EVALUATION OF THE DESIGN OF A FAMILY PRACTICE HEALTHCARE CLINIC USING DISCRETE-EVENT SIMULATION

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ABSTRACT

With increased pressures from governmental and insurance agencies, today's physician devotes less time to patient care and more time to administration. To alleviate this problem, Biological & Popular Culture, Inc. (Biopop) proposed the building of partnerships with healthcare professionals to provide high-quality, cost-effective medical care in a physician network setting. To assist Biopop in evaluating potential operating procedures, a discrete-event simulation model has been constructed. The model is built in an object-oriented, visual manner utilizing the Visual Simulation Environment (VSE). The model examines both internal Biopop operations and external clinic operations. The research presented herein describes the design of the simulation model and details the analysis of the clinical environment.

A methodology for determining appropriate staffing and physical resources in a clinical environment is presented. This methodology takes advantage of several simulation-based statistical techniques, including batch means; fractional factorial design; and simultaneous ranking, selection, and multiple comparisons.

An explanation of the experimental design is provided and results of the experimentation are presented. Based upon the experimental results, conclusions are drawn and recommendations are made for an appropriate staffing and facility size for a two-physician family practice healthcare clinic.

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Chapter 1

Introduction

Increased bureaucratic and economic pressures from governmental and insurance agencies have resulted in today's physician devoting less time to patient care and more time to administration. Biological & Popular Culture, Inc. (Biopop) recognized this problem and sought to alleviate physicians of burdensome administrative, clerical, and scheduling work through the implementation of a Biopop-managed physician network. The goal of this network, dubbed *Queston*, was to form alliances with private physicians so that they might benefit from Biopop's advanced business technologies, as well as gain access to a wealth of professional expertise. The Queston network aimed to manage clinical office operations and handle all routine, but essential, interactions between the physician's office and managed care organizations and insurance companies.

The Queston concept is predicated upon the establishment of a network composed of clinics (i.e., outpatient medical facilities where patient care is delivered) located throughout the United States. These clinics would rely on a centralized information center to manage their non-medical operations. Operations such as patient scheduling

and billing which are typically handled at individual clinics would be processed by the Queston information center, allowing the physician to focus solely on the practice of medicine. Biopop would also serve as a business consultant to its Queston member clinics, evaluating both physical space and staffing needs. By providing clinic-specific facility and staffing recommendations, Biopop sought to increase patient flow and customer satisfaction at Queston clinics.

To assist Biopop in evaluating potential operating procedures both at Queston clinics and at the Queston information center, a discrete-event simulation model has been developed. The model was built using Orca Computer, Inc.'s object-oriented, domain independent visual simulation software, the Visual Simulation Environment (VSE) (Balci et al. 1998). The use of visual simulation has been acknowledged as beneficial (Bell and O'Keefe 1994) and the use of the object-oriented paradigm (OOP) provides the added benefits of model reusability and maintainability.

The research presented herein describes the design of the simulation model and details the analysis of the clinical environment. In particular, a multiattribute decision variable is derived to evaluate clinic effectiveness (CE). This CE statistic is collected from the model for each simulated day and grouped using the method of batch means (Banks et al. 1996). A combined ranking, selection, and multiple comparisons with the best procedure (Nelson and Matejcik 1995) is then used to evaluate proposed clinic designs. Based upon the experimental results, conclusions are drawn and recommendations are made for appropriate staffing and facility size for a two-physician family practice healthcare clinic.

The remaining chapters are organized as follows: Chapter 2 presents an overview of discrete-event simulation applied to healthcare, focusing primarily on outpatient clinics. Chapter 3 is meant to provide an overview of the simulation model and its elements, while Chapter 4 details the model's design and construction, including modeling techniques and simplifying assumptions. Chapter 5 describes the verification, validation, and testing techniques applied to the model. Chapter 6 addresses the steps necessary to adequately analyze the model's output. Specifically, development of the CE measure, establishment of a steady-state truncation point, implementation of the method of batch means, and factor screening through fractional factorial design are covered. Chapter 7 focuses on the combined ranking, selection, and multiple comparisons procedure used to determine the optimal clinic design. In addition to the details of implementation of this procedure, background on both ranking and selection and multiple comparison procedures is provided. Chapter 8 provides results and conclusions from the research, as well as future research directions.

Chapter 2

Literature Survey

The explosion of healthcare costs over the last thirty years has compelled a growing number of researchers to investigate methods of making the clinical environment more efficient. Discrete-event simulation's ability to reflect the dynamic nature of clinical systems and its growing ease of use has made it an attractive tool for operations research analysts studying healthcare issues. Numerous articles (see Figure 2.1) have been published during this period on the application of discrete-event simulation to the clinical environment. Although the survey presented herein focuses primarily on simulation in the outpatient clinical environment, several articles present more comprehensive reviews of simulation in healthcare. Jun et al. (1999) provide an extensive taxonomy of the literature on the simulation of single and multi-facility healthcare facilities (clinics and hospitals) over the past twenty years. England and Roberts (1978) and Valinsky (1975) provide literature reviews of healthcare in simulation prior to the mid-1970s.

In addition to comprehensive literature reviews, recent articles have presented tutorials for operations research analysts studying healthcare systems through the

application of discrete-event simulation. Banks and Carson (1987) and Mahachek (1992) provide tutorials on the steps required when conducting a healthcare system simulation study. Mahachek also provides details of a simulation study on hospital patient flow. Lowery (1996) discusses some of the issues facing an analyst when using simulation to study a healthcare system, such as degree of model complexity, definition of input distributions, model validation, and interpretation of findings. These articles provide useful information for practitioners interested in using discrete-event simulation to study healthcare systems and issues. Moreover, these articles focus on the unique factors inherent in healthcare systems and the application of simulation to address problems within such systems.

In general, the focus of healthcare simulation studies over the last twenty years can be classified into two major areas:

1. Patient Flow – Including patient scheduling and admissions policies, patient routing and flow schemes, and scheduling and availability of resources.
2. Allocation of Resources – Including bed sizing and planning, room sizing and planning, and staff sizing and planning.

2.1 Patient Flow

Hospitals and clinics are facing increasing competition for their services. To attract new patients and retain their patronage, they must be able to provide fast and efficient healthcare. Effective and efficient patient flow is indicated by high patient throughput, low patient waiting times, and short patient length of stay coupled with low clinic staff

overtime, high staff utilization rates, and low physician idle times. Three topics are central to patient flow:

i) patient scheduling and admissions policies,

ii) patient routing and flow schemes, and

iii) scheduling and availability of resources.

2.1.1 Patient Scheduling and Admissions Policies

Patient flow can be greatly affected by the procedures used to determine how patient appointments are scheduled, both in terms of when and how they are set in a given day and the length of time allocated for the appointment. By altering the rules that determine when appointments can be made (e.g., morning versus afternoon) and the length of time between appointments (appointment spacing), patient flow may be increased without incurring additional clinical costs or increasing patient waiting.

Most simulation studies that have focused on patient scheduling and admissions policies have analyzed outpatient clinics. Fetter and Thompson (1965) present one of the first simulation studies conducted on the operations of an individual clinic. They analyze the physician utilization rate with respect to patient waiting time by using many different input variables (e.g., patient load, patient early or late arrival patterns, no show rates, walk-in rates, appointment scheduling intervals, physician service times, interruptions, physician lunch and coffee breaks). They determine that if a physician's appointments increase from 60% of capacity to 90% of capacity, the total physician idle time decreases by 160 hours and the total patient waiting time increases by 1600 hours over a fifty day period. If this capacity increase were to be implemented, the simulation study suggests

that the physician's time would have to be worth ten times the patient's time to justify such a shift in patient scheduling and admission policies.

