McKee [32], describe the use of simulation to model the operations of an obstetrics clinic. Iskander and Carter [33] use simulation to allocate resources in a same day surgery clinic in anticipation of demand growth.

A small number of papers describe the development of generic modelling frameworks. Of note is Pitt [34], who describes the development of a generic modelling framework (PRISM) to support simulation modelling in health care. The system consists of a simulation engine, a user interface, and a database used to store data and model instances. A series of example models are described, including a whole hospital system with specific reference to bed occupancy. Pitt describes the intent of the system as "direct use by managers within the healthcare [system]." No detail, however, is provided on whether the system became operational.

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 [35]. 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.

3 Materials and methods

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 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 resource shortage exists makes queueing theory infeasible, and modelling with simulation the logical alternative.

To meet the objectives of the General Surgery Division, 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 robust (ensure a useable model that connects research and operational interests). Developing a model within these constraints is necessary for a comprehensive wait list management analysis.

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 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 transferred inpatient. 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 and the end point is when the patient is discharged from a bed. All patient steps 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. 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.

When developing the model it was important to ensure the simulation was 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.

The division of general surgery operates out of both QEII hospitals. 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 days are transferred to the first available bed at the VG site.

At the VG site the division is allotted 14.5 OR slots 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 14 and 15 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 Fig. 1. Approximately 2200 elective patients and 340 non-elective patients have general surgery operations at the VG site every year.

The simulation models three patient types: elective, non-elective, and non-surgery. Patient attributes needed for the model, such as diagnosis category, OR times, and LOS, are based on historical data. These and further parameters of the general surgery division are shown in Table 1.

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 eight general diagnoses proportional to the surgeon's historical patient casemix. The patient's LOS is also assigned before the patient is forwarded to the surgeon's queue where the wait for surgery begins.

Each of the surgeons manages their own queue and consequently selects who get access first, 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

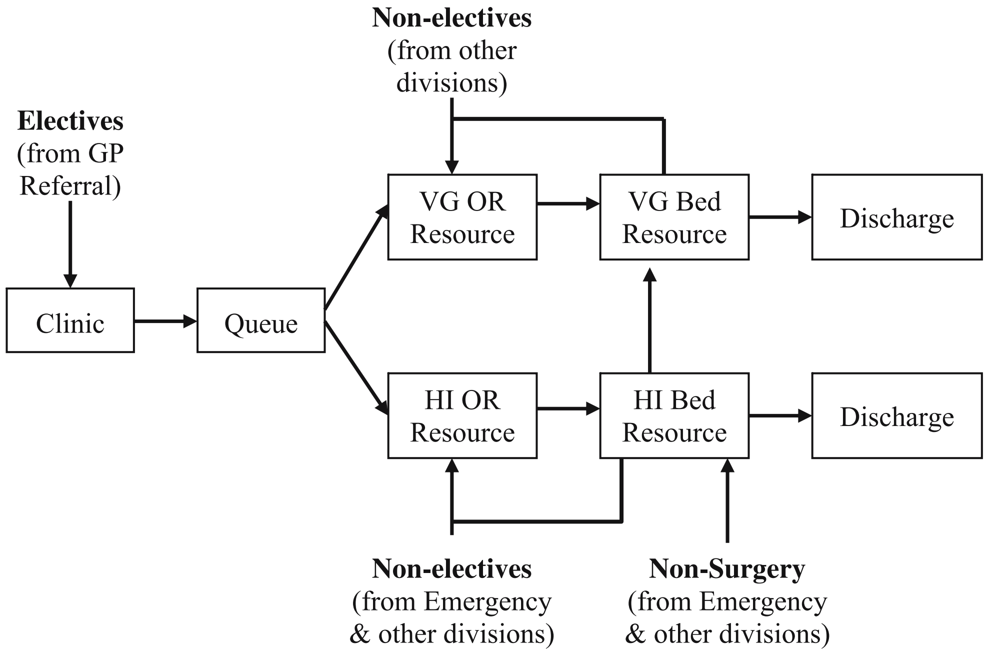


Fig. 1 Site specific patient flow

scheme was developed based on the observed wait time in each patient diagnosis category for each surgeon. This was used to model the surgeons' preference for each diagnosis groups. The average wait for patients of each diagnosis was determined for each surgeon. The 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. The model uses this de facto priority scheme to match the selection policy to the surgeon's case mix preference.

