Performance Improvement of Operating Rooms at WHSC Using Simulation and Optimization

By

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A Thesis submitted to the Faculty of Graduate Studies of

The University of Manitoba

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Of

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Abstract

The operating room (OR) is one of the most demanding departments at Winnipeg Health Science Center (WHSC) which is the main healthcare facility serving adult surgical patients in Manitoba, Northwestern Ontario, and Nunavut. The problems faced to the OR are the long waiting list of patients and the inefficient utilization of human resources and facilities. The OR needs to treat a large variety of patient types versatility and dynamically. A discrete event simulation tool is used for modeling the OR operation. The major work involving in this research includes data collection, simulation modeling, model validation and output analysis. The initial results have shown the simulation potential in the performance improvement of healthcare systems.

Based on the simulation model, Tabu Search (TS) is used as the optimizer in the meta-heuristics optimization method. The TS algorithm is used in conjunction with the simulation model of WHSC to find the optimum number of some resources in OR department.

The contribution of this research is the integration of simulation and optimization in the performance improvement of healthcare systems. Parts of the solution generated in this research have been recommended to the WHSC for the action of the performance improvement.

Acknowledgements

First of all, I am deeply indebted to Dr. Peng who led me to the wonderful world of simulation of health care systems. His stimulating suggestions and encouragement helped me in all the time of research and writing of this thesis.

I would like to express my gratitude to all those who gave me the possibility to complete this research. I want to thank Dr. EIMekkawy who helped me to build the simulation modeling step by step. I would like thank Yin Yin Tan who helped me to collect data from WHSC. I would also like thank colleagues in my office. I want to thank them for all their help, support, interest and valuable hints.

I must acknowledge Winnipeg Regional Health Authority and Winnipeg Health Science Centre whose financial support makes this research possible. Appreciation also goes to Drs. Michael Moffatt and Brock Wright for their support and comments for this research project. Thanks also go to staff members at WHSC who provide the data collection and comments for the simulation model.

Especially, I would like to give my special thanks to my husband Tong and my lovely son Evan whose patient love enabled me to complete this work.

Table of Contents

List of Tables

List of Figures

List of abbreviations

ABM: Agent-Based Modeling

ABMS: Agent-Based Modeling and Simulation

ABS: Agent-Based Simulation

ACO: Ant-Colony Optimization

DES: Discrete-Event Simulation

EKG: Electrocardiogram

GAs: Genetic Algorithms

GIS: Geographical Information System

IBM: Individual-Based Modeling

IHA: In-House Anaethetist

INP: Inpatients

IV: Intravenous

LOS: Length of Stay

MSS: Master Surgical Schedule

NAs: Nursing Assistants

OR: Operating Room

PAC: Pre-Admission Clinic

PACU: Post Anaesthesia Care Unit

PAs: Perioperative Aids

SA: Simulated Annealing

SD: System Dynamics

SDA: Same Day Admission Patients

SDP: Same Day Patients

SICU: Surgical Intensive Care Unit

SS: Scatter Search

TP: Transport Personnel

TS: Tabu Search

WHSC: Winnipeg Health Sciences Centre

Chapter 1: Introduction

1.1. Thesis Objectives

Winnipeg Health Sciences Center (WHSC) is a healthcare centre serving residents of Manitoba, Northwestern Ontario and Nunavut. The operating room (OR) is one of the most demanding department at WHSC. The WHSC cooperates with researchers at University of Manitoba to study its adult surgical patient flow for a solution of long waiting list of patients and inefficient utilization of resources. A collaborative team was formed in 2005.

The objective of this research is to use discrete-event simulation (DES) technology as a tool to improve the performance of the OR department at WHSC. The problem and the bottleneck in the OR are identified firstly based on the simulation. The decision can then be made for the system improvement.

The discrete-event simulation model is to aid the OR department of WHSC in evaluating the current efficiency of a surgical suite. The decision will be made for how either changing resources or changing the set of surgical procedures performed that would affect surgical suite performance. Simulation optimization is designed to seek the optimal performance of the OR department at WHSC.

1.2. Thesis Overview

In this thesis, a simulation model of the adult surgical patient flow processes at WHSC is built. Two main parts are included. One is the system simulation modeling and the performance evaluation. The other is the system optimization. Chapter 2 is a literature review which discusses the application of simulation models applied in the healthcare field. Four simulation approaches are introduced including discrete-event simulation (DES), system dynamics (SD), Monte Carlo, and agent-based modeling and simulation (ABMS). DES has advantages over other simulation approaches for building healthcare model. Recent advances are also discussed. Chapter 3 presents the current adult surgical patient flow in the operating room department, related units at WHSC and the current scheduling system in the OR department which are the foundation of the discrete-event simulation modeling. Chapter 4 shows more details of the simulation modeling from the data collecting, simulation model, model testing, and experimentation. Chapter 5 discusses the meta-heuristics optimization method using Tabu Search (TS) as the optimizer in simulation optimization. The comparison between current performance and the optimal performance obtained by TS is also presented. Finally, the research presented in this thesis is summarized in Chapter 6, in which the future work is also discussed.

Chapter 2: Literature Review

2.1. Introduction

Simulation has been widely and successfully used in many fields, including defense, manufacturing industry, service industries, finance and training. Operation research has been applied to the domain of healthcare for more than four decades. Operation research models have been successfully used to assist clinical decision making, facility location and planning, resources allocation, evaluation of treatments and organizational redesign. Simulation is one of the most popular used operation research methods, and is regarded as the feasible technique of choice in healthcare (Davies and Davies, 1994). Healthcare systems are uncertain and variable. Healthcare modeling can be very complicated. Healthcare systems need a stochastic modeling approach to deal effectively with complexity. Interaction and communication are required between the model and users (Brailsford 2007). Simulation is characterized by all these features and has been widely used in healthcare applications.

Four main simulation approaches are briefly described for the patient-level modeling in the first part of this chapter. The four approaches are discrete-event simulation (DES), system dynamics (SD), Monte Carlo simulation, and agent-based approaches. The use of these approaches in healthcare modeling is also discussed. Some of simulation modeling in healthcare applications is then illustrated by different objectives. Finally, the recent advances of simulation in healthcare, and some unique natures of healthcare problems are discussed.

2.2. Simulation Approaches

There are mainly four simulation approaches being used in healthcare modeling. The discrete-event simulation (DES) is the most widely used simulation approach in healthcare. Meanwhile system dynamics (SD) has been gaining in popularity in recent years. With the development of computer technology, agent-based approach has been also used in healthcare. Some commercial simulation software companies are developing simulation software especially for healthcare system using the agent-based modeling and simulation approach. Many demo models of healthcare using agent-based technology can be run on XJ technologies (XJ Technologies Company 2009) website that develops AnyLogic multimehod modeling methods including agent-based, discrete-event and system dynamics. Flexsim HC (Flexsim Software Products, Inc. 2009) is developed special for modeling the complexities and nuances of healthcare management. The Monte Carlo simulation has also been used.

Discrete-event simulation (DES) is a type of simulation approaches in which individual entities flow around a network of queues for services, and entities have characteristics which determine their pathway through the network (Brailsford 2007). DES appears to be tailor-made for hospital systems in which patients join waiting lists for appointments, investigations and treatments, and patients have individual characteristics for their pathway through the hospital system. DES has many advantages in mathematics. DES takes account of the medical history. Service time distributions can be based on individual characteristics and the previous history. Complex logical rules can be used to determine patients' routing through the system or the outcome of a treatment. Randomness, variability and uncertainty can be obtained, as long as the simulation model runs for enough time. Virtually anything can be modeled depending on the flexibility of the software chosen. The most valuable advantage is a variety of software packages available at a wide range of prices, most of which have a kind of graphical facility which makes the user to visualize the model easily.

System dynamics simulation (SD) is a continuous simulation approach in which there are no individual entities. Entities are an indistinguishable mass which flows around the model like water in a central heating system, accumulating in tanks or radiators, with inflows and outflows governed by valves or rates (Brailsford 2007). Patients become water-like mass in the model which is less active to healthcare professionals. Moreover, SD models are deterministic and a stochastic element is not needed any more. The basic assumption in SD is that length of stay in a stock is exponentially distributed. Furthermore, SD software does not have the attractive graphics of DES. However, SD has many features which DES lacks. The basic principle of SD is the structure determines behavior. If the structural relationships between the elements of the system are understood, the emergent behavior of that system can be understood as a whole. SD is concerned with feedback and unanticipated effects. SD models can be used at a more speculative or strategic level, for larger populations and longer time horizons since SD models are not dependent on huge quantities of high quality data. The most valuable feature of SD is that the models run very fast in general, and multiple iterations are not required. The model can be run interactively in real time with decision-makers.

Monte Carlo simulation is a type of simulation that depends on repeated random sampling and statistical analysis to calculate the results (Raychaudhuri 2008). The simulation approach is closely based on random experiments in which the specific result is not known beforehand. Monte Carlo simulation is considered as a methodical way of doing what-if analysis. This simulation method can assist a modeler to methodically investigate the complete range of risk related with each risky input variable. This approach has some disadvantages (Raychaudhuri 2008). First, it might be difficult to evaluate the best and worst case scenarios for each input variable. Second, all the input variables may not be at their best or worst levels at the same time. Decision making tends to be difficult as well if more than one scenario is being considered. Also, as an experimenter increases the number of cases to consider, model versioning and storing becomes difficult. An experimenter might be tempted to run various ad-hoc values of the input parameters, often called what-if analysis, but it is not practical to go through all possible values of each input parameter. By far, Monte Carlo simulation is being used in engineering disciplines for various reasons. One of the most common uses is to estimate reliability of mechanical components in mechanical engineering (Raychaudhuri 2008).

Agent-based modeling and simulation (ABMS) is a new simulation approach to modeling systems consisting of autonomous, interacting agents. It is one of the most exciting practical developments in modeling since the invention of relational database (Macal and North 2008). ABMS connects with many other fields including complexity science, systems science, systems dynamics, computer science, management science, several branches of the social sciences, and traditional modeling and simulation. ABMS draws on these fields for its theoretical foundation, for its conceptual view and philosophy, and for applicable modeling techniques. Agent-based modeling and simulation is also known as ABM (agent-based modeling), ABS (agent-based systems or simulation), and IBM (individual-based modeling). So far, there is no universal agreement on the precise definition of the term "agent". Any type of independent component including software, model, and individual is considered to be an agent (Bonabeau 2001). To make a practical model, agents have certain characteristics including attributes, behavioral rules, memory, resources, decision making sophistication, and rules to modify behavioral rules. Agent-based modeling and simulation is becoming so widespread because the world we live in is becoming more complex. The systems that we need to analyze and model are becoming more complex in terms of their interdependencies. Some systems have always been too complex for us to adequately model. Data are organized into databases at finer levels of granularity. The most important one is that computational power is advancing rapidly. ABMS is coming to the front and catching people's eyes. There are some software and toolkits using to make ABMS applications. ABMS has been used in manufacturing operations for several years. ABMS is being used in healthcare field too. In Stiglic's paper (2005), a multi-agent system was applied for patient and staff scheduling in ambulatory health care environments.

2.3. Applications of the Simulation Modeling

Simulation has been a very useful tool for healthcare systems. Different objectives have been reached for the improvement of healthcare systems using simulation. Several studies reported the organizational benefits and cost savings of applying simulation to hospital planning and scheduling (Barnes 1997). Other applied simulation effort focused on the operational process flow of specific healthcare delivery units (Lowery 1994). The main capability of simulation is to analyze what-if scenarios, which allows significant exploration of multiple options, without spending enormous amounts of expense on staffing, training, and equipment (Barnes et al, 1997). Computer simulation has been an effective tool for operational analysis of the stochastic processes of healthcare delivery (Lowery et al, 1994). In the last four decades, the use of simulation as a planning and decision-making tool has been spreading rapidly in the healthcare arena. Simulation can model and analyze real-world problems that cannot be successfully approached by other types of analytical techniques.

Simulation has been applied in healthcare with success. Specialized applications targeting emergency rooms and other operation issues at large institutions are well documented (Centeno 2003). Testing scenarios of changes in processing methods, resources location and scheduling without major physical investment and risk is a key objective in the application of healthcare simulation (Morrison and Bird 2003). For example, some successful simulation applications in healthcare include: a simulation model of the emergency department in a general hospital to examine patient flows and the patient waiting time (Takakuwa and Shiozaki 2004); the simulation to estimate the maximum level of demand in an emergency room and the configuration of resources required (Baesler 2003); a discrete event simulation model to analyze the renal transplant waiting list and to reduce the size of the waiting list (Abellán 2004); a patient scheduling simulation model to capture four components of outpatient clinic scheduling systems including external demand for appointments, supply of provider timeslots, the patient flow logic and the scheduling algorithm (Guo 2004); and a computer simulation model of the hospital layout for the efficient design and use of resources, as well as assist in planning decisions (Osidach and Fu 2003).

The simulation model can be used to minimize the need of facilities. A model is used by Baesler (2003) to create a curve for predicting the behavior of variable patient's time and to estimate the maximum possible demand that the system can absorb. An experiment is conducted in the simulation model to define the minimum number of physical and human resources required to serve the demand. Wiinamaki (2003) uses a simulation model to analyze the detailed process of the emergency care centre based on the layout, number of rooms and beds, and operation hours.