Evenly distributing patient demand has been used to improve patient throughput and decrease patient waiting times in outpatient clinics. Smith and Warner (1971) compare the case in which patients arrive according to a uniform arrival pattern versus patient arrival patterns that are highly variable. They show that the uniform arrival pattern can decrease the average patient length of stay at the clinic by over 40% (from 40.6 minutes to 24.0 minutes). Similarly, Rising et al. (1973) attempt to smooth physician demand by increasing the number of appointments slots in an outpatient clinic on those days that have the least number of walk-ins. Their results show a 13.4% increase in patient throughput and decreased clinic overtime. Kho and Johnson (1976) and Kachhal et al. (1981) show that performance can be improved when demand for outpatient services is evenly distributed in a radiology department and in an ear, nose, and throat clinic, respectively.

In contrast to uniform scheduling, several researchers have investigated alternative scheduling rules. Bailey (1952) describes a rule that schedules two patients at the beginning of every session (morning or afternoon), with all other patients scheduled at equal intervals thereafter. This rule yields acceptable results for both patients (in terms of waiting times) and staff (in terms of utilization), assuming that all patients have the same service time distributions and that all patients arrive punctually at their scheduled appointment times. In a similar study, Smith et al. (1979) use a modified-wave scheduling scheme for an outpatient clinic to find the maximum number of patients a physician can see while minimizing patient waiting times. This scheme schedules more

patients at the beginning of each hour and less towards the end of the hour, thereby allowing the physician to absorb unexpected delays throughout the hour and still remain on schedule for the beginning of the next hour. They show this schedule to be superior to the uniform scheduling scheme in terms of patient flow and patient waiting times. Williams et al. (1967) study the relationship between physician utilization and patient waiting times in an outpatient clinic using a staggered block scheduling system (eight patients arriving every half hour) and a single block scheduling system (sixteen patients arriving simultaneously). The single block system lessens the physician's idle time but increases patient waiting times. The staggered block system substantially decreases patient waiting times with no decrement (though no increase) in the utilization of the physician.

Klassen and Rohleder (1996) use simulation to study the best time to schedule patients with large medical treatment service time variances. They analyze several rules and find that scheduling such patients toward the end of an appointment session minimizes the patient's waiting time and the physician's idle time. Additionally, they analyze the best position for unscheduled appointment slots for potentially urgent calls and found no conclusive evidence for a superior scheduling rule. Likewise, Swisher et al. (1997) experiment on scheduling more patients with larger mean service time in the morning session, rather than the afternoon, in an outpatient clinic. They find that staff overtime decreases sharply but the amount of time the physician has for lunch also decreases.

Walter (1973) studies the effect of using several different appointment schemes in a radiology department. By segregating patients with similar examination time

distributions into inpatient and outpatient sessions, he finds that a substantial staff time savings is possible. He also finds that the practice of giving multiple bookings for a given appointment time (i.e., overbooking) yields a small increase in staff utilization while substantially increasing the patient waiting time. Additionally, he finds that efficiency always improves when the proportion of patients with scheduled appointments increases. Goitein (1990) supports these conclusions using Monte Carlo simulation to examine factors such as physician idle time relative to patient waiting time. He finds that if the physician overbooks the schedule, even slightly, patients experience very long waiting times. His model provides insights into how delays build up throughout the day in a clinic as a result of statistical fluctuations.

2.1.2 Patient Routing and Flow Schemes

Discrete-event simulation's capability to model complex patient flow through a hospital or clinic has made it a popular tool for assessing patient routing and flow schemes. Concern over patient flow is most often seen in emergency room settings, where patients arrive without appointments and require treatment over a large and varied set of ailments and conditions. These ailments can range from the benign (e.g., mild sports injuries) to the fatal (e.g., heart attacks, gunshot wounds). Though the arrival of patients is highly unpredictable, the sequence by which patients can be treated (i.e., routed) can be controlled by medical staff. By altering patient routing and flow, it may be possible to minimize patient waiting times and increase staff utilization rates.

Garcia et al. (1995) analyze the effects of using a fast track lane to reduce waiting times of low priority patients in an emergency room. Emergency rooms are prioritized

according to the seriousness of patient ailment, hence low priority patients regularly wait for excessively long periods of time. A fast track lane is a lane dedicated to serving a particular level of patient (in this case, non-urgent patients). They found that a fast track lane that uses a minimal amount of resources could greatly reduce patient waiting times. In a simulation model of the emergency department at the University of Louisville Hospital, Kraitsik and Bossmeyer (1993) suggest using a fast track lane as well as using a "stat" lab for processing high volume tests to improve patient throughput. Kirtland et al. (1995) examine eleven alternatives to improve patient flow in an emergency department. They found that the combination of three of the alternatives (a fast track lane, treatment area waiting for in-service patients, and point-of-care lab testing) can reduce the average patient time in system by thirty-eight minutes.

McGuire (1994, 1997) uses the simulation software package MedModel to determine how to reduce the length of stay for patients in an emergency service department in a SunHealth Alliance hospital. Several alternatives were recommended from the simulation study results, including the addition of a clerk during peak hours, adding a holding area for waiting patients, extending the hours of the fast track lane, and using physicians instead of residents in the fast track area. Blake and Carter (1996) analyze an emergency department at the Children's Hospital of Eastern Ontario. Based upon their simulation study results, a fast track lane for treating patients with minor injuries was implemented.

Ritondo and Freedman (1993) show that changing a procedural policy (of ordering tests while in triage) results in a decrease in patient waiting times in an emergency room and an increase in patient throughput. Edwards et al. (1994) compare

the results of simulation studies in two medical clinics that use different queuing systems: serial processing, where patients wait in a single queue, and quasi-parallel processing, where patients are directed to the shortest queue to maintain flow. They show that patient waiting times can be reduced by up to 30% using quasi-parallel processing.

2.1.3 Scheduling and Availability of Resources

Typically, healthcare simulation studies focusing on scheduling policies address the scheduling of *patients*. A number of studies, however, have addressed the problem from the opposite perspective. These studies address ways in which *medical staff* can be scheduled to meet patient demand, while patient arrivals are left unchanged. In fact, some clinics, such as walk-in clinics, are unable to change the arrival rate of patients and must schedule their staff accordingly. Furthermore, concurrently scheduling staff *and* patients could be used to better meet demand and better allocate resources.

Incorporating the idea of concurrent scheduling, Alessandra et al. (1978) study both medical staffing levels and patient arrival rates to ease bottlenecks and to improve patient throughput. Eight alternatives, involving varying the staffing pattern and the patient scheduling scheme, are analyzed. The best alternative proved to be keeping the staffing level and patient arrival rate the same, but distributing the current morning appointment patients to the afternoon shift.