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

Table 1 Summary of general surgery division

Characteristics	VG Site	HI Site
Patient types	Elective	Elective, non-elective, non-surgery
Funded beds	42	14
Historical bed Usage	41	16
Max stay	No Max	3 days (after which patients are transferred to the VG Site)
Weekly OR hours	145	90
Elective cases per year	~2,200	~750

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. After surgery, the surgeon and the OR resource are released and made available for the next patient. 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. Outpatients exit the simulation after surgery without delay whereas inpatients maintain control of their bed resources for the full length of 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. Please note that the Intensive Care Unit (ICU) is not included in the model since the general surgery population rarely requires this resource and moreover, the specific focus of the study is to look at cancer treatment rather than traumas.

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 of non-elective patients. 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. After these 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 are made available for surgery.

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 surgery on the non-elective queue. To model this, elective patients are given a higher priority for surgery but require an additional resource to enter the OR. This additional resource becomes unavailable in the afternoon. Once non-elective patients are selected for surgery their post surgery flow is identical to elective patients that receive surgery at the HI 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.

The final patient type included in the model is the non-surgery patient type. These patients, which are only present at the HI site, do not undergo surgery and only consume bed resources. 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.

3.1 Simulation self-development

The simulation accesses a central database, which stores all the model parameters, and builds itself to reflect those parameters over three phases. By doing this we allow the model to be robust and programmable by non-simulation experts. Visual Basic Macros (VBM) programmed in ARENA transform the model through these phases 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 distribution and parameters for that attribute 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 once, the simulation no longer accesses Excel, and consequently 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.

4 Model data

Blake et al. [28] 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."

This study is unique in that the concerns created by disparate, individually held data sources were 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.

Capital Health's peri-operative management system, Surgi-Server, maintains a database of information regarding every surgery performed in the OR at both sites. The entrance and exit time for all surgeries is recorded, giving sufficient information to calculate each patient's total surgery time and the turnaround time between cases at each site. In addition to site, a patient identifier, surgery date, patient type and surgeon is available.

Capital Health's Discharge Abstract Database 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. The final system used to gather data about the division is the patient registration and scheduling system. The data from this system was used to determine when patients see their surgeon in a pre-surgery clinic. By combining this system with the Surgi-Server system it was possible to determine the wait time for surgery and the rate at which new patients are added to the surgeons queue. (We believe that such data is unique in the Canadian context).

The change in elective wait times for each category is shown below in Table 2. The wait time for elective surgeries computed monthly from historical records between January 2003 and July 2005 is shown below in Fig. 2.

Proceeding from the figure it can be seen that the wait times for elective general surgery have grown over the past two and a half years. A regression analysis, shown in Table 3, supported this claim, as the 95% confidence interval for the slope does not include 0. Furthermore the analysis demonstrates that the wait time has grown on average by 1.08 days per month during this time frame.

4.1 Input variables

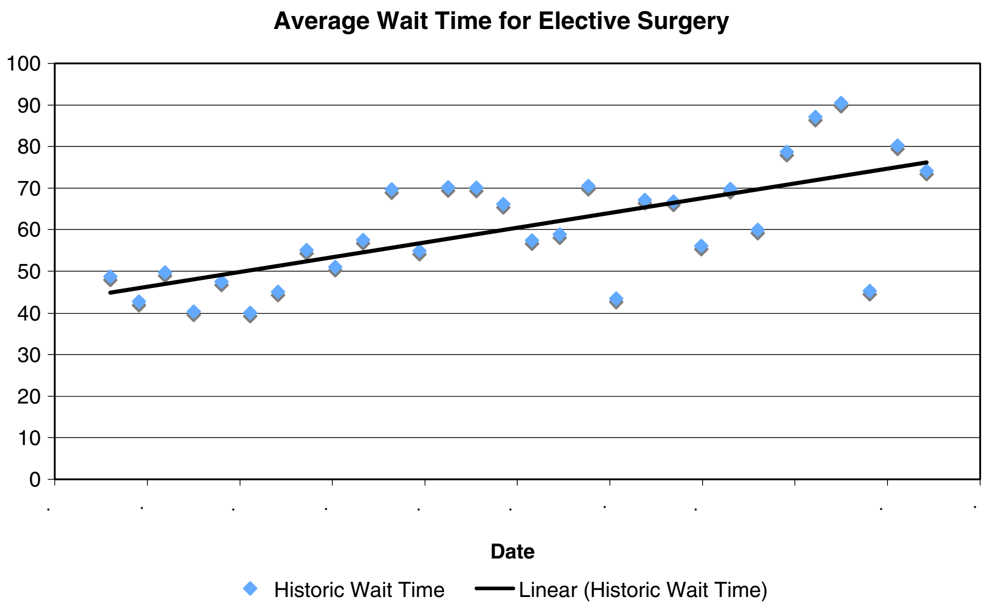
From the composite dataset, the parameters for the simulation's main input variables can be computed. The main input variables for the model are OR time, LOS and arrival rates. The OR time for all the patients was examined to determine if the data should be disaggregated to allow for a better fit. The records were divided by site and a 95% confidence interval was computed for their OR time. As Table 4 shows, a statistical difference between the OR Time at each site was observed. Table 4 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 statistically different. Thus distributions were fit to OR time data that was divided by site and by diagnosis category.