The OR is one of the most demanding departments in hospitals. Simulation modeling has been used to depict the operation processing and to evaluate the possible alternatives to reduce the length of patient stay in the OR and to improve the operation in hospitals. Samaha (2003) gathered data for 24 hours per day over a seven-day period. Each operation is evaluated through the simulation model. An operation model is built and possible alternatives are simulated by Blasak (2003) to allow a medical center to make only necessary changes for reducing the length of patient stay in the hospital.

2.4. Recent Advances in the Healthcare Modeling

Many other interesting advances have been made in recent years. Advances have been developed in combining simulation with other techniques, for example optimization or geographical modeling. Advances have also been made by modeling human behavior.

Many ready-made simulation packages now have built-in optimizers. For instance, ARENA involves a tool called OptQuest which can use a variety of meta-heuristics including SS, TS and neural networks. Simul8 has an add-on tool called Optimiz which uses neural networks to guide simulation runs. The model for diabetic retinopathy developed by Davies et al (2000) was used as the basis for an exploratory paper by Brailsford et al (2007) in which simulation model was built with ant-colony optimization (ACO). The model was to simulate the effects of different screening strategies on a population of diabetic patients, and to compare them in terms of two objective functions: Min C/E, cost-effectiveness (minimum incremental cost per year of sight saved, compared with a no-screening baseline) and Max E, maximum effectiveness (years of sight saved). The model described how ACO is used to optimize these two objectives, and the issues involved in optimizing stochastic variables. The model presented results for a range of different assumptions and scenarios about the format of screening programmers, using realistic data, to make policy recommendations on the basis of the findings. Although the model was very slow to run on a practical level, the exploration can be imitated in computational approaches to the solution of search and optimization problems which has led to a large number of successful applications.

Geographical information system (GIS) captures, stores, analyzes, manages, and presents data that are linked to location. Technically, GIS is geographic information systems which include mapping software and the application with remote sensing, land surveying, aerial photography, mathematics, photogrammetric, geography, and tools that can be implemented with GIS software. Harper, Phillips and Gallagher (2005) developed a DES model incorporating a GIS for the regional planning of oral and maxillofacial surgery across London. In the model, individual patients were sampled at random points in the map using the GIS, and their travel times to a chosen center were then sampled from a travel distribution, depending on the sampled mode of transport. This method outperforms classical facility location methods, in which demand is assumed to arise at discrete nodes rather than at individually sampled location.

The simulation model in healthcare is much more complex than the simulation model in production industries. One vital reason is that the entities in the healthcare model are human beings who are alive with lives while the entities in production industries are materials. Human behavior affects the outcomes greatly in practice. Modeling of human behavior is not limited to the field of healthcare, but also to other fields. In manufacturing industry, the impact of worker behavior can be substantial, even in production industries for example automobile manufacture (Baines and Kay 2002). In healthcare field, the human behavior can be more significant. For instance, patients may not complete a course of a prescribed medication because they find the side-effects unpleasant. A study designed to evaluate the medication which ignores such behavioral factors may give unreliable results. Several models of health-related behavior have been developed. Becker (1974) developed a Health Belief Model. Ajzen (1991) developed a Theory of Planned Behavior. Schmidt (2000) developed an approach named PECS, which considered the physical, emotional, cognitive and social aspects of human behavior. Brailsford and Schmidt (2003) developed a DES model which combined PECS with the Health Belief model to model attendance for diabetic retinopathy screening, based on the model of Davies (2000). Skykes (2007) used the Theory of Planned Behavior to model a woman's probability of attending for mammography for breast cancer screening.

Chapter 3: Description of Surgical Patient Flow at Winnipeg Health Sciences Center

Winnipeg Health Sciences Center (WHSC) of Manitoba is the major trauma center serving the whole province of Manitoba besides Northwestern Ontario and Nunavut. WHSC's adult Operation Room (OR) department is the main place at which surgeries are executed on both elective patients and emergency patients. Mechanical and Manufacturing Engineering Department of University of Manitoba organized a team to cooperate with WHSC. This research is to apply technologies to reduce the waiting time for treatment and to improve the efficiency of OR department at WHSC.

YinYin Tan worked the first phase of this research. It took her one year to talk with managers, nurses, surgeons and other people in the OR department and related departments at WHSC. She also observed the behaviors in the OR department of WHSC. She particularized each step of the patient's flow and each nurse's job in her report which is a part of her thesis (Tan 2008). The surgical patient flow of the OR department and the data of resources was summarized based on her report. One year later, I joined her to collect more detailed data which are five-week elective surgical patients' data including the travel time from one unit to another unit, the cleaning time in the OR theatre, the setup time of the OR theatre, and the processing time of the operation, etc. In this chapter, I briefly introduce the patient types, the OR and related units, the work flow in OR, and the scheduling which are part of data applied in the simulation modeling.

3.1. Patient Types

There are two main types of patients in the OR department of WHSC. One type is the elective surgical patients who have appointments for the surgeries. The other type is the emergency surgical patients who come unanticipated to the OR department via ambulances for a surgery. Figure 3-1 shows the structure of patient types.

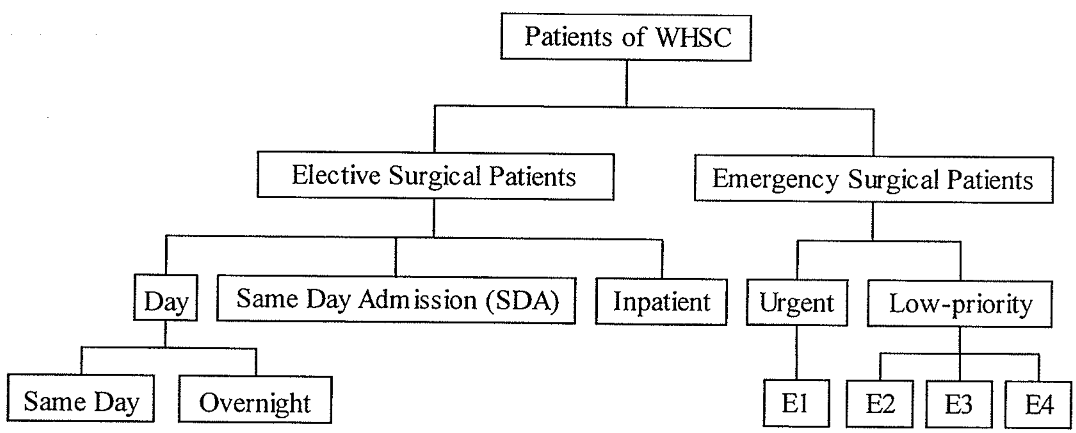

Figure 3-1 : Patient types of WHSC

Elective surgical patients at WHSC are categorized into three sub-types: Day patients including Same Day patients (SDP) and Overnight patients; Same Day Admission (SDA); and Inpatient.

Day and SDA patients are generally admitted to the OR department of WHSC on the day when their surgery is performed. Day patients are expected to be discharged within 24 hours after their surgery. Depending on their expected discharge time, Day patients are divided into either SDP or Overnight patients. SDP patients are discharged on the same day of the surgery while Overnight patients are discharged in the next morning after their surgery. SDA patients arrive at WHSC on the day of surgery and will need to stay for more than 24 hours. Patients who need to be admitted one day or more days prior to their surgery are assorted with Inpatients.

Emergency surgical patients at WHSC are classified into four levels, E1, E2, E3, and E4, based on their acuity. E1 patients are the most urgent patients who need surgery immediately. E2 level is less urgent than E1. E2, E3, E4 patients are usually carried out their surgery within four, eight and thirty-six hours respectively. Emergency patients arrive at the Emergency Department. If they need surgery, they will be admitted to a bed in an inpatient unit pre-operatively and post-operatively. Some of emergency surgical patients whose case is not urgent will be viewed as elective surgical patients. These patients will be made an appointed surgery to fit into elective slates.

3.2. OR Department and Related Departments

Some patients visit pre-admission clinic (PAC) a few days before their surgery. On the surgery day, each patient goes through admitting department, pre-operative units, OR department, recovery units, and post-operative units in sequence. Figure 3-2 shows the structure of OR department and related units at WHSC. In this section, I briefly discuss the function of each department which is related to the simulation modeling.

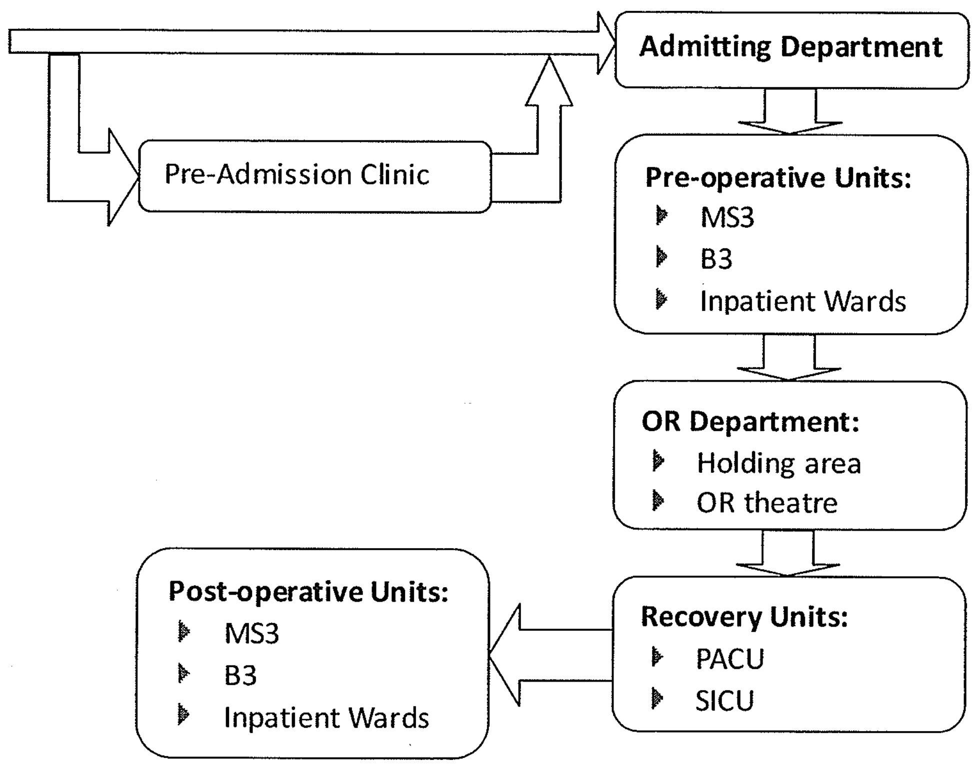

Figure 3-2 : The structure of OR department and related units at WHSC

3.2.1. Pre-Admission Clinic

The Pre-Admission Clinic (PAC) is a clinic which assesses patient's medical fitness for surgery anesthesia and other necessary pre-operative work. Patients and their families have also a chance to be informed about the expectation before and after the surgery. Elective surgical patients excluding Inpatients may usually be noticed to attend PAC between a few days and two weeks of their appointed surgery. It usually takes about one to three hours for the patients to visit PAC. A nurse and an anesthetist will see each patient. The nurse will discuss some issues with the patient such as patient's health and medical history, the necessary preparations for the operation, and the discharge plan. The anesthetist will perform the assessment of the patient's medical condition, determine their fitness for the operation, and discuss anesthetist options. Other professionals may also see the patient if necessary such as physiotherapist or cardiac surgery nurse. All patients will be required pre-operative investigations for example blood tests, x-ray, and etc. Finally the patient should have a complete understanding of the process of the surgery, anesthesia, hospital stay, and discharge.

3.2.2. Admitting Department

Admitting department is the place to collect patients' standard information including patient's name, date of birth, address, health insurance number, etc. All elective patients first stop at the admitting department on the day of admission. If a patient was registered over the phone previously, it is only a few minutes for the patient to do the registration at admitting department. Otherwise, it will take no more than ten minutes to process the registration if there is not a long line.

Most patients are asked to arrive about two hours before the surgery excluding inpatients that are noticed to arrive once an inpatient bed is available for them. Some are required to arrive earlier if they need additional pre-operative test or medication requirements.

3.2.3. Pre-operative Units

Pre-operative units are places where all patients are assessed by a nurse before going to the OR department. A patient's assessment includes documenting the patient's vital signs, medical history, fitness for surgery, and other concerns that the OR department should be aware of prior to surgery. After registering at the admitting department, patients go to their pre-operative units.

Different type patients go to three different pre-operative units. SDP and SDA patients go to units called MS3 or B3, Overnight patients go to B3, and Inpatients go to inpatient wards. The patient flow of pre-operative units is shown in Figure 3-3.