A number of simulation studies have addressed the scheduling of nursing staff in emergency rooms. These studies are typically motivated by the often conflicting objectives of providing high-quality emergency care and reducing costs. Draeger (1992) simulates nurse workload in an emergency room and its effect on the average number of

patients, average time in system, average number of patients waiting, and average patient waiting time. Comparing the current schedule's performance to those of two alternative staffing schedules, the author finds an alternative that could reduce both the average patient time in system (by 23%) and the average patient waiting time (by 57%), without increasing costs. Similarly, Evans et al. (1996) describe a way to reduce the average patient length of stay in an emergency room by determining the optimal number of nurses and technicians that should be on duty during four emergency room shifts. Kumar and Kapur (1989) examine ten nurse scheduling policy alternatives, selecting and implementing the policy that yields the highest nurse utilization rate.

Lambo (1983) applies a recursive linear programming and simulation methodology to examine staffing problems in a healthcare center in Nigeria. In the study, the clinic was observed to be at 50% capacity due to the misallocation of personnel. After making staffing pattern and other policy changes, capacity increased by 60% and patient waiting times were reduced by 45 minutes on average.

2.2 Allocation of Resources

With the rise in cost of providing quality healthcare, clinic and hospital administrators are increasingly interested in optimally allocating scarce healthcare resources. Informed decision-making on healthcare resource allocation is essential for clinics to maintain patient satisfaction while reducing costs. Discrete-event simulation's ability to allow the analyst to play "what if?" games with staffing, equipment, and facility size without altering the actual physical system has made it a popular tool in the allocation of

healthcare resources. Jun et al. (1999) classify the allocation of healthcare resources into three areas:

i) bed sizing and planning,

ii) room sizing and planning, and

iii) staff sizing and planning.

Since bed sizing and planning is performed in a hospital setting and not in outpatient clinics, it is excluded for the purpose of this thesis' literature survey. The reader is referred to Jun et al. (1999) for information on the application of discrete-event simulation to hospital bed sizing and planning.

2.2.1 Room Sizing and Planning

The continuing trend towards the development of freestanding surgicenters by hospitals coupled with a push towards more outpatient appointments has put increased pressure on healthcare decision-makers to either expand their current facilities or build new ones. Although much of this research has focused on the needs of surgicenters, the analysis of the basic tradeoffs between capital expenditures and patient service levels is applicable in the outpatient clinical environment.

Olson and Dux (1994) use simulation modeling to study the decision to expand the Waukesha Memorial surgicenter in Waukesha, Wisconsin, USA from seven to eight operating rooms. The study reveals that an eighth operating room would only serve to meet the hospital's needs for one to two years, at a cost of $500,000. However, their analysis of the surgicenter's cross-departmental and administrative needs reveals that an ambulatory surgery center that separates inpatient and outpatient procedures would better

serve the hospital's future healthcare delivery needs. Likewise, Amladi (1984) uses simulation to assist in the sizing and planning of a new outpatient surgical facility by considering the tradeoffs between patient waiting time and facility size.

Meier et al. (1985) consider eleven different scenarios in both a hospital ambulatory center and a freestanding surgicenter by varying the number of examination rooms and shifts in patient demand. They find that existing room capacity is adequate to handle patient demand for the next five years. Iskander and Carter (1991) also found that current facilities were sufficient for future growth in a study of an outpatient healthcare unit in an ambulatory care center. However, they suggest a threefold increase in the size of the waiting room.

Levy et al. (1989) analyze the operational characteristics of an outpatient service center at Anderson Memorial Hospital in Anderson, South Carolina, USA to determine whether to merge the operations of this center with an offsite outpatient diagnostic center. Their model collects data on the utilization of the servers, the total number of patients in the service center, the maximum and average times spent in the service center, the maximum and average times spent in each service queue, and the total number of patients in each service queue. This information is used to specify staffing and facility sizing requirements. In another facility integration study, Mahachek and Knabe (1984) use simulation to analyze a cost-cutting proposal to combine an obstetrics clinic and a gynecology clinic into a single facility. Their simulation analysis concludes that this proposal would not be successful due to a shortage of examination rooms in the combined facility.

2.2.2 Staff Sizing and Planning

The provision of high-quality, efficient healthcare requires the proper allocation of highly skilled medical professionals. This makes staff sizing and planning an important factor in designing healthcare delivery systems. Moreover, the tradeoff between insufficient staff to meet demand (hence unacceptable patient waiting times) and underutilization of staff can have disastrous effects on the viability of a medical facility. Simulation has played an important role in addressing this tradeoff.

Hashimoto and Bell (1996) conduct a time-motion study to collect data for a simulation model of a general practice outpatient clinic. They show that increasing the number of physicians, and consequently the number of patients, without increasing the support staff can significantly increase the total time spent at the clinic for patients. By limiting the number of physicians to four and increasing the number of dischargers to two, they were able decrease the average patient total time at the clinic by almost 25% (from 75.4 minutes to 57.1 minutes). Wilt and Goddin (1989) evaluate patient waiting times to determine appropriate staffing levels in an outpatient clinic. McHugh (1989) examines the adequacy of various nurse staffing policies and their effects on cost, understaffing, and overstaffing in a hospital. Her analysis shows that 55% of the maximum workload produces a good balance between the three measures. Swisher et al. (1997) discuss a simulation model of a family practice outpatient clinic. In certain cases, they found that adding additional medical staff members has a negligible effect on the average patient total time at the clinic and clinic overtime.

Stafford (1976) and Aggarwal and Stafford (1976) develop a multi-facility simulation model of a university health center that incorporates fourteen separate stations

(e.g., receptionist area, injections, dentistry, gynecology, physical therapy, radiology, and pharmacy). Using student population figures and seven performance measures, they are able to estimate the level of demand for services in the clinic. They also show that patient interarrival times are distributed negative exponential with the mean changing according to the time of day, and patient service times are distributed Erlang-k. Using this data, they investigate the effects of adding another pharmacist to the pharmacy. A multi-factor experimental design was developed to examine the relationships between the controllable (input) system variables and the output system performance measures. They show that different calling population sizes and different levels of staffing can impact the system performance measures at each station. Additionally, the aggregation of two or more similar facilities can cause an increase in the average number of patients waiting at each of the remaining facilities and the average waiting times of the patients. However, these increases were offset by a significant decrease in the staff idle times and staff costs.

O'Kane (1981), Klafehn (1987), and Coffin et al. (1993) each analyze staff allocation in radiology laboratories in an effort to improve patient service. Klafehn and Connolly (1993) model an outpatient hematology laboratory using Proof Animation from Wolverine Software. They compare a number of staffing configurations and found that if the staff is cross-trained (hence can be more fully utilized), patient waiting times can be reduced. Vemuri (1984) and Ishimoto et al. (1990) each explore the operations of a pharmacy unit in a hospital. Using simulation, they find the optimal medical staff size and mix that reduces patient waiting times. Lopez-Valcarcel and Perez (1994) evaluate eight alternative scenarios in an emergency department simulation by varying the number of staff, the patient arrival rates, and the service times of diagnostic equipment (alterable

by purchasing better equipment). They recommend that the patient arrival rate should not exceed twelve patients per hour. Moreover, they recommend that investments in human resources would be more effective than investments in newer (better) equipment. In contrast, Bodtker et al. (1992) and Godolphin et al. (1992) determine that a reduction in staff by at least one staff member can be achieved if better equipment is purchased.