A similar analysis was performed on the LOS 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

Table 2 Historic wait times (days) by category for elective surgery

	Breast Cancer	Thyroid Cancer	Colorectal Cancer	Ostomy Closure (ILEO)	Ostomy Closure (Colostomy)	Cholecstectomy (Lap)	Cholecystectomy (Open)	Other
April to June (2003)	20	60	38	41	78	39	28	47
July to Sept (2003)	22	61	20	83	41	47	62	61
Oct to Dec (2003)	23	108	46	62	40	51		70
Jan to Feb (2004)	23	91	59	102	39	61	80	79

Fig. 2 Trend in average wait time for elective surgery



categories. The confidence intervals for the three factors are shown below in Table 5. Thus, the LOS data was divided by patient type and diagnosis category before fitting it to distributions.

5 Model validation

To ensure that the model is an accurate representation of general surgery, the Schellenberger 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 and was performing as designed.

Next, 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 ensured patient utilized resources and were serviced as would be expected from the historical data. The effective use of OR time and the utilization of beds are both independent of the metric of interest, waiting time. As a final test the wait time for patients in the model were compared to the historical data. The plot of both the actual and modelled wait time is shown below in Fig. 3.

Again a linear regression analysis was completed which 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

Table 3 Wait time regression analysis

	Slope
Coefficients	1.08
Standard Error	0.22
t Stat	4.97
p value	0.00
Lower 95%	0.64
Upper 95%	1.53

Table 4 Ninety-five percent confidence intervals for OR time

		X-bar	LCI	UCI
Site	HI Site	95.8	123.1	130.3
	VG Site	126.8	93.2	93.2
Type	Elective	115.8	112.6	118.9
	Non-Elective	114.2	110.3	118.3
Category	1	97.3	93.0	101.7
	2	181.6	171.8	191.4
	3	174.9	163.2	186.5
	4	93.7	84.6	102.7
	5	180.3	165	195.6
	6	91.9	90.0	93.8
	7	121.8	113.1	130.6
	8	113.4	110	116.8

Table 5 Ninety-five percent confidence intervals for LOS

		X-bar	LCI	UCI
Site	HI Site	4.5	4.1	5
	VG Site	4.5	4.2	4.8
Type	Elective	9.1	8.4	9.9
	Non-Elective	2.6	2.4	2.8
	Non-Surgery	3.9	3.4	4.4
Category	1	0.6	0.5	0.7
	2	1.6	1.4	1.8
	3	11.2	10.1	12.2
	4	6.6	5.3	8
	5	7.2	6.3	8.2
	6	1.1	0.9	1.4
	7	6.4	4.8	8.1
	8	5.1	4.7	5.4

actual wait times was computed. A 95% confidence interval for these 30 differences was computed revealing an upper bound of 4.91 and a lower bound of −3.68. Since the confidence interval contains 0 it was concluded that there is no significant difference between the historical mean wait times and the modelled mean wait times.

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 consumed as the historical data indicated. Finally, the main metric of interest, wait time, was proven to be consistent in the simulation. Thus, it can be concluded that the model performs as designed and that the design is an accurate depiction of the general surgery system.

6 Model output

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 0 and thus it can be concluded that there is no statistically significant improvement as the result of adding 15% more OR Time. See Table 6 for a summary of the calculations.