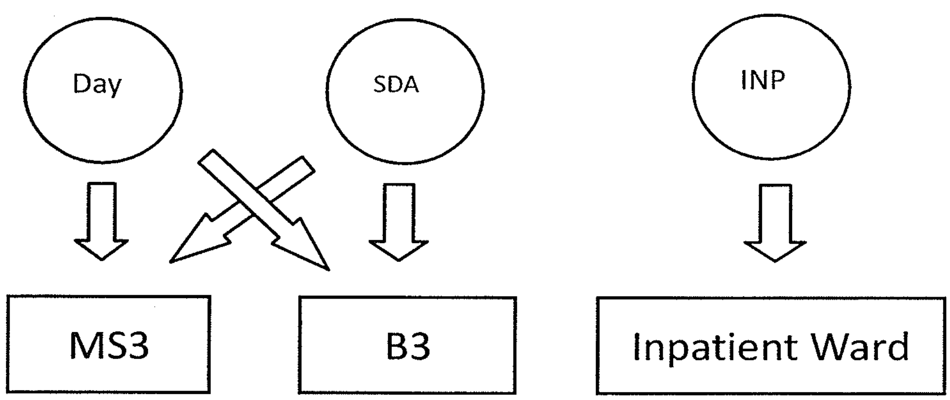

Figure 3-3 : The patient flow in Pre-Operative units

MS3 is open from 5:30am to 6:00pm, Monday to Friday. MS3 has seventeen beds and their patient volume is primarily made up of elective surgical patients.

B3 is open twenty-four hours a day. B3 handles a wide variety of patient types. One bed is reserved for SDA patients and three beds are reserved for Day patients every weekday.

Inpatient unit is open 24 hours a day too. There are many inpatient units, each corresponding to a particular services, and each having a different number of available beds. Some inpatient units contain step-down units, which are meant for patients with high acuity.

3.2.4. Operating Room Department

Operating Room (OR) department is the vital department where surgeries are performed. There are thirteen operating theatres in the OR department of WHSC. For each surgery, the patient's surgeon will be present with an anesthetist and usually three OR nurses. The anesthetist and the three OR nurses are assigned to a particular operating theatre for one of their shift. They may be moved to help another theatre depending on certain situations.

The elective slate runs from 7:30 to 15:30 from Monday to Friday each week. The emergency slate runs from 15:30 to 22:30, Monday to Friday, and usually has two staffed operating theatres. Of course very urgent emergency cases are still performed after 22:30. On the weekends, there is no elective slate and two operating theatres are staffed solely for emergency procedures. Some emergency patients who are not very urgent usually are handled in the elective slate as elective patients. This research will only consider the elective patients.

There are many other people who support OR department besides the surgical team. For example, two transport personnels (TPs) are assigned for picking up elective patients from pre-operative units before the surgery. Peri-operative aides (PAs) work for a variety of activities, for instance, supporting nurses with operating theatre set-ups, stocking supplies, transporting patients to their operating theatre from the holding area, assisting in patients, and cleaning the operating theatres when cases are finished.

3.2.5. Recovery Units

After finishing the surgery, patients will be transferred to recovery units immediately. Recovery units prevent and treat complications after surgery and anesthesia. There are two main recovery units, Post-Anesthesia Care Unit (PACU) and Surgical Intensive Care Unit (SICU). PACU is the main recovery unit. Most of elective patients are transferred to PACU after surgery. A small number of elective surgical patients who require special cares will be transferred to SICU.

PACU is usually able to accommodate a maximum of twelve patients at a time. Most patients stay in PACU between two and four hours. The time the patient stays in PACU depends on the complexity of the patient's surgery and the individual reaction to the surgery. A nurse is assigned to the patient after the patient arrives at PACU. The nurse provides care according to anesthesia's order and does some tests such as temperature measurement, blood pressure test, X-rays etc. Two nursing assistants (NAs) transport the patient to post-operative units after the patient is ready.

SICU is a ten-bed unit similar to the PACU, while SICU mainly handles patients that have experienced greater trauma or major surgical procedures.

3.2.6. Post-Operative Units

Post-operative units include MS3, B3 and Inpatient units. For Day patients and Inpatients, their post-operative unit will be the same as their pre-operative unit, while SDA patients will go to an inpatient unit post-operatively. The time that the elective surgical patient spends in post-operative units can be estimated for days. It is harder to estimate the length of stay for emergency surgical patients because most emergency patients are critically ill or have major trauma.

3.3. The Current Surgical Patient Flow

All elective surgical patients must go to the admitting department in the morning time or two hours before their surgeries. It takes them approximately ten minutes to register their information and to fill forms.

Day patients and SDA patients go to MS3 or B3 pre-operatively. Inpatients and some less urgent patients go to Inpatient ward pre-operatively. For Day and SDA patients who already went to PAC before their surgery will take less time for assessment in pre-operative units. Most patients are tested in pre-operative units, such as blood test, X-ray etc.

When the OR theatre is ready for the patient, TPs will pick up the patient in the pre-operative units then transport the patient to the holding area (also called music room). One of nurses and anesthetist will interview the patient respectively. Then the patient will be wheeled into the OR theatre. The patient will be put to sleep by the anesthetist in the operating room. The patient will have to be prepped and positioned by the OR nurses and anesthetist, and the PAs may be present to help. Then once the surgeon arrives, surgery can start. There will be at least one scrub nurse who sets up the instruments and passes the patient to the surgeon, while the others will be circulating for supplying, charting, emptying the laundry, etc. When the process is completed, the anesthetist will wake the patient up and take the patient to recovery unit (PACU or SICU) along with the surgeon. Meanwhile, the nurses will then put away all the instruments and send them to sterile processing department to disassemble, sterilize, and reassemble. PAs will clean up the room. When the room is clean, the nurses begin setting up for the next patient.

When patients arrive at PACU, the patient will be assigned a nurse who will take a report from the patient's anesthetist, while the patient's surgeon will write down post-op orders. The nurse will then follow the anesthetist's orders. It needs to be aware of any issues (e.g. dressings, antibiotics) and to see if there are extra things that need to be done, such as making sure antibiotic medications or IV solutions have been started. If a patient's surgeons wants the patient to do some tests, such as x-rays and EKGs, either the unit clerk or a nurse will call the respective department (e.g. Radiology for x-rays) to inform them of the test needed so that they can send someone to the PACU.

Day patients return to MS3 or B3 post-operatively, while SDA patients and inpatients go to inpatient ward post-operatively. The nurse will read doctor's orders in patient's chart to assess the patient right away. After that, the patient will be checked at regular intervals.

SDP patients are discharged on the same day of the surgery while Overnight patients are discharged the next morning after their surgery. SDA and inpatients will be discharged more than 24 hours after the surgery.

The Figure 3-4 shows the elective surgical patient flow at the OR department of WHSC. The simulation model in this research was built based on the elective surgical flow which is described in this chapter. The simulation model includes patient arrival, registration in Admitting department, pre-operative units, OR theatres, PACU, and post-operative units. Day patients and SDA patients will be discharged. Inpatients that need another surgery later will go back to Inpatient wards.

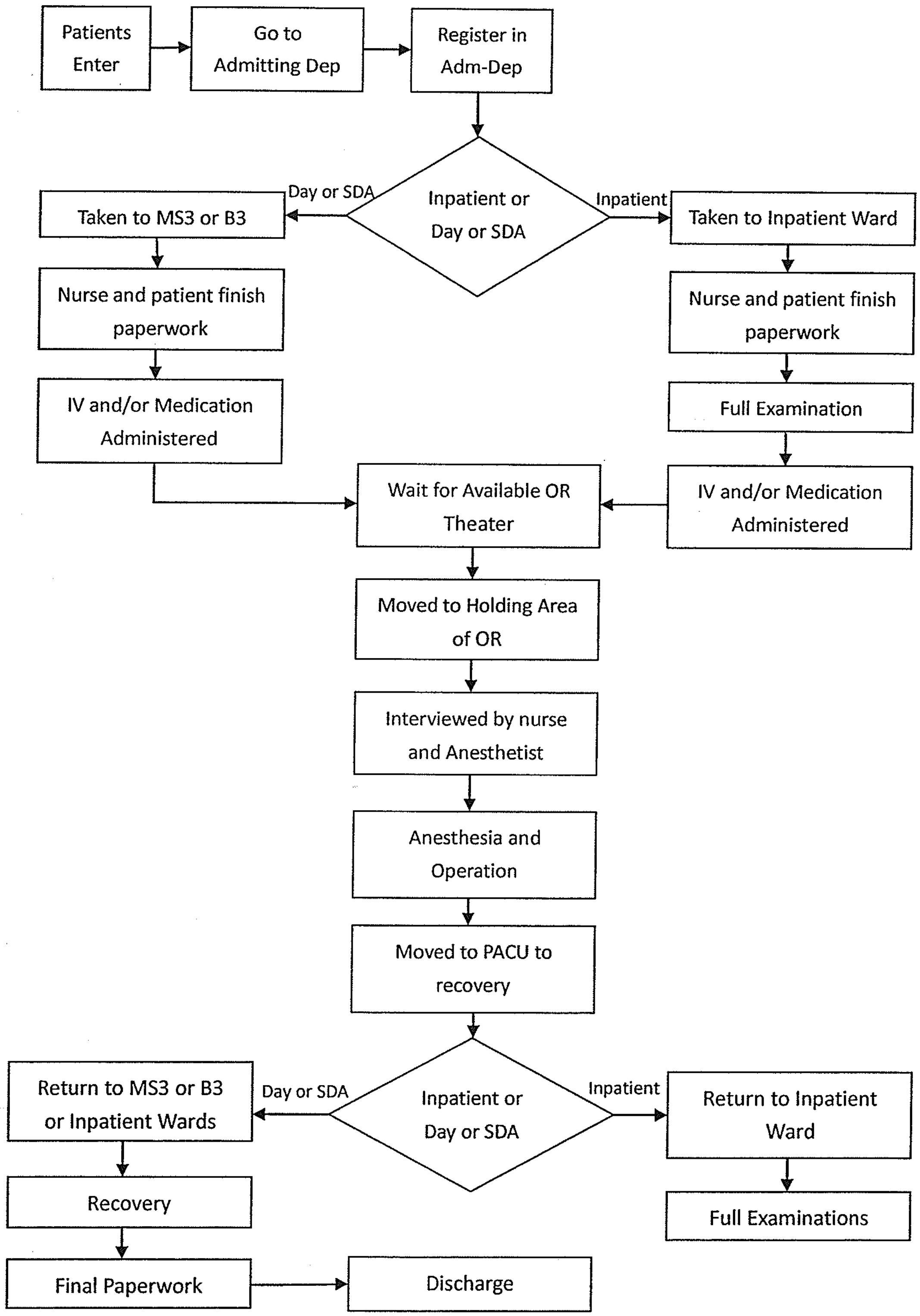

Figure 3-4: The elective patient flow at the OR department of WHSC

3.4. The OR Scheduling System

Surgical cases are scheduled using a block scheduling policy. First of all, a master surgical schedule (MSS) is created. The MSS consists of blocks illustrating the number of operating rooms that will be open and staffed on a particular day, and in each theatre's open hours. The blocks in MSS may be full days (eight hours), half days (hour hours), or some variation. Each block is allocated to a particular service. Certain services are regularly assigned the same operating rooms for the size and equipment requirements. For instance, OR theatre one is usually assigned to cardiac surgeries. Once these allocations have been settled down, the manager of each service will split their respective blocks into individual blocks belonging to a specific surgeon who will decide which patient will come to WHSC to complete their surgery.

Blocks for emergency cases may be involved in MSS. These blocks are only devoted to pending emergency cases and are scheduled a day beforehand by the OR department. Some blocks are open for any type of emergency cases, and others may be dedicated to a particular service.

Chapter 4: Simulation Modeling

4.1. Performance Measures

This research applies a discrete event simulation technique to identify the resources utilization. The objective is to evaluate the efficiency of surgical suites and to determine the potential maximum capacity in the OR department of WHSC under selected environmental factors. It will provide the basis for the recommendation of the surgical performance improvement in either changing resources or changing the set of surgical procedures.

It is critical for hospitals to plan their capacity in response to a growing resource demand. Although an increasing patient throughput could meet both increased demand for the health care, it should not be based on the sacrifice of patient satisfaction. Therefore, this research will search for an optimal solution considering following data: the number of each type of patient processed, the patient stay time in the hospital, the utilization of operating rooms, OR teams performance, Nurses, and other related recourses used.

4.2. Data Collection

Data are essential for a simulation model. Data are collected via interviewing managers, surgeons, nurses and other clerical personnel, by reading through patient's recorded paper files and by observations. Three type data are collected. The first type data are related to the working flow which is described in detail in Chapter 3. The second type data are about resources in the OR department, which is also mentioned in Chapter 3. The patient type is presented in Table 4-1. The resources data in the OR department are summarized in Table 4-2. The resources in other units related to the OR department are summarized in Table 4-3. The third type data are related to the time distribution, such as the travel time from one unit to another unit, the cleaning time in the OR theatre, and the processing time of the operation. Table 4-4 is a list of data items used as input for the model of the OR patient flow. There are 13 OR theatres in the OR department. They are located in one floor as shown in Figure 4-1.