2.3 Survey Conclusions and Future Directions

The scope of application of discrete-event simulation to healthcare has been quite broad over the past twenty-five years. All of the healthcare simulation studies reported in the literature are similar in that they attempt to understand, in some manner, the relationship between various controllable system inputs (e.g., patient scheduling and admissions rules, patient routing and flow schemes, facility and staff resource allocation) and various performance measure outputs (e.g., patient throughput, patient waiting time, physician and staff utilization). Each article shows how varying one or many inputs affects some or all of the outputs.

The articles also demonstrate that as the demand for more efficient healthcare systems and the ease-of-use of simulation packages have both increased, so has the application of discrete-event simulation to healthcare. This trend is made obvious by Figure 2.1 which presents the number of healthcare simulation articles published (as cited by Jun et al. 1999) from 1973 to 1997 in five year increments. There is no reason to believe that this trend will diminish as simulation software continues to become more powerful and pressure from governmental and insurance agencies continues to demand cost efficiency in the clinical environment.

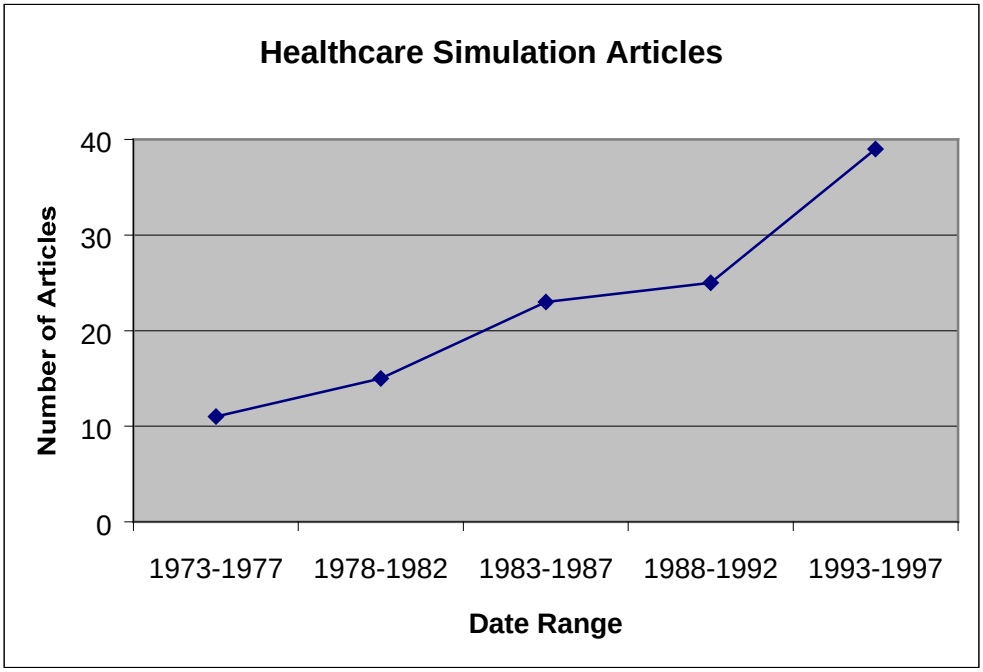


Figure 2.1: The Growth of the Application of Simulation to Healthcare

One dramatic change driving increased usage of simulation in the last ten years has been the addition of animation to simulation software packages. Although animation does not guarantee model correctness (Paul 1989), it can greatly aid in the verification and validation of model (Gipps 1986, Sargent 1992). Moreover, animation in simulation is an effective tool for presenting models to non-technical decision-makers in an intuitive manner. Simulation software vendors have embraced animation. In fact, ProModel's MedModel (Keller 1994, Carroll 1996) is designed specifically for the simulation and animation of healthcare systems. Jones and Hirst (1986) present an early article on the benefits of animation in healthcare simulation. In their case, allowing decision-makers to view the effects of different policies in a surgical unit played an integral role in gaining model acceptance and ultimately in the selection of revised policies. Others (McGuire 1997, Evans et al. 1996, Paul and Kuljis 1995, McGuire 1994, Ritondo and Freedman

1993) have also effectively used animation to establish greater credibility for using simulation to analyze healthcare systems.

In addition to the increasing use of animation, a growing number of operations research analysts are combining optimization techniques with discrete-event simulation. Simulation allows the analyst to model the complex dynamic nature of a clinic in a manner that is not possible using many optimization modeling techniques. For example, linear programming has a limited capacity for modeling complex details of patient scheduling and routing. However, discrete-event simulation is *descriptive* in nature, while optimization techniques are *prescriptive*. That is, optimization techniques prescribe optimal or near-optimal solutions by nature. Although sometimes a formidable task, combining simulation and optimization techniques can take advantage of the strengths of each.

Several healthcare analysts have successfully combined these techniques to find the best staffing allocations and facility sizes. A common technique when applying an optimization methodology to simulation models of healthcare clinics is a recursive method employed by Kropp et al. (1978), Carlson et al. (1979), and Kropp and Hershey (1979). First, an optimization technique is used to analyze and reduce the number of alternatives of the system at an aggregate level (the total system level). These results are then used in a more complex and detailed simulation model of the same system that identifies additional information and acceptability of the results. Finally, these additional constraints are passed back into the optimization model with this process repeated iteratively. Similarly, Butler et al. (1992) employ a two phase approach by first using quadratic integer programming to address facility layout and capacity allocation questions

and then a simulation model to capture the complexities associated with alternative scheduling rules and bed assignment.

The above studies use a variety of optimization techniques to arrive at parameters for the simulation model. Generally, recursive simulation optimization techniques can be very difficult, and therefore, costly to implement in the healthcare sector. However, in recent years, a number of simulation software packages have appeared that provide an optimization add-on to the software (see Jacobson et al. 1999). Instead of an exhaustive, time-consuming, and indiscriminate search for an optimal alternative, simulation software companies are now starting to provide special search algorithms to guide a simulation model to an optimal or near-optimal solution. A growing feature among these add-ons is support for ranking and selection and multiple comparison procedures (Carson 1996). These procedures are statistical tools that allow the analyst to select the best alternative configuration from among a small, finite number (i.e., 2 to 20) of competing alternatives. Recent unification of these two theories (Matejcik and Nelson 1993) has made their application more popular.

Overall, it appears that the application of discrete-event simulation to healthcare will continue to grow. Advances in simulation software animation coupled with enhanced simulation software output analysis and optimization capabilities will play an integral role in future healthcare simulation projects. Operations research analysts will be able to present simulation results via animation in an intuitive manner to non-technical decision-makers, thereby increasing the probability of model acceptance and lessening resistance to policy implementation. In addition, the power to include optimization

routines in simulation models will allow the analyst to quickly find an optimal or near-optimal solution to the problem at hand.

Chapter 3

Overview of the Simulation Model

The primary objective in developing the simulation model is to provide a tool for decision-making in the clinical environment, specifically in family practice outpatient facilities. The model allows medical decision-makers (e.g., physicians) a means of visualizing changes to the patient-physician encounter while allowing operations researchers to study the effects of those changes on key decision variables and performance measures. Both the physician and the operations research analyst are interested in designing patient-physician encounters that trade off patient throughput (which should be maximized), patient waiting times (which should be minimized), medical staff utilization (which should be maximized), and clinic overtime (which should be minimized) while still delivering quality healthcare.