In contrast, when four extra beds are added the throughput rises from 226 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 0 and it was concluded that a statistically significant improvement in throughput was achieved by adding four VG beds. (See Table 6 for a

Fig. 3 Modelled average wait time for elective surgery

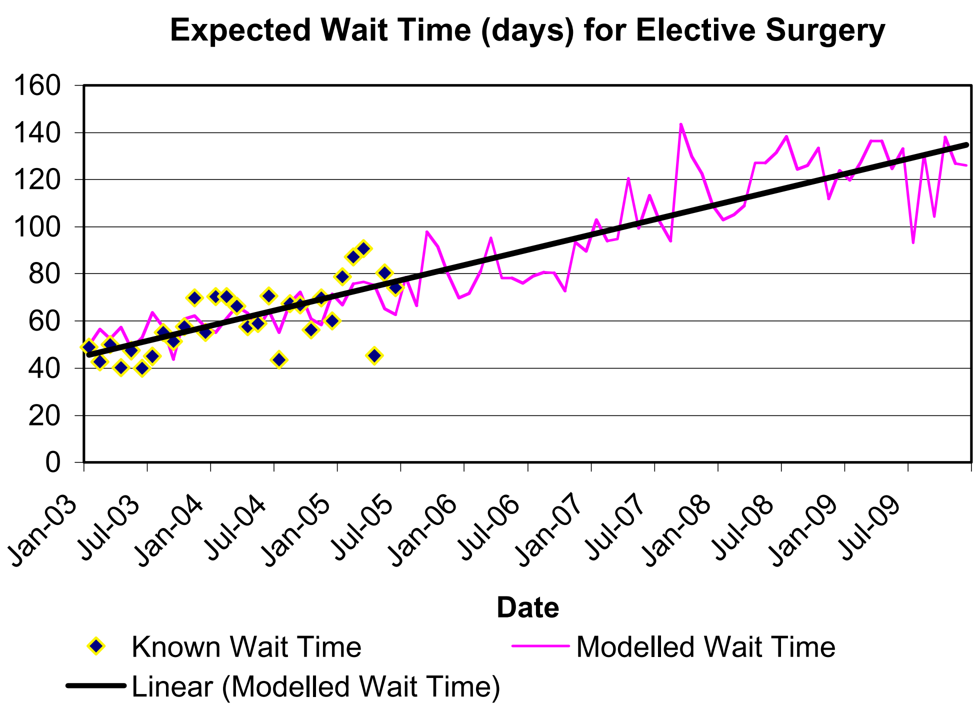


Table 6 Confidence intervals for bottleneck analysis

	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

summary of the calculations) The bottleneck analysis is continued by decreasing the OR time and adding more VG beds to further gauge how sensitive throughput is to resource levels. From this analysis we conclude that the bed resource is the bottleneck of this system. The complete results are shown below in Fig. 4.

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 from other divisions. The simulation uses 16 beds at the HI site and 41 beds at the VG site as the base scenario to reflect actual practice. A sensitivity analysis was performed on dispersion of beds between sites while maintaining a total of 56 for the division. Seven allotments were considered with each evaluated by elective patient throughput and non-elective patient wait times.

The throughput of elective patients is especially sensitive to the number of VG beds available, as shown in Fig. 5. The cause is twofold: first as the number of beds at the HI increases so too 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, the decision rule that transfers patients after three days 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.

The next metric used to evaluate the bed dispersion is the wait for non-elective patients. This wait time proved to be sensitive to the number of beds available, as shown in Fig. 6. 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 HI beds is decreased, the wait time for non-elective patients grows significantly. Thus we conclude 16 beds is the minimum required to meet the demands of the patients at the HI site.

It is clear that decreasing the number of VG beds will have a significant negative effect on elective patient throughput. However, it was also apparent from the wait time for non-elective patients, that a decrease in beds at the HI site will result in a significantly longer wait for non-elective surgery. From this 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.