Table 4-1: Elective patient types

No.	Patient Type	Description
1	Day	Day Patients
2	SDA	Same Day Admission Patients
3	INP	Inpatients (Including some less urgent emergency patient)

Table 4-2: The resources in OR

No.	Items	Quantity
1	Operating Rooms/beds	13
2	Front desk	1
3	Hold Area (Music room)	6 chairs
4	PACU	12 beds
5	Operating Room Nurses	36
6	Perioperative Aides (Pas)	3
7	Transport Personnel	2
8	Anaesthetists	12
9	IHA (Backup Anaesthetist)	1

Table 4-3: The resources related to OR department

No.	Items	Quantity
1	Admitting	1
2	MS3	6 Beds
3	B3	4 Beds
4	Inpatient ward	164 Beds

Table 4-4: A data list collected for the simulation model

No.	Items
1	The admitting time
2	The arrival time to pre-op units which are MS3, B3, Inpatient ward
3	The leave time from pre-op units
4	The arrival time to OR
5	The leave time from OR
6	The arrival time to post-op units
7	The discharge time
8	The start time of OR setup
9	The end time of OR setup
10	The start time of OR cleaning
11	The end time of OR cleaning

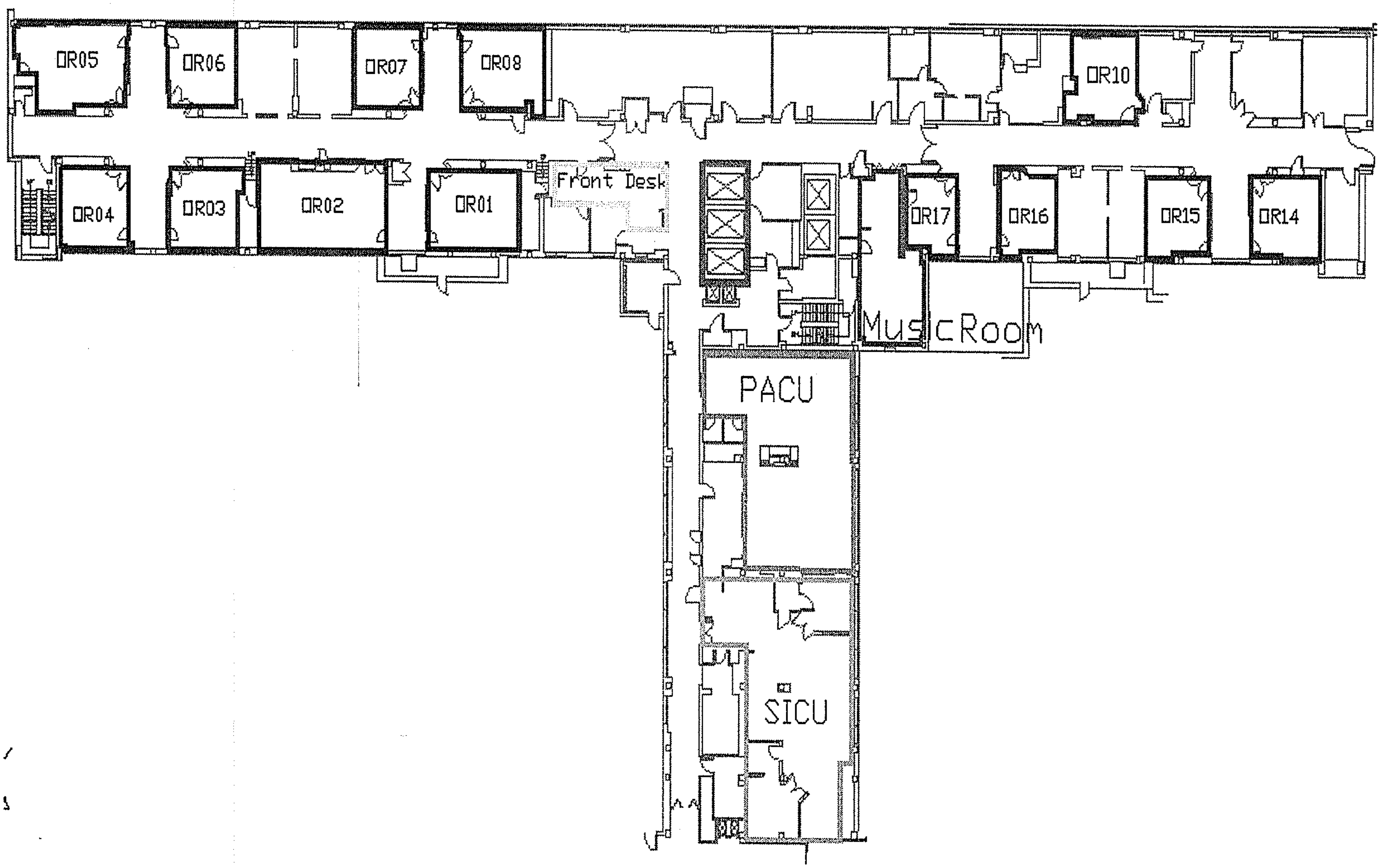

Figure 4-1： Layout of OR department at WHSC

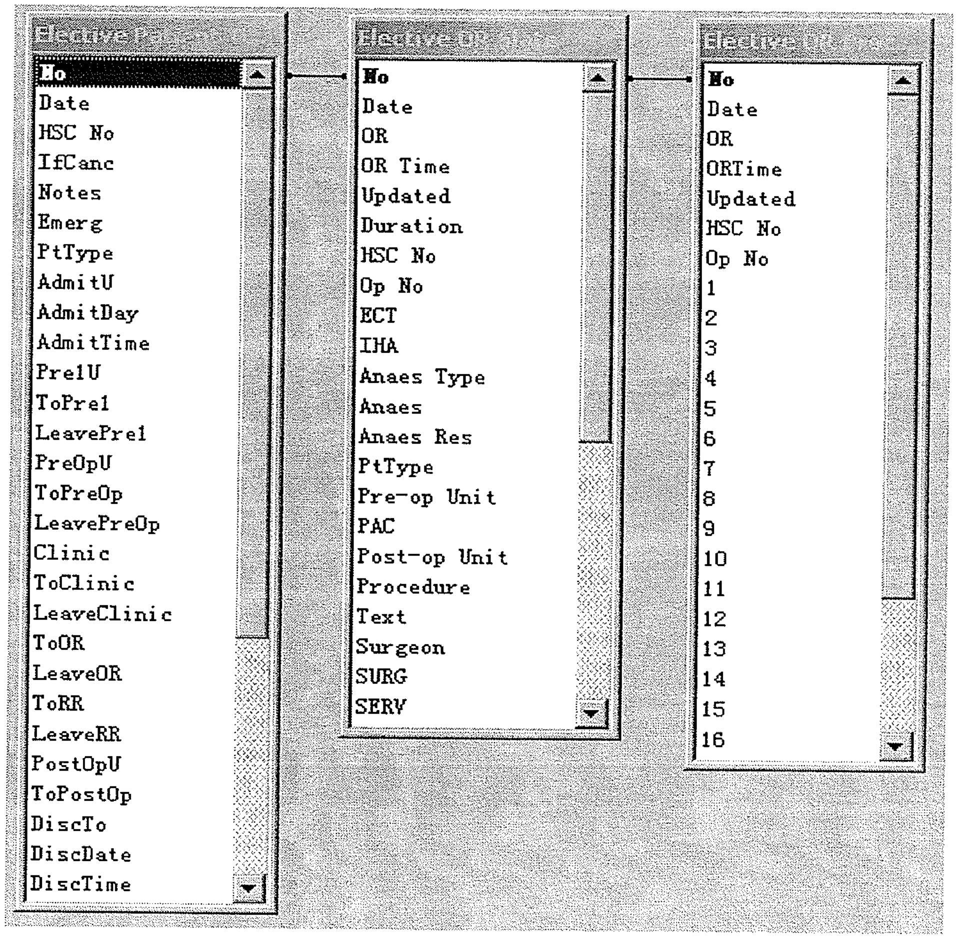

Figure 4-2 : Tables in database to record collected data

Five weeks elective surgical patients' data are collected from WHSC. The total number of patients is 740. Three tables are used in the database to record the collected data as shown in Figure 4-2. The table one in Figure 4-2 named elective OR procedure time is to record the processing time in the OR department, such as the time when the theatre is ready for the operation, the time that a patient arrives at the OR theatre, the time that the surgeon arrives, the time when the operation ends, the time when the patient leaves the OR department, and etc. The table two in Figure 4-2 named elective OR slate is to record the information of the elective surgical patients, such as the date of the surgery, the duration of an operation, surgeon's name, the pre-op unit, the post-op unit, the patient type, and the anesthesia type, etc. The table three in Figure 4-2 called elective patient time is to record the processing time in the related units, such as the time that a patient arrives at the admitting department, the time when the patient arrives at pre-op units, the time when the patient leaves the pre-op units, the time when the patient reaches the OR department, the time when the patient leaves the OR department, the time when the patient arrives at the PACU, the time when the patient leaves the PACU, the time when the patient arrives at the post-op units, the time when the patient discharges, and etc. The information of each patient takes one record in each table. The relationships of tables are linked using key numbers that are a series of numbers.

The five weeks elective surgical patient data are basis of the simulation modeling. We read through all the hand-writing paper documents which looked like a sealed book for us. The OR department has a data collection form which is used to record the specific time of each process including the patient arrival time, the operation beginning time, the surgeon arrival time, the setup time, the cleaning time, and etc. Other related departments do not have the special form to collect all the time. Nurses just wrote down the arrival time and leave time for each patient in patient's file. There is no requirement to record more precise time for the patient. The nurses are busy for the patient flow. The time they recorded may not be the precise especially in inpatient ward. They record the time after they finish their job when they are not busy. They might forget the precise arrival and leave time of patients and wrote down the rough time. Sometimes they even forgot to write down the time. As a consequence, some unreasonable data are discarded in the data analysis.

Based on the collected data of the patient arrival and leave time, beginning time and ending time of each job, the processing time and the travel time are identified and summarized in Table 4-5 and Table 4-6.

Table 4-5: Main distributions of processing time (unit: minutes)

Items	Time	Place
Admitting	UNIFORM (2,10,4)	Admitting
Interview	NEGEXP(10,10)	Holding area
Assessment	NEGEXP(10,11)	Holding area
Surgery	Duration (12)	Operating Room
Recovery	TRIANGLE (0,144,657,6)	PACU
OR cleaning	TRIANGLE (0,14,28,19)	Operating Room
OR setup	TRIANGLE (0,15,36,20)	Operating Room

Table 4-6: Travel time between different units (unit: minutes)

From-To	Distributions
Pre-op units to OR	TRIANGLE (0,21,41,1)
OR to PACU	TRIANGLE (0,4,10,20)
PACU to post-op unit	TRIANGLE (0,8,24,2)

4.3. Simulation Model

WITNESS (Lanner Group 2009) software is used as the simulation tool in this research. WITNESS has functions of visual, interactive, and interpretative modeling. It has features of friendly GUI, and easy to learn with a modular and hierarchical structure. It also includes many other useful tools such as comprehensive statistical input and reports, linkage-databases, direct spreadsheet link in/out, XML formats and HTML reports.

Python (Python Software Foundation 2009) is used for data operation and data analysis. It is a dynamic object-oriented programming language which offers a strong support for integration with other languages and tools and comes with extensive standard libraries. Python is distributed under an OSI-approved open source license.

AutoCAD is used drawing the layout of the OR department at WHSC. The drawing is made to scale and considered all pertinent features to this research. A snapshot of the subject area is shown in Figure 4-3.

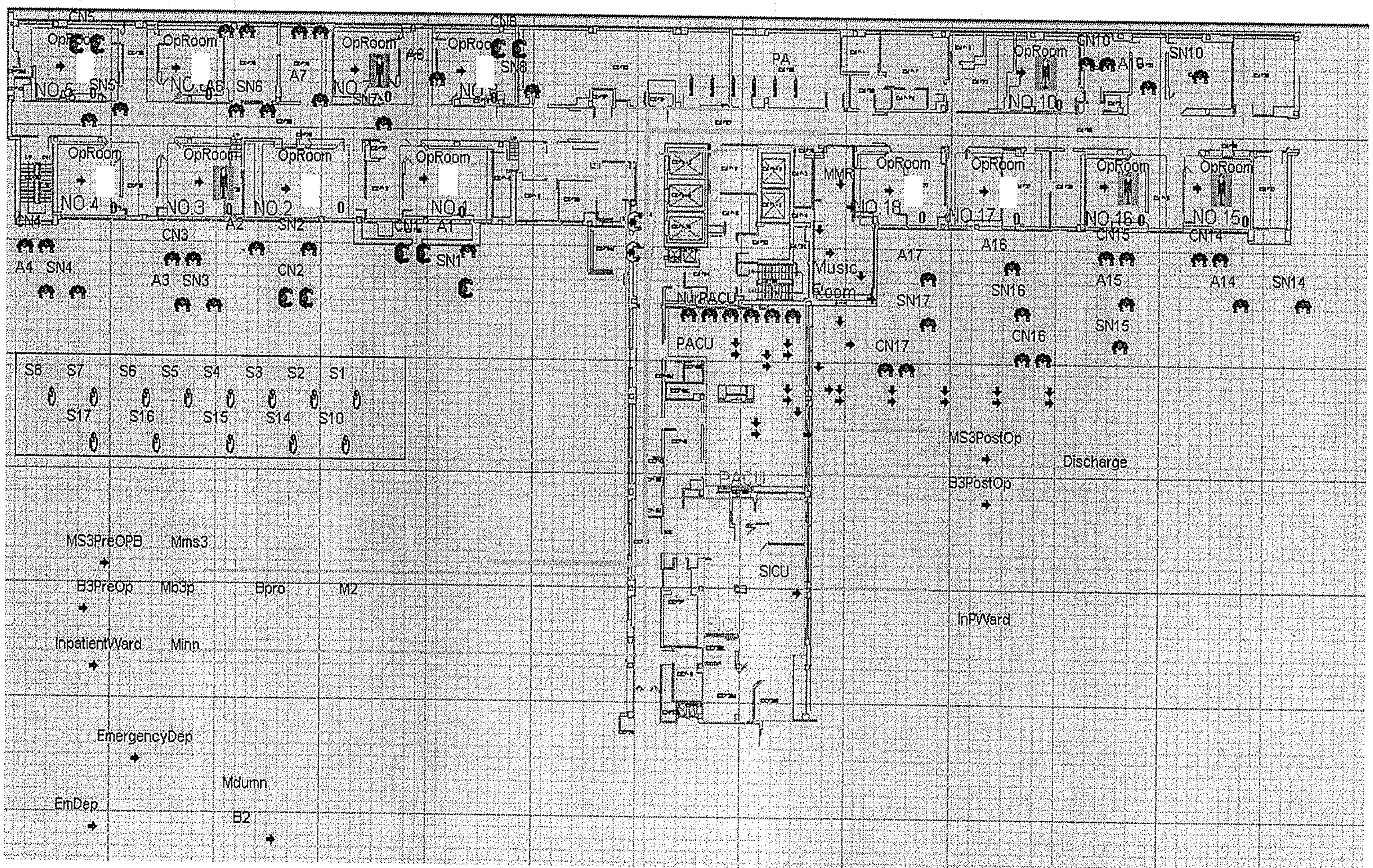

Figure 4-3: A screen shot of the simulation model

A simulation model is built according to the particular elective surgical patient flow in the OR department of WHSC. Patients are entities while the OR department and related units are operation facilities. Surgeons, nurses, and the OR team are operators. An anesthetist and three nurses who are called OR team are assigned to one given operating room on their shift, the surgeons come to the OR department according to their schedule.