The simulation model uses the discrete-event worldview in its implementation and is constructed in a hierarchical fashion. The model's top level represents the continental United States of America (see Figure 3.1). On this level there are two objects: a centralized information center and a family practice outpatient clinic. The information

center is composed of a user-defined number of operators capable of receiving calls and scheduling appointments for patients from the geographic regions surrounding network clinics. Note that since this research focuses on the study of the clinical environment and not the operation of the network as a whole, only one clinic is currently contained in the model to facilitate model experimentation.

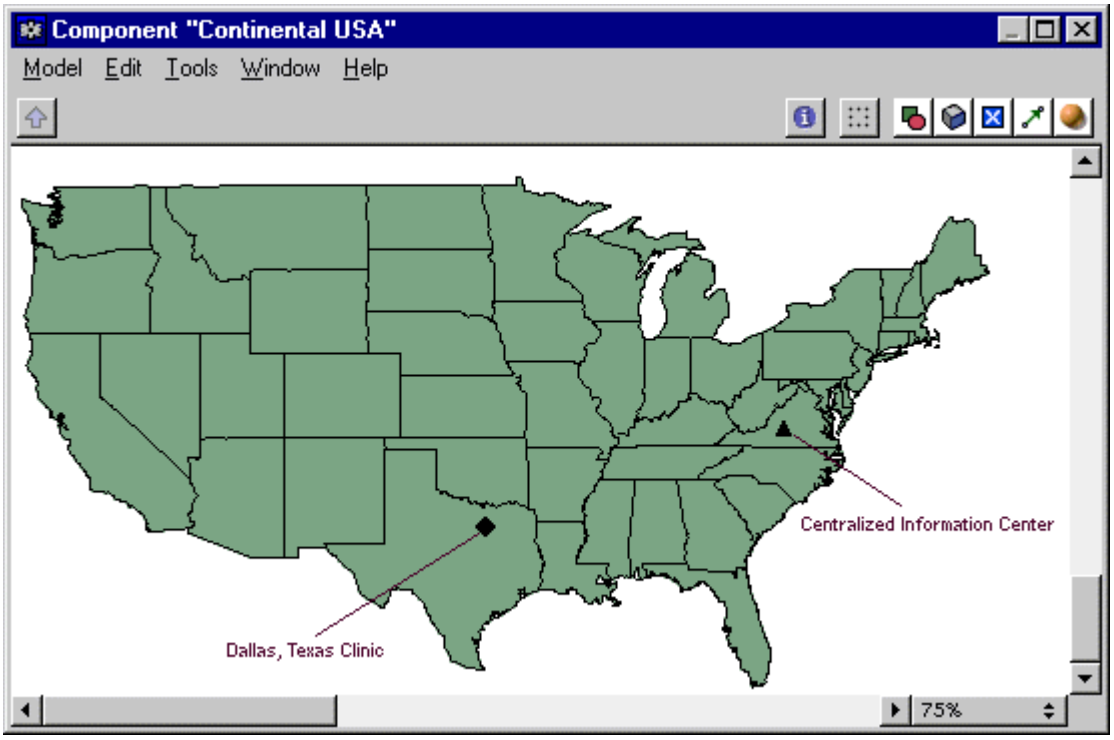


Figure 3.1: The Top Level of the Simulation Model

By specifying the model's calendar size (a model-specific variable) and the simulation run length (an experiment-specific VSE parameter), the model can be run for any user-specified length of time. However, the typical user will run the model for a fifteen month period, using the first month as a warm-up period and the final fourteen months to represent the system's steady state behavior (see Chapter 6 for details). The arbitrary start date associated with the first model day is October 1, 2002. Dates are used

by the model to provide an intuitive reference as to the status of a model run and to determine model holidays. The user may choose to use or not use holidays in the model by altering the boolean (true/false) variable USE_HOLIDAYS in the *Constants* panel (see Figure 3.3). If holidays are used, the clinic is closed on a pre-defined set of dates (see Table 3.1), otherwise the clinic remains open on all weekdays.

Table 3.1: Model Holidays and Their Observance

Holiday	Model Observance
New Year's Day	January 1
Martin Luther King Day	Third Monday in January
President's Day	Third Monday in February
Memorial Day	Last Monday in May
Independence Day	July 4
Labor Day	First Monday in September
Columbus Day	Second Monday in October
Thanksgiving Day	Fourth Thursday in November
Christmas Day	December 25

The simulation model's focus, a family practice outpatient clinic, is a completely scaleable facility with several user-defined parameters, including:

- composition of the medical staff
- number of registration windows
- number of check-in rooms
- number of examination rooms
- number of specialty rooms

The clinic's design takes advantage of the object-oriented paradigm (OOP), as implemented by VSE. OOP allows model components to be specified as objects that can be instantiated (created) multiple times within the model. Object reusability is a major

benefit of OOP and allows a great deal of flexibility within the model. For example, instead of requiring a fixed number of examination rooms in the clinic, the desired number of examination rooms can be defined as an input parameter value in VSE's *Input Data* window (see Figure 3.2). VSE allows input parameter data value sets to be defined so that a particular set of parameter values can be chosen for use in an experiment. In the above example, the number of examination rooms specified for the selected data value set would be automatically instantiated within the model at run time (e.g., 6 examination rooms for the Baseline data set or 4 examination rooms for the FF1 data set in Figure 3.2). This approach is taken throughout the model, allowing the user to define many of the key components by simply changing the input data value set at run time. Additionally, VSE's *Constants* panel (see Figure 3.3) allows the user to specify global constant values for the model. Fixed values that the analyst does not expect to be altered on a per-experiment basis can be easily defined here instead of in the *Input Data* window.