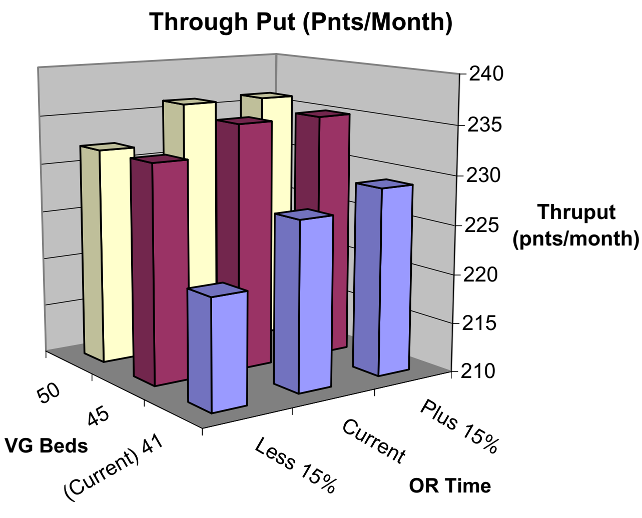


Fig. 4 Modelled impact of resources

7 Model projections

On average, CDHA surgeons keep their patients in beds for 0.55 days longer than would be expected from the Canadian Institute for Health Information (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 results are shown in Fig. 7.

A shortage of anesthesiologists within Capital Health had been a major dilemma for all divisions in the department of surgery during the study period. The shortage caused ORs at the QEII to operate at 92% capacity in January 2005 [36]. As a result, the General Surgery Division experienced 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 slot/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 results are shown in Fig. 7.

Figure 7 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 the standard set by CIHI will slow the growth of the wait time. Finally, adding four VG beds and one extra VG OR slot/week

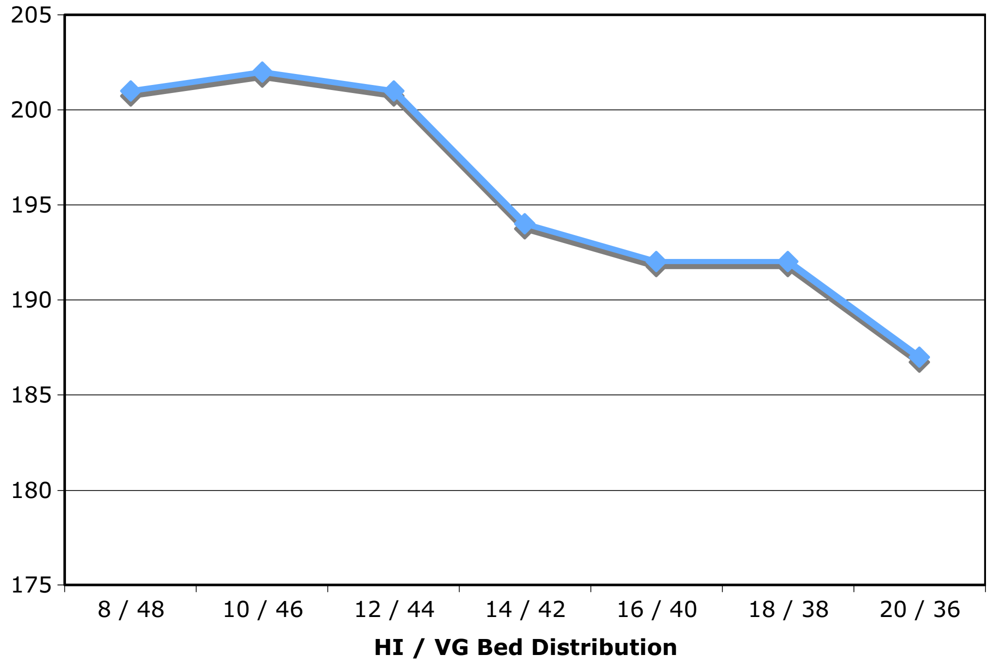


Fig. 5 Patient throughput as a function of beds per site

is the only scenario that will eliminate the wait time growth and cause a substantial decrease in wait times. However, 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.