All elective surgical patients come to the OR department based on the appointed date and time. Patients may cancel their surgeries for a variety of reasons from the patients or from the OR department before their surgeries. One case was cancelled for each day on average while twenty-eight cases were carried out for each day on average. The cancellation ratio is about 4.67%.

The procedure in the OR department is much more complicated than a simple processing in a mechanical workshop. Module called *OR_department* (see Figure 4-4) is used to simulate the complex process in one OR theatre including the setup and cleaning procedure. It is assumed that the OR theatre is always ready for the first patient who comes into the system. Four cycles are set for each OR theatre, surgery cycle, null cycle, cleaning cycle and setup cycle. The null cycle is zero processing time procedure used to move the patient out of the OR theatre and input a dumb entity. After the patient is moved to PACU, the OR theatre is cleaned and set up for the next appointed coming patient. The Figure 4-5 shows the work flow of the module *OR_Department.*

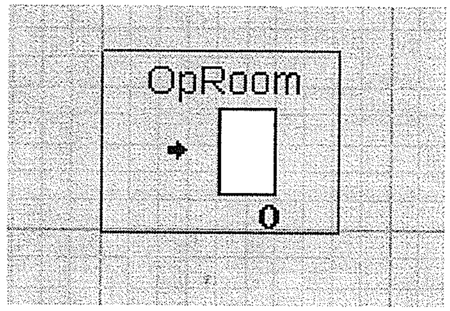

Figure 4-4 : The module *OR_department*

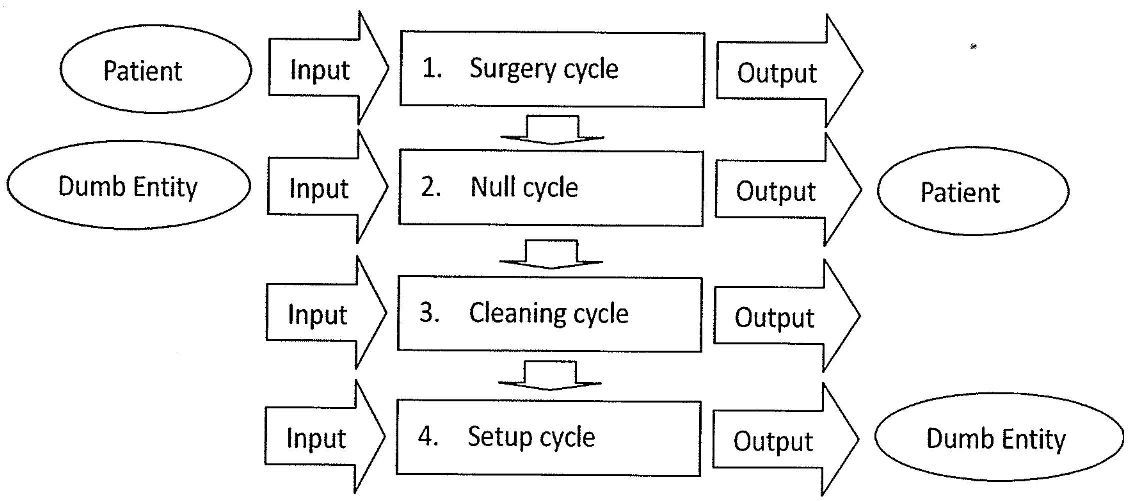

Figure 4-5 : The work flow of module *OR_Department*

Definition of attributes:
The first column is the patient type
The second column is the quantity of arrival patient
The third column is the time when the patient arrives
ORNo = The number of operating room
Duration = The surgery processing time
No =The serial number of the patient
PreOP = Pre-operative unit
PostOP = Post-operative unit
PAC = If patient went to PAC or not before surgery, 1 means that patient went to PAC before the surgery. The default value is 0 which means the patient didn't go to PAC before his/her surgery.

Part of scheduling file:

```
INP 1   365 ORNo=8  Duration=241 NO=1   PreOP="D2"
SDA 1   373 ORNo=1  Duration=295 NO=2   PreOP="GMS3"   PostOP="A3"  PAC=1
SDA 1   373 ORNo=2  Duration=296 NO=3   PreOP="GMS3"   PostOP="A3"  PAC=1
SD  1   394 ORNo=16 Duration=124 NO=4   PreOP="GMS3"
SDA 1   410 ORNo=3  Duration=242 NO=5   PreOP="GMS3"   PostOP="D2"  PAC=1
SD  1   428 ORNo=15 Duration=63  NO=6   PreOP="GB3"
.
```

Figure 4-6 : The part of the OR scheduling

The elective surgical patients arrive at the OR department of WHSC according to the schedule. The input schedule in the simulation model has a special format which is listed in Figure 4-6. There are total nine columns. The first column stands for the patient type which is called part type in WITNESS. The second column is the number of patients who will arrive synchronously. The third column is the time when the patient arrives. The time unit used in WITNESS is minute. The forth column is the *ORNo* which is the OR theatre where the patient will be. The fifth column is the *Duration* of the processing for the surgery. The sixth column is the serial number of the patient. The seventh column is the

Pre-OP or pre-operative unit where the patient will go. The eighth column is the *Post-OP* or post-operative unit where the patient will go after the surgery. And the ninth column is the *PAC* showing the patient has been in PAC before the surgery day if the *PAC* equals 1, the examination time in pre-operative unit will be shorter than the patients who have not been there. The decision maker may change a schedule to be best fit to the OR department operation based on the current work flow and resources.

Python plays a role to cooperate with the WITNESS simulation software for the data operation and data analysis. The scheduling is generated using Python to query the *elective_patient_time* table in the database. The input data are imported into the WITNESS simulation model using text files. The processed data are written in output files. Python reads data from these files, and implements all functions needed in the processing. Python is also connected to a Microsoft Access database to record all patient information. Python retrieves data from the database to analyze data and to generate the distributions.

The system variables in simulation model listed in Table 4-7 are used for the system performance analysis.

Table 4-7: Variables used in the model

No	Item	Description
1	No	The number of the patient
2	ArrivalTime	The patient admitting time
3	MRBegings	The time when the patient arrives at the holding area
4	OPBegins	The time when the OR begins
5	OPEnds	The time when the OR ends
6	PACUBegins	The time when the patient arrives to PACU
7	LeaveTime	The time when the patient discharges
8	LOS	The length of stay
9	count	The count in the simulation model

4.4. Verification and Validation of the Model

Verification and validation make sure that the model built is right for the basic test of the simulation model. The key of the model verification and validation is to guarantee the assumptions of the conceptual model are right and close to the reality.

One technique known as historical data validation was used to examine the accuracy and consistency of the model discussed. Based on the data collected from the WHSC and the detailed patient record includes patient type, doctor, surgery type, anesthesia type, the admitting time, arrival time to OR, the time taken to PACU, time moved back to post-operative units, and time patient discharged, a complete database is built for the system validation.

The WHSC operates under a block schedule which allocates one operating room for a certain type of surgery for either a four or eight hour block. For instance, on Monday three available operating rooms may service general, cardiac, and ophthalmology surgeries all day long. While on Tuesday, OR1 may service orthopedic surgeries all day, while OR2 services obstetrics in the morning and general surgeries in the afternoon, and OR3 services ophthalmology surgeries all day.

As the historical data validation technique is based on the collected data, the more the accuracy of the collected data is, the closer the model is to the real world. Five weeks data of the actual patient from the hospital are compiled. This gives us enough data to create a representative system with appropriate surgery percentages. One replication of the model represents five weeks in the surgical theatres. Five weeks were simulated for 6 replications. The quantity of patients processed in each day, average length of stay (LOS) for different patients, average busy time of OR each day, cancellation cases of each week in the OR department were calculated for the real system and the simulation model. The data in Table 4-8 show that the simulation results are very close to the reality of the collected actual data.

Table 4-8: The model testing

No	Items	Reality	Simulation results
1	Patient count of each day	26	27
2	Average LOS for Day patients	901 minutes	923.0 minutes
3	Average LOS for SDA patients	6063 minutes	6130.0 minutes
4	Average LOS for inpatients	23401 minutes	23560.0 minutes
5	Average busy time of the OR each day	421 minutes	413 minutes
6	Cancellation cases of week day	7 cases	6 cases

4.5. Experimentation

The simulation model enables scenarios to analyze how observed variables in the OR department will be affected by the data or resources change. By changing some of inputs, the model is able to show how the performance is automatically changed when resources and other pertinent data are revised.

Based on the data collected from five weeks, the model running lengths and warm up periods of 25 days, and 3 days respectively are used for each replication to allow for the system to reach realistic operating conditions before collecting appropriate statistics. 6 replications of the simulation have been undertaken.

Simulation is run based on different scenarios. The overall utilization rates for each case can be displayed for doctors, nurses and beds. The length of stay of patients in the OR is simulated. It is assumed that a fully loaded one week appointment is as input for the simulation. The simulation shows the detailed daily operations with patient arrivals and resource constraints.

The experimental data created include the arrival time of the patient and the category of the patient. Preliminary simulation experiments indicate that when more patients are expected to be processed at the OR department, the patient waiting time would become longer, unless the additional beds are allocated. Then, a stepwise procedure of operations planning is proposed to reduce the patient waiting time. Through a series of simulation experiments, the patient waiting time can be minimized, by adjusting appropriate resources in the OR department.

Table 4-9 shows the average length of stay (LOS) of different patients and the reduced ratio of LOS under different resource conditions. The assumed resources changes used in the simulation include the number of the beds in PACU, the number of the OR theatres, and the number of chairs in holding area. Figure 4-7 shows the reduced LOS of Day patients with the resources of row No. 4 comparing with using the resources of row No. 1

in Table 4-9. It shows in Figure 4-7 that the frequency of short stay ($0 < x < 1400$) is increased and the frequency of long stay is decreased ($x \geq 1400$).

Table 4-9: The comparison of the resources change

No	Resources			Day		SDA		Inpatient	
	Beds in OR	Beds in PACU	Chairs in holding area	Average LOS	Change	Average LOS	Change	Average LOS	Change
1	13	12	6	923.0	0	6130.0	0	23560.0	0
2	13	12	10	865.0	6%	5993.0	2%	23298.0	4%
3	13	14	10	791.0	14%	5901.0	8%	23123.0	9%
4	14	14	10	717.0	22%	5843.0	14%	22986.0	17%

Table 4-10: Changing the number of TPs

No	Number of TPs	Day patients		SDA patients		Inpatients	
		Average LOS	Change	Average LOS	Change	Average LOS	Change
1	2	923.0	0	6130.0	0	23560.0	0
2	3	901.0	2.30%	6102.0	0.46%	23536.0	0.10%
3	5	853.0	7.60%	6062.0	3.20%	23494.0	2.01%
4	7	793.0	14.00%	5989.0	7.60%	23382.0	5.04%

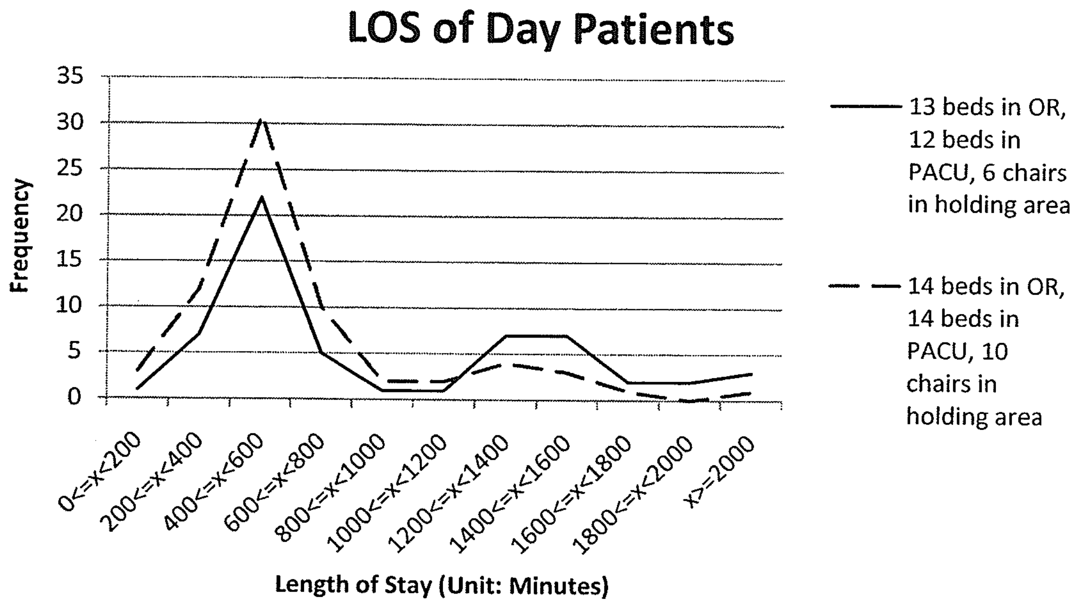

Figure 4-7 : Reduced LOS of SD patients

Table 4-10 shows the improvement when increasing the number of TP. When the number of TP is increased from 2 to 5, the average LOS of Day patients is decreased 7.60%, the average LOS of SDA patients is decreased 3.20%, and the average LOS of inpatients is decreased 2.01%. Patients are transported to operating room almost at the same time in the morning as all operating rooms are empty. Currently, there are only two TPs who move patients from the pre-op unit to the operating room.