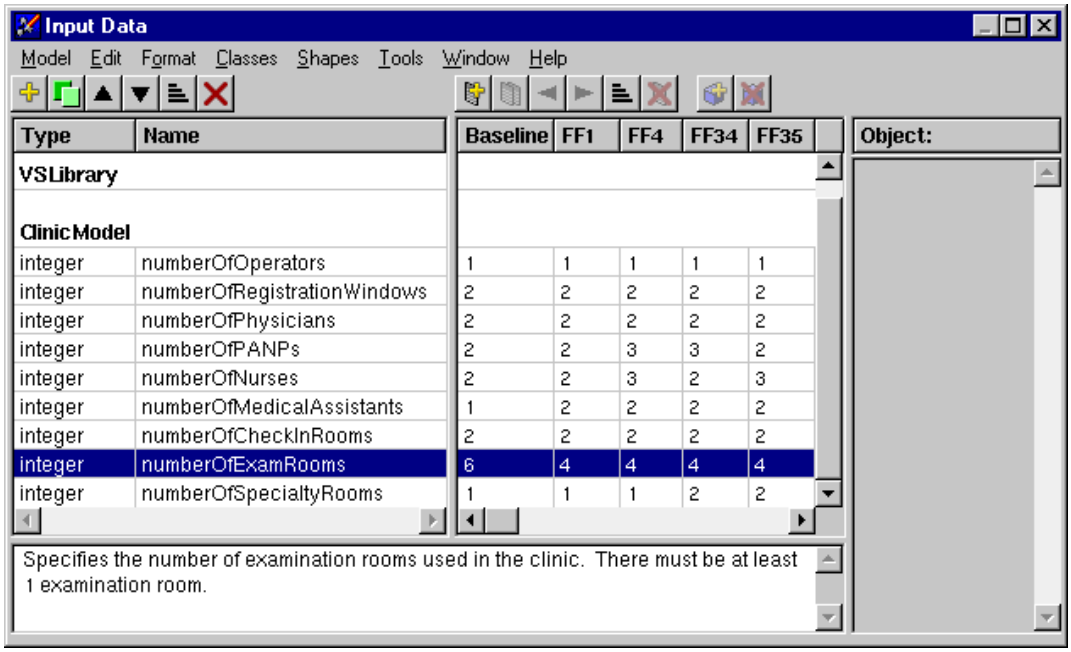


Figure 3.2: The Simulation Model's Input Data Window

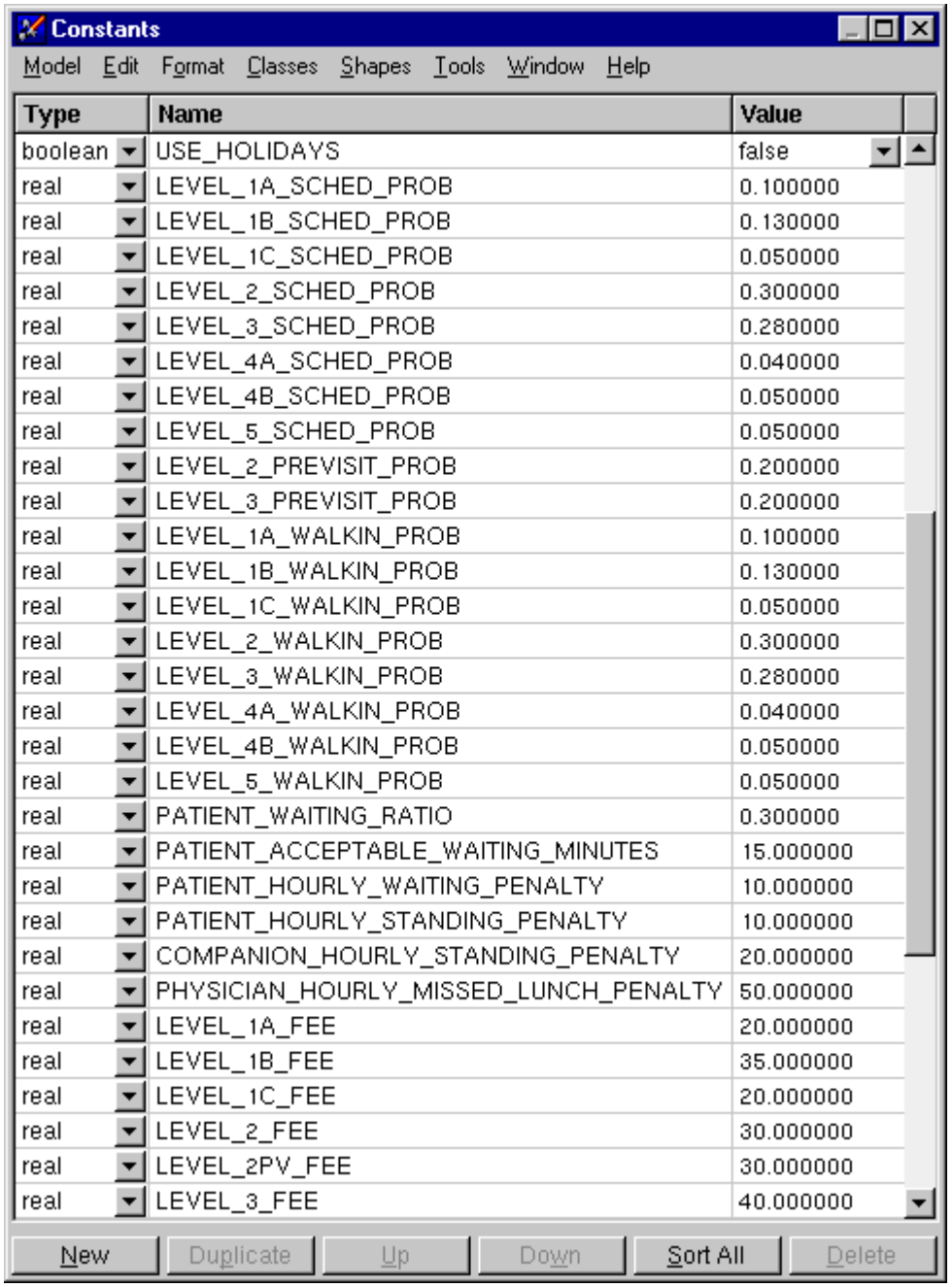


Figure 3.3: The Simulation Model's Constants Panel

VSE also allows the model to take advantage of two other very important features of OOP: inheritance and polymorphism (Orca Computer, Inc. 1998). Inheritance is a relationship between an object and its object class which allows the object to use the attributes and operations of the object class (Yourdon et al. 1995). This means, for

example, that the objects *patient* and *medical staff member* could both inherit attributes and methods from the class *person* (see Figure 3.4). Moreover, the objects *physician* and *nurse* could then inherit attributes and methods from the class *medical staff member*. The class *person* is referred to as the superclass in relation to it subclasses *patient* and *medical staff member*. Inheritance allows the modeler to store generic object methods in the superclass, while storing only object-specific methods in the subclass. For example, methods for assessing a person's physical location within the clinic are stored in the *person* class and inherited by its subclasses, while methods specific to each subclass are encapsulated within that subclass. VSE also allows polymorphism wherein an object can override or alter a method it inherits from its superclass (Yourdon et al. 1995). This means that an object sending a message need not know what specific subclass of *person* is receiving the message. The same message can be passed both to *patient* and *medical staff member* and each object interprets the message in its own manner.

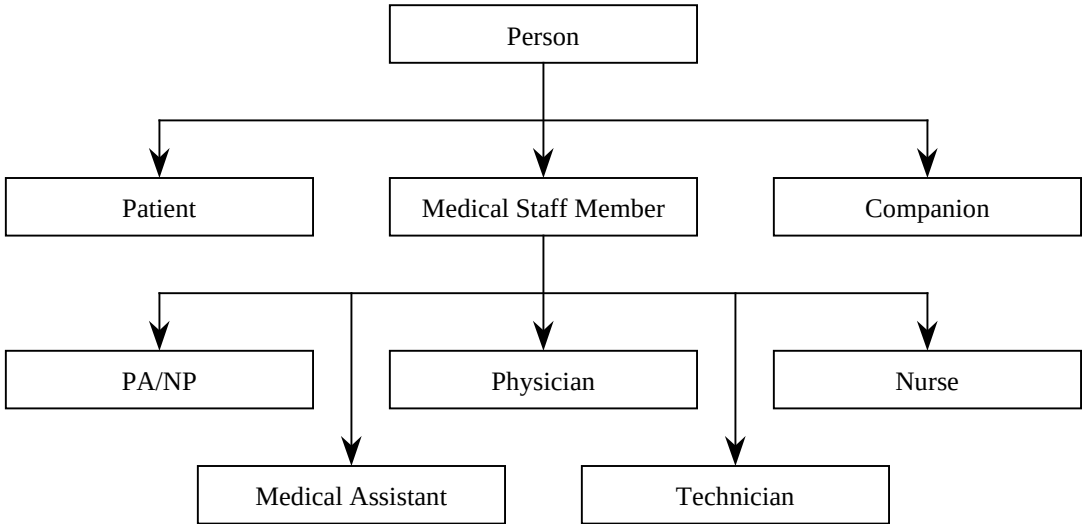
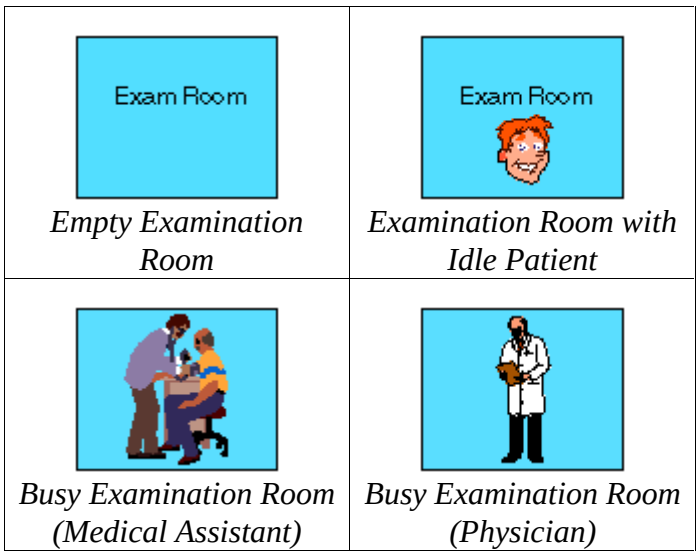