8 Recommendations and conclusions

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. A responsible and effective solution should contain commitments for additional beds and OR time, in combination with more stringent use of

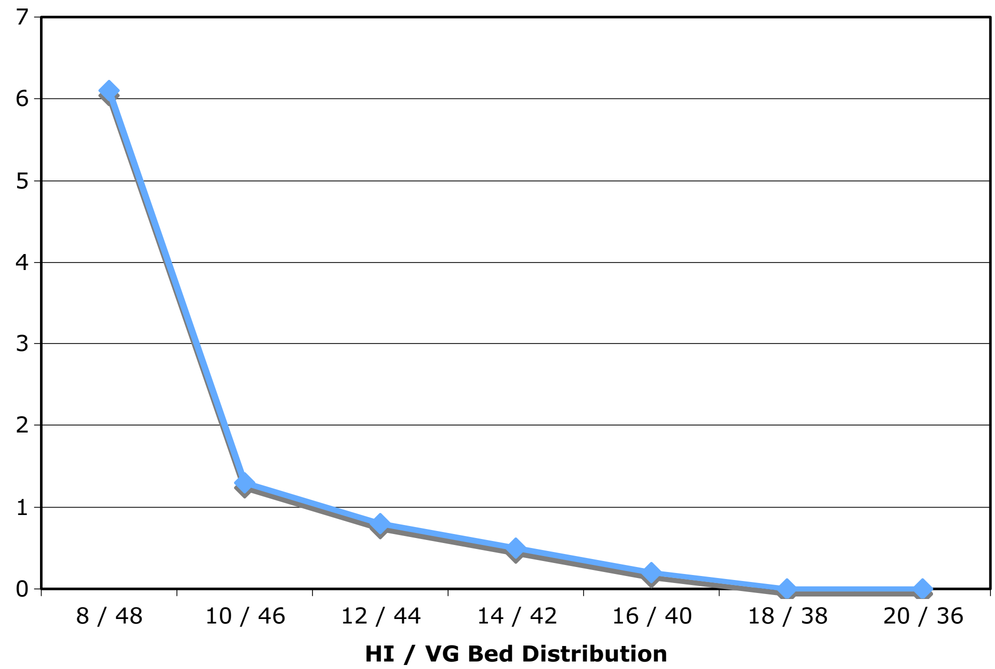


Fig. 6 Non-elective patient waits as a function of beds per site

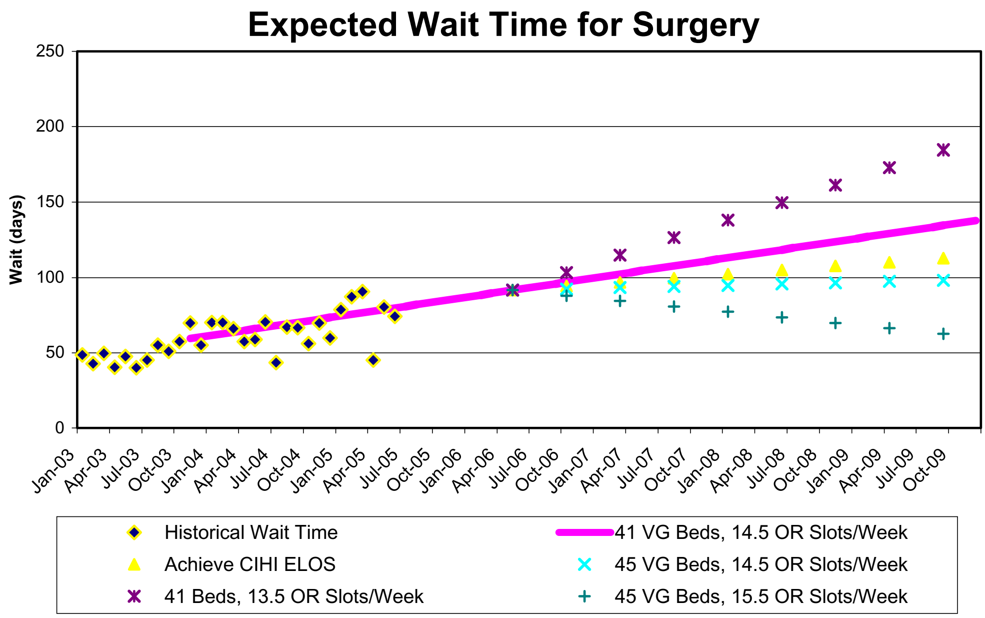


Fig. 7 Multiple scenario wait time projections

both resources. If implemented, the following recommendations will reverse the 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.
- At the VG site beds are currently utilized at approximately 97%, leading to the cancellation of 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 time 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.

9 Summary

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; 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.

The simulation showed 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 shown that both are achieving their emergency operational requirements with the minimum number of beds possible. Overuse of beds proved to be an issue, as the expected LOS 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.

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