4.6. Conclusions

This research shows that simulation is an efficient tool for identifying problems and improving performance of healthcare systems. The simulation model is valuable to present the current work flow and to predict the bottleneck in healthcare systems. The simulation model developed initially demonstrates that the resources in the OR department of WHSC is a main bottleneck for the longer stay of patients in the hospital.

In this research, simulation models provide a reasonable assessment of OR's efficiency, resource utilizations and other performance measures. By using the simulation, a useful evaluation for the OR provides a chance to analyze and improve the current operation processing. The output of the simulation shows the analysis result with a verity of formation. The graphical user interface provides an effective tool for decision-making of the OR operation.

Chapter 5: Optimization of the Simulation Model

Simulation is a valuable technology to examine what-if scenario along the time to obtain the solution of problems. However, simulation cannot automatically provide an optimal solution (Law 2002). An analyst normally tests a relatively small number of system configurations to choose the one that appears to give the best performance. Simulation is also extremely expensive in computation (Fu 2001). The computational requirements of a single replication of the simulation model of interest can probably exceed the typical computation time of any medium-sized linear program in which there are thousands of variables. The optimization package is integrated in most of discrete-event simulation software based on the availability of the computer capacity and improved heuristic optimization search techniques. Simulation optimization is the most recently significant new simulation advances (Fu 2001, Law and Kelton 2000). Optimization of simulation models analyses and finds the possibly model specification that leads to an optimal performance. In other words, optimization of simulation models is to obtain the optimization of performance measures based on output from the stochastic simulation (Fu 2001). In this research, a meta-heuristic simulation optimization model is proposed to determine the maximum capacity of the OR department at WHSC. The model seeks to maximize the capacity of the OR department, and to reduce the patient processing time.

5.1. Literature Review

Simulation Optimization has been widely used in many fields, such as manufacturing systems, supply chains, call centers, financial, and inventory control systems. There is a variety of methods of the optimization such as Ranking & Selection, Response Surface Methodology, and Gradient-Based Procedures. Meta-heuristics is a popular method as it provides the search guide to overcome the trap of local optimality for complex optimization problems. Four meta-heuristics methods have primarily been applied with some success to simulation optimization: Simulated Annealing, Genetic Algorithms, Tabu Search (TS) and Scatter Search (SS). Simulated annealing (SA) may be considered as an example of a random search procedure whose main disadvantage is the long computational time required to find the high quality reasonable solution (April 2003). Genetic algorithms (GAs) are search techniques used in computing to obtain the optimal solution of problems with evolutionary techniques inspired by the evolutionary biology such as inheritance, mutation, selection, and crossover. GAs are often applied as an approach to solve global optimization problems. But as a general rule GAs might be useful in problems that have a complex fitness landscape as recombination which is designed to move the population away from local optima (Bies 2006). SS is an evolutionary algorithm too which is often combined with other methods (Fu et al 2005). SS operates on a set of points named reference points that constitute good solutions obtained from previous solution efforts. TS is distinguished by including adaptive memory into the heuristic search. TS has proved to be one of the most effective and widely used approaches that are at the core of the simulation optimization software widely used (Michael Fu 2001). OptQuest is unique optimization software which can be bundled with other commercial simulation environments like Arena and Crystal Ball. The algorithm integrates a combination of strategies based on Tabu search and scatter search along with neural networks (Fu 2001).

Meta-heuristics simulation optimization is now widely used by commercial simulation software from 1990 (April 2003). The simulation model is basically viewed as a black box function evaluator in the meta-heuristics approach. The meta-heuristics optimizer chooses a set of values for the input parameters and uses the responses generated by the simulation model to make decisions regarding the selection of the next trial solution.

As one of the meta-heuristics simulation optimization, TS has been rapidly and exponentially growing over the past several years. The rapid growth of TS applications is disclosed by the fact that a Google search on "tabu search" returns more than 90,000 pages. TS applications reach the fields of telecommunications, VLSI design, resource planning, financial analysis, space planning, energy, distribution, molecular engineering, pattern classification, logistics, flexible manufacturing, environmental conservation, biomedical analysis, and mineral management (Fu 2000).

In Yang's paper (2004), the Tabu search simulation optimization approach was applied to solve the FSMPs (the flow shop with multiple processors) scheduling problem. The empirical results that the author got were great promise for the practical application. In Dengiz's paper (2000), the TS algorithm was used with a simulation model of JIT system to achieve the optimum number of kanbans. The results show that TS algorithm is better than the RS algorithms. The TS method is encouraging to be applied for simulation optimization.

Alternative strategies were proposed to perform simulation using an optimization method based on the TS in Abdullah's paper (2005). The results show that TS performance can be improved by simply adjustments in a TS procedure instead of increasing the number of simulation replications to save the computational time. An approach that used TS combined with simulation to schedule product through a set of machines was proposed in Daniel's paper (2002). Improved schedules were produced compared to simple dispatching rules. The proposed approach is easier to find the optimal solution for the small problems.

Simulation optimization models are also applied in the healthcare area. Balasubramanian et al (2007) proposed a multi-period meta-heuristic simulation optimization model for determining the panel design of a set of physicians working in a primary care environment using genetic algorithm (GA) approach as the optimizer. The model is to maximize patient visits, reduce patient waiting time, and minimize overtime. The results of the study demonstrate that significant improvements over the existing panel design are possible based on the author's assumptions.

5.2. Meta-heuristic Approach

Classical approaches of simulation optimization include 4 main methods: stochastic approximation, response surface methodology, random search, and sample path optimization. Although these four approaches cover the most of literature in simulation optimization, they have not been formulated for the simulation software system. The meta-heuristics methods are being developed to supply optimization capabilities by preeminent commercial simulation software companies.

Since 1990, the simulation software system has started including the packages of optimization function. Every commercial simulation software package includes an optimization module that does some kind of search for optimal values of input parameters rather than just for the statistical estimation. The developments of computational power and the advance in meta-heuristic research make the implementations of simulation optimization procedures practical.

The meta-heuristic approach considers the simulation model as a black box function evaluator. In this research, TS is used as an optimizer while the simulation model of the operating room built in WITNESS is viewed as a black box function evaluator (as Figure 5-1). The meta-heuristic optimizer chooses a set of values for the input parameters and uses the responses returned by the simulation model to make decisions regarding the selection of the next trial solution.

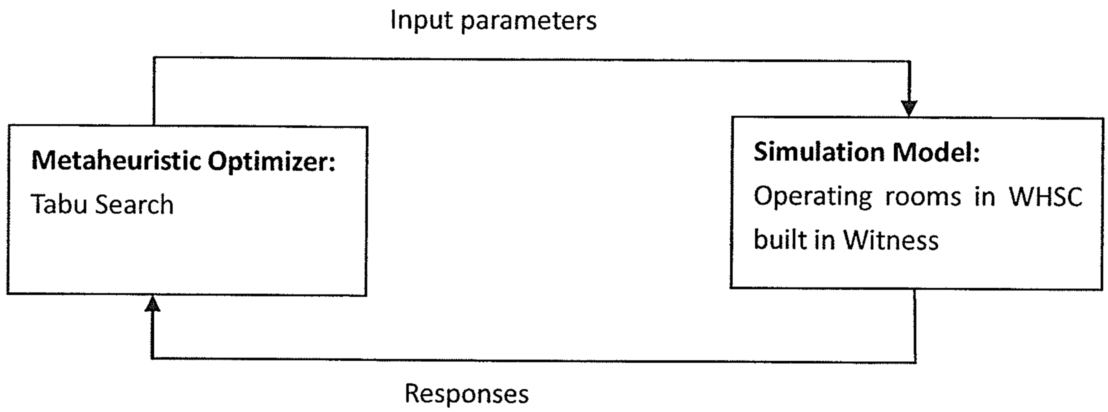

Figure 5-1 : Black box approach to simulation optimization

The simulation software WITNESS does have the optimization package. As an education version used for this research the optimization package is not included in the simulation software. The simulation optimization has to be done in another way.

5.3. The Problem Formulation

The background and the simulation model have been described in Chapter 3 and Chapter 4. The optimization model is based on the simulation model built in Chapter 4. The simulation model is to do the performance measures. The aim of this research is to accommodate the maximum visit of patients to the OR department at WHSC in a certain period in order to reduce the processing time of the patients.

The problem assumptions are as follows:

- There are no delays for the first surgical patient. In practice, the first surgical patient might be delayed for other reason except that the OR is ready.
- The OR team assigned for the OR theatre is always available for the OR theatre. In practice, the nurse might go to other emergency OR theatre if there are not enough nurses to help.
- First arrived, first served based on the schedule. In practice, the surgical patient will go to the OR theatre after the patient is ready and also the OR theatre is ready.
- The surgical patients go directly to the units where they need to go. The delays caused by the patients are not counted in. If the surgical patients delay, the surgery is considered as a cancellation. In practice, patients cancel their surgeries for their own reasons. Their delays also cause the cancellation of their surgeries.

The objective function is to maximize the patients visits to the OR department at WHSC. The processing time of each surgical patient starts from the admitting time at the admitting department and ends at the time when the patient is moved to post-operatively units.

The objective function is defined as:

$$Maximum\ TP(y) = E[f(y)] \tag{1}$$

Subject to:

$$QHA_{min} \leq y_1 \leq QHA_{max}$$

$$QPACU_{min} \leq y_2 \leq QPACU_{max}$$

$$QOR_{min} \leq y_3 \leq QOR_{max}$$

$$QMS3_{min} \leq y_4 \leq QMS3_{max}$$

$$QB3_{min} \leq y_5 \leq QB3_{max}$$

$$\sum_{i=1}^{5} C_i y_i + \sum_{l=1}^{m} C^{PT} \times PT_l \leq C_t$$

$$PT_l^{SD} \leq PT\_SD$$

$$PT_l^{SDA} \leq PT\_SDA$$

$$PT_l^{INP} \leq PT\_INP$$

y_1, y_2, y_3, y_4, y_5 are integers;

Where:

m is the number of the patient;

QHA_{min} is the minimal quantity of chairs in holding area;

QHA_{max} is the maximal quantity of chairs in holding area;

$QPACU_{min}$ is the minimal quantity of beds in PACU;

$QPACU_{max}$ is the maximal quantity of beds in PACU;

QOR_{min} is the minimal quantity of beds in OR;

QOR_{max} is the maximal quantity of beds in OR;

$QMS3_{min}$ is the minimal quantity of beds in MS3;

$QMS3_{max}$ is the maximal quantity of beds in MS3;

$QB3_{min}$ is the minimal quantity of beds in B3;

$QB3_{max}$ is the maximal quantity of beds in B3;

C_i are the costs of deferent resources;

C^{PT} is the cost of length of stay (LOS);

C_t is the total expected cost;

PT_l is the LOS of each patient;

PT_l^{SD} is the LOS of Day patient;

PT_l^{SDA} is the LOS of SDA patient;

PT_l^{INP} is the LOS of inpatient;

PT_SD is the longest LOS of Day patient;

PT_SDA is the longest LOS of SDA patient;

PT_INP is the longest LOS of inpatient;

In Function (1), it is assumed that $TP(y)$ is unavailable directly and need be estimated through simulation modeling in the simulation optimization setting (Fu and et al, 2005). $E[f(y)]$ stands for the built simulation model. y is an array with five elements which are input parameters of the simulation model. TP is the visits of patients. Five vital parameters have been tested. y_1 is the number of chairs in the holding area; y_2 is the quantity of beds in the PACU; and y_3 is the amount of operating rooms in OR department. y_4 is the quantity of beds in MS3; y_5 is the quantity of beds in B3. The sample array of a solution is like [6, 5, 10, 3, 2], that is that there are 6 chairs in the holding area, 5 beds in PACU, 10 ORs, 3 beds in MS3, and 2 beds in B3.