Figure 3.4: The Person Class and its Subclasses

All objects within the clinic take advantage of the visual nature of the model. Depending upon an object's state, the image used to represent the object varies. For example, when a patient enters an examination room, the image of the examination room changes to reflect the patient's presence. Upon the arrival of a medical staff member, the image changes again to reflect that the room is now busy. Moreover, the type of medical staff member assisting the patient is indicated by the image used. The use of different images to represent the state of an object is displayed in Figure 3.5, which shows clockwise from top left: an empty examination room, an examination room with a patient awaiting medical service, a busy examination room with a physician servicing a patient, and a busy examination room with a medical assistant servicing a patient.



Empty Examination Room

Examination Room with Idle Patient

Busy Examination Room (Medical Assistant)

Busy Examination Room (Physician)

Figure 3.5: Images of an Examination Room

During each model run, a variety of output statistics are collected on clinic performance (e.g., medical staff utilization, facility utilization, patient throughput, staffing costs, patient revenues, patient time in system). The particular research presented herein uses a multiattribute performance measure composed of the model's key output

statistics to evaluate clinic effectiveness (see Chapter 6). However, model users are not limited to the use of this multiattribute measure and may choose any model output measure or measures of interest to analyze. Analysis of these statistics allows the operations research analyst to provide fast, accurate feedback to medical decision-makers on the potential impact of clinic operating policy changes.

Chapter 4

Model Design and Construction

The first steps in any modeling study are the investigation of the real-world system, if possible, and the definition of the scope for the model based upon the study's objectives. Due to time constraints and a limited budget, it was not possible to collect data on all aspects of a physician practice. However, to assist with this matter, Biopop assembled a team of experienced medical experts (medical professionals ranging from a physician to a claims coder) to support model development. The medical experts furnished valuable insights into the operations of a clinic from both published studies and data and from their own personal experiences when no published information was available. They also provided feedback on the model's validity as development progressed (see Chapter 5). Working closely with the medical experts, a generic family practice clinic simulation model was developed. This model includes a standard clinic layout, standard medical personnel, and standard patient types. In addition, a template for the Queston information center, which acts as the scheduling and information exchange for all network clinics, was developed.

4.1 Clinic Layout

Physically, the clinic is laid out in six major areas (see Figure 4.1):

- registration
- waiting room
- medical area
- internal waiting area
- physician office area
- medical staff office area

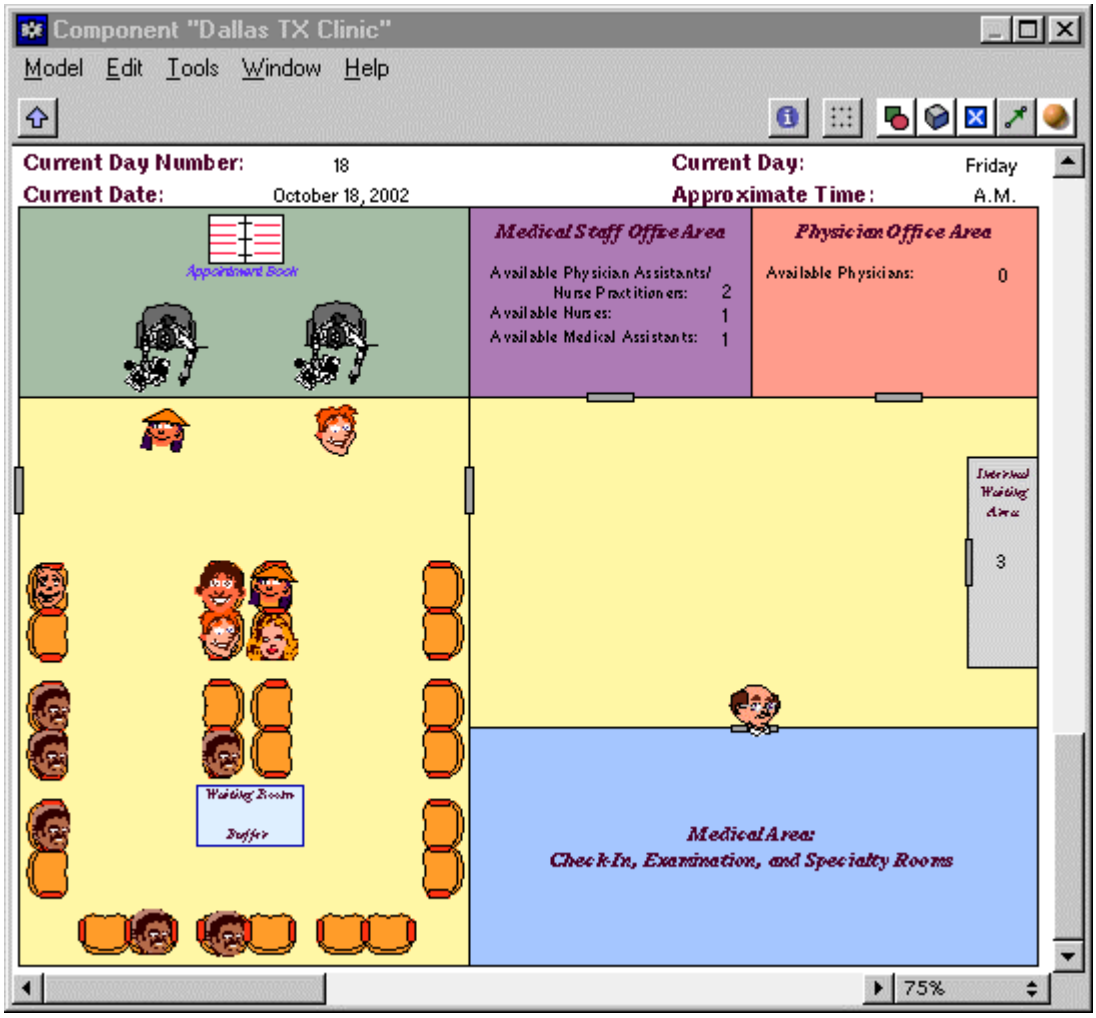


Figure 4.1: The Simulation Model's Clinic

The *registration area* houses the clerical staff who service patients as they enter and exit the clinic. Patients wait in the *waiting room* until a check-in room becomes available or if there is no available registration window. The *medical area* (see Figure 4.2) is composed of the check-in, examination, and specialty rooms. A check-in room, as defined in the model, is not typically a room in most clinics, but rather, an area in which medical staff collect initial information on patients prior to entering an examination room (e.g., height and weight measurements, blood pressure). Examination rooms are where patients undergo medical examinations or procedures. A specialty room houses any special equipment a clinic may have (e.g., x-ray machines). Note that the model imposes no pre-specified upper bound on the number of each such room that the user may define for a clinic, though physical space limitations and budget constraints in an actual clinic naturally impose such bounds. However, lower bounds are imposed: the clinic must have at least one registration area, one examination room, and one check-in room.