The cost constraint is assumed because the data about cost was not collected. The costs for the resources are uncertain depend on different quality from different brand on the market. It is assumed that these resources are from one brand. The cost of OR could be variable for different type of surgery which need different type of equipments. The cost of OR is assumed based on the basic standard operating room.

The minimal quantity of resources could be 0. In order to reduce the computational time, the minimal quantity of resources is assumed. It is assumed that the minimal quantity of chairs in the holding area, the beds in PACU, and the ORs is three. And also the minimal quantity of beds in MS3 and B3 is assumed to be one. The maximal quantity of resources is determined based on the space in the different units. The assumption about maximal quantity of resources is that there are at most eight chairs in the holding area, fifteen beds in PACU, seventeen ORs, six beds in MS3 and four beds in B3.

The longest LOS of different type patients is based on the collected data from WHSC. The longest LOS of Day patient is assumed to be eight hours, the longest LOS of SDA is assumed to be twenty-four hours and the longest LOS of inpatient is assumed to be five days.

There are at least 28,080 resources ($6 \times 13 \times 15 \times 6 \times 4 = 28{,}080$) combination points that may need to be studied in the simulation model to examine resources in the different departments including chairs in holding area, beds in PACU, and operating rooms. If more resources are considered such as beds in pre-unit, beds in post-unit, beds in SICU, nurses in each department etc, the problem would require examining over 414,720 different resource combination points. Due to the computational nature of the number of resources in the operating room, the problem can be much more complex as the number of the resources increase or more resources are involved.

5.4. Tabu Search (TS)

Tabu Search (TS) is a local search procedure to find a global optimum method that was proposed by Glover (1989). TS is regarded as a technique based on selected concepts from artificial intelligence. It follows the effective TS process which leads search to achieve good solutions in complicated solution spaces. To avoid catching in seeking a locally optimal solution, flexible memory, which can be short-term memory or long-term memory, is being used to record the recent solutions in the search procedure.

TS is presented as an iterative procedure that scans the solution space beginning with an initial solution, then moving action from one solution y to another solution y' which is located in its neighborhood $f(y)$. A solution y' might be accepted to escape the entrapment of a local optimum when y' is worse than the current solution y. Tabu tenure or tabu list is used to avoid the cyclic searching path. To avoid cycling which means to revisit a solution, the recently performed moves are stored on a tabu list for a certain number of iterations. Moves on the tabu list are prohibited. The best candidate is forced not to select from the tabu list. In some cases, however, a move in tabu list may improve upon the best feasible so far, then it can be accepted as the best candidate, which is called aspiration criterion. Aspiration criterion is used to release a better solution when a move is in tabu list. Furthermore, another rationale behind using an aspiration criterion is that moves are also forbidden to search directly towards unvisited yet attractive solutions. The search will be stopped when the stopping criterion is satisfied. The search process is shown in Figure 5-2. The description above is usually referred to as a "simple TS". A more advanced type of TS uses frequency-based memory intensification and frequency-based memory diversification. The TS including intensification and diversification is denoted by "TS" (Glover 1993).

```
Set i = 0, generate an initial solution
Do {
        Generate neighborhood from current solution
        Evaluate each neighbor, and update the best solution and current solution
        Update the tabu attribute
        Set i = i + 1
    }   While   (The stopping criterion is not satisfied)
```

Figure 5-2 : The search process of TS

The notations used in the developed algorithm are listed below:

y_0: Initial solution,

y: Current solution,

y': Neighbor solution,

y'_{best}: Best neighbor solution,

y_{best}: Best solution,

T_i: Tabu tenure size of increase moves,

T_d: Tabu tenure size of decrease moves,

i: Index of search iteration,

i_{max}: Stopping criterion (the maximal number of search iterations),

$M(y)$: A move that yields solution y.

The details are discussed as follows.

i. Initial solution

The initial solution influences the quality of the final solution. The initial solution in the TS algorithm is chosen randomly.

ii. Moves

In the TS operation, the current solution leads to reach the neighbors solution. The pairwise-exchange method is often used as a move to obtain a neighborhood solution in the permutation-type problem (Glover et al. 1995). Solutions of the problem are expressed by an array with five elements which involve the number of chairs in the holding area, the quantity of beds in the PACU, the amount of operating rooms in OR department, the quantity of beds in MS3, and the quantity of beds in B3. Increasing and decreasing feasible moves (Berna 2000) are used to obtain neighbors of any solution. A sample solution [6, 4, 5, 3, 2] stands for 6 chairs in the holding area of OR, 4 beds in PACU, 5 operating rooms in OR, 3 beds in MS3, and 2 beds in B3.

iii. Neighborhood size

Neighborhood size is the size of candidate list to be examined in a single iteration. There are three strategies of neighborhood selection discussed by Ben-Daya and Al-Fawzan (1998) as follows.

- Scan the complete neighborhood and select the best solution;
- Choose a subset of neighbors and search the best solution;
- Choose the "elite" neighborhood that improves the current solution.

The whole neighborhood searching with TS generates the high quality solutions but very expensive in computation. A subset of neighbors is often used to save the computational consuming. The size of the subset is the vital factor. The larger the subset size, the longer the computational time. The "elite" neighborhood is often used when the computational burden is in consideration. Based on the complexity of the question, different neighborhood is decided. In this research, all possible neighbors of the current solution are examined in each iteration, because the number of neighbors is not too large. The possible neighbors of a sample solution [6, 4, 5, 3, 2] are given as Table 5-1.

Table 5-1: The neighbors of a sample solution [6, 4, 5, 3, 2]

[5, 3, 5, 3, 2]	[6, 3, 5, 3, 2]	[6, 4, 4, 3, 2]	[6, 4, 5, 4, 2]	[6, 4, 5, 3, 3]
[7, 3, 5, 3, 2]	[6, 5, 5, 3, 2]	[6, 4, 6, 3, 2]	[6, 4, 5, 2, 2]	[6, 4, 5, 3, 1]

iv. Performance evaluation

The simulation model built by a discrete-event simulator is used to evaluate the performance of each TS move. The developed TS algorithm calls the simulation model to calculate the throughput of patients correspond to considered neighbor solution. Then the best neighbor is selected as the new current solution, if the neighbor is not obtained via a Tabu move.

v. Aspiration criterion

The best solution may be unvisited or forbidden based on selected attributes of moves. Aspiration criterion is used to overridden the tabu rule. The simple type of aspiration criterion is to accept a tabu move if it produces a new best solution. After the all non-tabu moves are searched, no better solution can be found than the current solution. The aspiration criterion overrides the tabu rule if the best search resulting from tabu list surpasses the best solution found so far. The aspiration criterion used in this research removes the tabu condition when any tested move yields a better solution than best solution obtained by so far.

vi. Tabu list

The choice of appropriate types of tabu lists depends on the problem. In a general way, the tabu lists are designed to drive the search to different regions of the search space (Glover 1993). In this research, two different tabu lists call t_increase and t_decrease are used to record the activated resources, after any increasing or decreasing move operation.

vii. Intensification and diversification

Using flexible memory makes TS to behave as an intelligent search technique. To avoid going back to a solution visited earlier, TS uses memory to remember the most recently performed steps. Memory is in addition used in TS to do learning process in which the common properties of good solution are discovered so far based on the having visited several solutions. Either short term memory (Berna 2000) or long term memory (Yang 2004) is used to avoid that the search region is fixed.

Two tabu list *t_increase* and *t_decrease* are built to record the tabu conditions associated with the moves a selected increase or decrease move at iteration i, $t\_decrease(increase\_m) = i$ or $t\_increase(decrease\_m) = i$. Any tested increase or decrease move is tabu at current iteration $j\ (j > i)$, if $t\_increase(test\_increase\_m) + Ti \geq j$ or $t\_decrease(test\_decrease\_m) + Td \geq j$. This structure is called recency-based which is also a short term memory (Glover 1989).

viii. Tabu tenure size

Tabu tenure size is an important parameter for TS. Tabu tenure size is to prevent the search from repeating move performed in the recent past. Tabu tenure size is empirical. When the tenure size is too large, the solution quality is deteriorated. When the tenure size is too small, the occurrence of cycling is possible. The best size lies in an intermediate range between these extremes. Yang et al (1999) presented a variable tenure size to be an integer between $n/3$ and $3n/2$, where n is the problem size. In this research, n is the amount of resources. Four alternative tenure sizes were set for this research: *0.4n, 0.6n, 0.8n*, and *1.0n*. The results are shown in Figure 5-3 and Figure 5-4. The experimental results show that the tenure-sizes are determined to be $T_i = 0.6n$ iterations and $T_d = 0.8n$ iterations for better solution and less iteration.

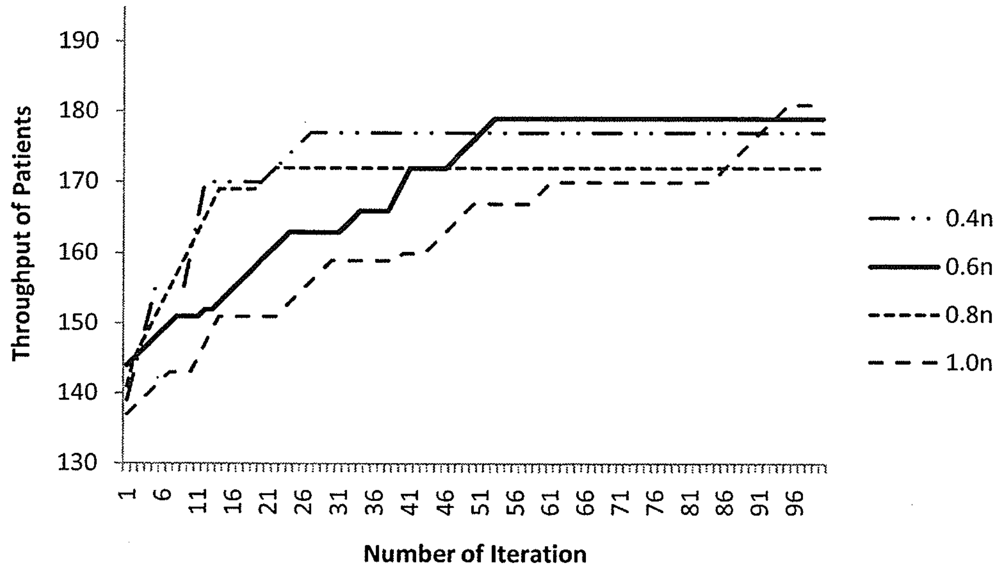

Figure 5-3 : Tenure size T_i

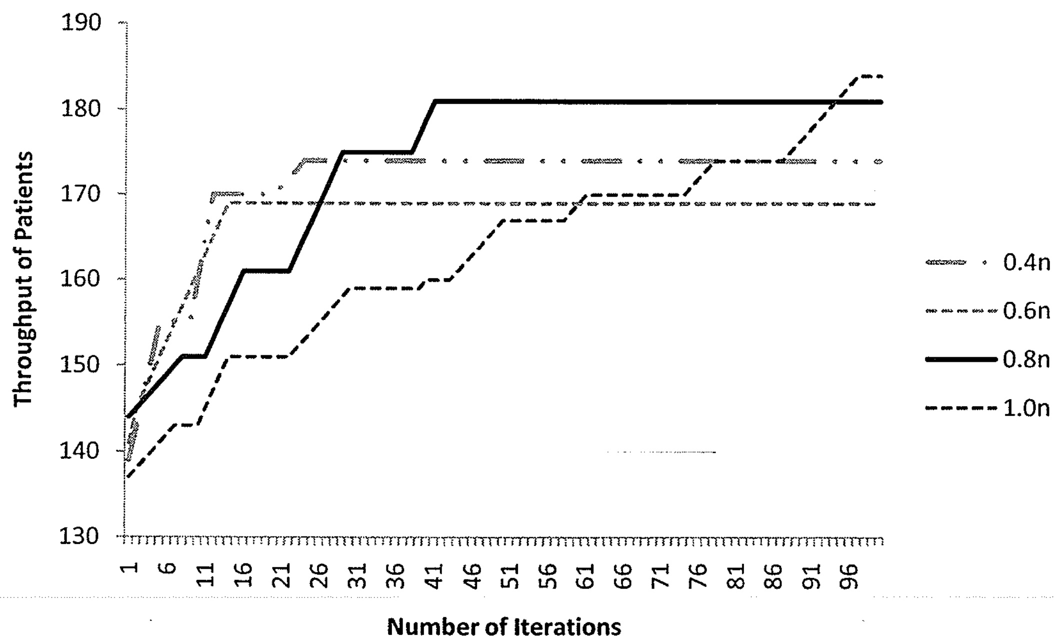

Figure 5-4 : Tenure size T_d

ix. Stopping criteria

Several methods can be applied to terminate the iteration. The ideal stop condition is that an optimal solution is found. Also if the maximum number of iterations is satisfied, then the program is stopped (Fred Glover 1989). There are other conditions to stop the logic. The simplest one is using some logical combination of the above methods. The developed TS algorithm is terminated when either a chosen maximum iteration number is reached or the best solution of each iteration is close enough to each other in certain iterations.

The steps of TS algorithm are as follows:

Step 1. Choose the initial solution y_0. Let current solution $y = y_0$ and best solution $y_{best} = y_0$. Let $i = 0$ and begin with empty tenure lists.

Step 2. Repeat

Step 2.1. Generate the neighbors y', for current solution y and call the simulation model to calculate the function $TP(y')$.

Step 2.2. Choose the best solution y'_{best}. If $TP(y'_{best})$ is better than $TP(y_{best})$, then let $y_{best} = y'_{best}$, and go to step 2.4.

Step 2.3. If $(M(y'_{best})$ is in tabu list and $TP(y'_{best})$ is worse than $TP(y_{best}))$ then let $TP(y'_{best}) = \infty$ and go to step 2.2. Else let current solution $y = y'_{best}$.

Step 2.4. Let $i = i + 1$.

Step 3. Until $i \geq i_{max}$.

The Figure 5-5 shows the flow chart of the algorithm.

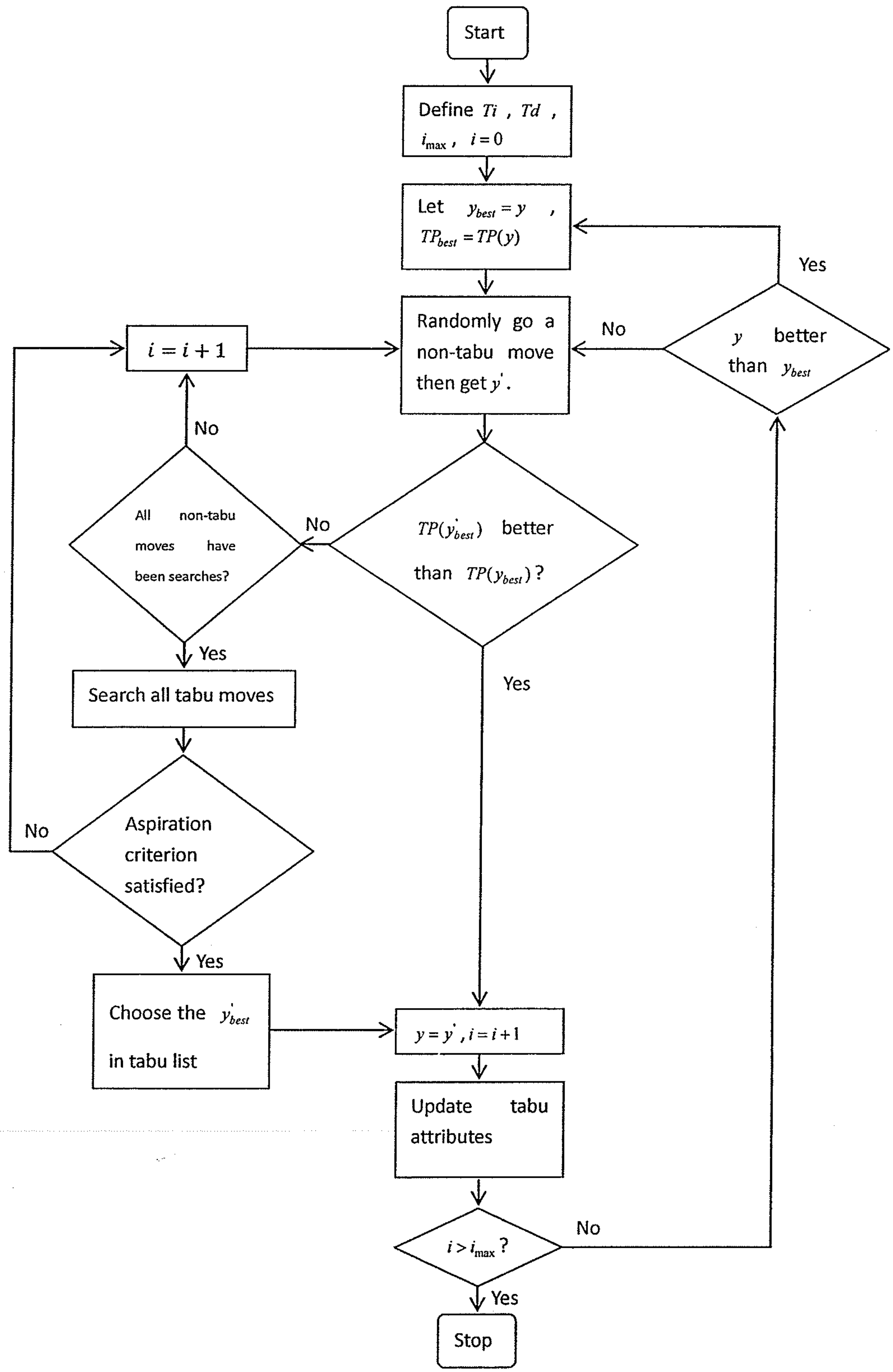

Figure 5-5: The flow chart of the developed TS

5.5. Results and Analysis

The optimal solution shows that the best configuration requires 7 chairs in holding area, 11 beds in PACU, 15 operating rooms, 5 beds in MS3, and 3 beds in B3, the maximum throughput of patients is 179 when the simulation time is set to 7200 minutes.

Table 5-2 presents the heuristics results of the computational experiments based on three parameters: the coefficient of variation that is found by the relevant heuristic in each replication, number of iterations searched by the relevant heuristic until finding the best solution and the computational time.

Table 5-2: Results of the Computational Experiments

Items	Values
Coefficient of variation	0.0398
Number of Iterations	37
Computational time (Sec.)	1031

Figure 5-6 shows the convergence of the TS algorithm. The horizontal axis stands for the iterations searched.

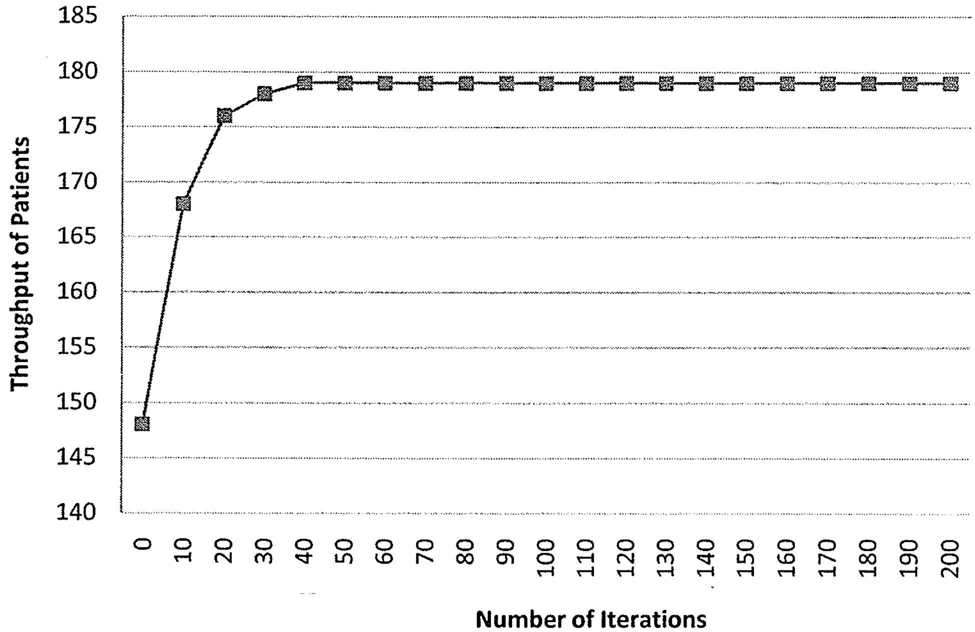

Figure 5-6 : Convergence of the TS Algorithm

The optimal solution is used to compare with the current system for adult elective surgical operation at WHSC. The resources currently used include 13 operating rooms, 6 chairs in holding area, 12 beds in PACU, 6 beds in MS3, and 4 beds in B3. The simulation model was first run under current surgery loads. The simulation model was then run under a condition in the maximum capacity of the system without overtime. To obtain the results for the maximum capacity, patients were allowed to enter the system, as long as their expected time in the system did not exceed the end of the day. The optimal solution is used as the input parameters which are 15 operating rooms, 7 chairs in holding area, 11 beds in PACU, 5 beds in MS3, and 3 beds in B3. The comparison results are listed in Table 5-3. Time of LOS starts from registration in admitting unit, and ends at time when patients are moved out of PACU for all type of patients. ORs are not dedicated to special type of patients. S1 is the scenario under the current system while S2 is the scenario under the optimal solution obtained by the TS method. Inpatients stay much longer time in inpatient wards. More concerns are focused on Day and SDA patients who have much more relations with MS3 and B3.

Table 5-3: Comparison of OR utilization statistics

	Day		SDA		All Patients		
	S1	S2	S1	S2	S1	S2	Change
Number of Patients Treated	48	58	55	67	148	179	21%
Busy time of OR (Min.)					2065	2180	6%
Average time in OR (Min.)	81	67	187	154	149	123	17%
Average time of LOS (Min.)	261	216	367	301	334	273	19%

The results present that 21% more patients are treated under the condition of S2 than the condition of S1. The average time in OR for all patients under the condition of S2 is 17% less than the time under condition of S1. The LOS under the condition S2 is also shorter than the time under the condition of S1.

5.6. Conclusions and Future Research of Simulation Optimization

In this research, a simulation searched heuristic procedure based on TS was developed. This research is a preliminary step of the optimization of the simulation model of the OR department at WHSC. The result shows that it is encouraging to do simulation optimization using TS approach to solve the problems. The most promising benefit of simulation optimization is saving computational time. For this problem, if we were to rely solely on simulation to solve the problem, we would have to perform $6 \times 13 \times 15 \times 6 \times 4 = 28{,}080$ experiments. If we want a sample size of at least 10 runs per trial solution in order to obtain the desired level of precision, and assume that each experiment takes about 1 minute, then a complete enumeration of all possible solutions would take about 28,080 minutes, which is approximately 19.5 days with 24 hours a day running. Therefore, the simulation optimization saved a lot of time. Less than 30 minutes were taken to obtain the optimum solutions of the simulation model of the OR department at WHSC.

I just used my toes to touch the ocean of simulation optimization in this research. In this model, the limit number of resources was involved in the optimization model and only one performance was used to evaluate the simulation model. In the future, along with the development of the simulation model, more resources including nurses, beds in post-operatively units, beds in inpatient wards, should be considered as the decision variables in the optimization model. More objectives may also be included in the future research to minimize the average waiting time, minimize the length of stay, and minimize the total expected asset cost. Finally, alternatives to the block scheduling system may also be investigated.

Chapter 6: Conclusions and Future Work

6.1. Contributions of This Research

Healthcare providers today are confronted with several pressures such as increasing equipment costs, a shortage of qualified healthcare professionals, and limited hospital facilities. With the health care costs rising, the health care industry is increasingly faced with the problem of growing demand. If the caseload is beyond maximum capacity, patient satisfaction decreases because of increased waiting times, surgeons and nurses become physically and mentally exhausted, and the hospital incurs the cost of overtime. Winnipeg Health Sciences Center (WHSC) broke the ice to start a project to analyze its adult surgical patient flow and to produce possible methods of the improvement. First of all, the researchers need to understand the current efficiency of the operating room (OR) department which is the most demanding department at WHSC, then to find the bottle-neck problem, in order to finally provide some feasible solutions. This led to the development of discrete-event simulation model of the OR at WHSC for the maximum capacity of OR analysis presented in this thesis.

Due to the complexity of health care systems and their essential variability, simulation is widely and successfully applied for analysis in this field. Consequently, a simulation model is built to determine the current efficiency of the surgical suite and to predict the bottleneck at WHSC.

Based on the built simulation model, a Tabu Search algorithm is developed to find the optimal resources of the OR department at WHSC. Comparison between current systems at WHSC and the optimal resource configuration obtained by TS shows that 21% more patients can be processed, the processing time in OR can be shortened 17%, the LOS is reduced 19%.

6.2. Conclusions

This research shows that simulation is an efficient tool for identifying problems and improving performance of healthcare systems. The simulation model is valuable to present the current working flow and to predict the bottleneck in healthcare systems. The simulation model developed initially demonstrates that the resources in the OR department of WHSC is a main bottleneck for the longer stay of patients in the hospital.

In this research, simulation models provide a reasonable assessment of OR's efficiency, resource utilizations and other performance measures. By using the simulation, a useful evaluation for the OR provides a chance to analyze and improve the current operation processing. The output of the simulation shows the analysis result with a verity of formation. The graphical user interface provides an effective tool for decision-making of the OR operation.

6.3. Future Work

The work described in this research is an initial step for the performance improvement of the OR department at WHSC. For the further work, first of all, more data need to be collected to complete this model including the emergency cases, nurse's shift, and the data related to cost. The emergency surgical patients cased in the OR department should be considered. More resources may also be included in the simulation optimization.

The simulation of healthcare is different from manufacturing simulation which mainly deals with the material flow. Healthcare is a human-centered system including doctors, nurses, patients, and assistants. Human behaviors are different from those of machines. The future work should also emphasize human behaviors in healthcare systems, such as the physical, emotional, cognitive and social aspects. The processing time of the tests and operations vary based on patient's age, gender, physical condition, and personalities. Doctors' situation also affects the processing time of each operation. The more human behaviors involved in the simulation model will make the model more reliable.

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