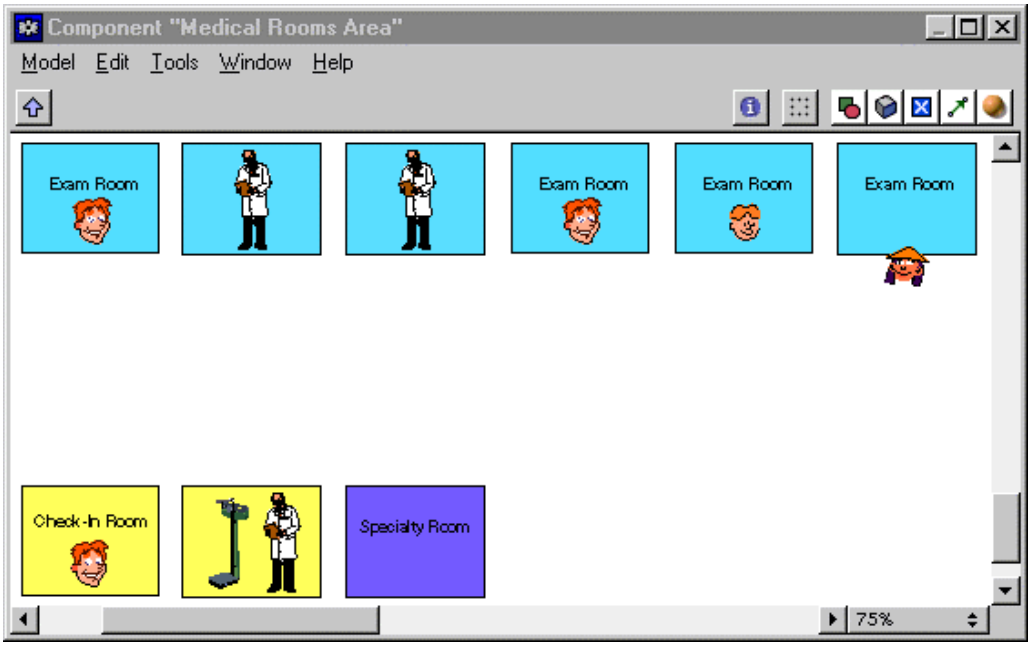


Figure 4.2: The Clinic's Medical Area

The *internal waiting area* is for patients who have been admitted to the medical area, but are awaiting the availability of an examination or specialty room. For example, a patient may complete service in an examination room and need to move to a specialty room for x-rays. If another patient is already occupying the specialty room, the first patient will move to the internal waiting area. A key concept of the Queston philosophy is the maximum utilization of resources. Therefore, instead of allowing patients to wait in an examination room, occupying space in a valuable service area, patients wait in an internal waiting area.

The *physician office area* and the *medical staff office area* house the physicians and medical staff while they are either taking notes on a patient or they are idle. After servicing a patient, the physician returns to his/her office and records information about the encounter for an exponentially distributed (with user-defined parameter λ) amount of time. Likewise, each medical staff member returns to the medical staff office area after treating a patient. The medical staff members, however, record information and perform services related to the patient for an amount of time that varies as a function of the length of the patient-staff encounter. To simplify this relationship, a linear function is used. In particular, if a medical staff member spends τ minutes in servicing a patient, then $\tau/3$ minutes are spent directly treating the patient, while $2\tau/3$ minutes are spent in the medical staff office area working on services related to the patient (e.g., taking notes, retrieving test results).

The differentiation between the physician's post-service office time and the other medical staff members' post-service office time stems from the observation of an actual family practice clinic in Christiansburg, Virginia, USA. While studying the clinic, it was

noted that although the nurse practitioners, nurses, and medical assistants spent only a short amount of time with patients, they spent (on average) twice that amount of time performing patient-related tasks outside of the examination room (hence the linear relationship described above). The physicians, however, spent a significantly greater amount of time with patients and performed very little patient-related work after an examination.

4.2 Clinic Human Resource Definition

The key human resources in the clinical environment, as identified by the team of medical experts, are:

- physicians
- physician assistants
- nurse practitioners
- nurses
- medical assistants
- lab technicians
- clerical staff

Consultation with the team of medical experts suggested that the physician assistant and nurse practitioner categories be combined into a single medical staff category (labeled PA/NP) on the assumption that the typical physician practice only staffs one, but not both, of these personnel types. Therefore, the model allows the user to choose the clinic's staffing in terms of physicians, PA/NPs, nurses, and medical assistants. The number of lab technicians is determined by the number of specialty rooms

selected in the model (one technician per specialty room). Likewise, the number of clerical staff persons is determined by the number of registration windows selected (one clerical staff person per registration window). Each staff member type is represented by a unique image as it moves throughout the model, making it easily identifiable.

4.3 Patient Definition and Development

The identification of patients for the clinic proved more complex than the identification of the medical staff. Through an iterative process of presentation and review with the medical experts, a set of distinct categories for patients in a family practice setting was developed. These categories have their basis in the American Medical Association's codification of patient evaluation and management services provided in a physician's office. The *Physicians' Current Procedural Terminology* (American Medical Association 1996) defines five general patient levels which require an increasing amount of a physician's time and decision-making abilities. American physicians use these levels to codify patient evaluation and management services for insurance or governmental reimbursement. The patient categories defined for the simulation model are based upon these five levels, with some further sub-categorization. In total, ten patient categories were developed. Like the American Medical Association's levels, the model's patient categories increase in time and decision-making ability required as the category number increases. For example, a Category 1 patient may only require a blood pressure check, while a Category 5 patient may require immediate medical attention for a life-threatening ailment. Also included in this patient breakdown are categories for patients who come for pre-visit tests (Categories 2PV and 3PV) and patients who are new to the clinic

(Category 4A). Table 4.1 provides a listing of the patient categories (excluding the pre-visit categories) with samples of patient ailments and/or medical services required and each category's probability of occurrence. As with all objects in the simulation model, a unique image is used to identify each patient category.

Table 4.1: Patient Categories, Examples, and Associated Probabilities

Patient Category	Example of Patient Ailment or Service Required	Probability of Occurrence
1 A	Blood Pressure Check, Tuberculosis Test Reading	0.10
1 B	Immunization, Phlebotomy	0.13
1 C	Dressing Change	0.05
2	Sore Throat, Fever, Fatigue, Headache	0.30
3	Hypertension, Diabetes, Asthma, Flu	0.28
4 A	New Patient	0.04
4 B	Rheumatoid Arthritis	0.05
5	Chronic Ailment Complication	0.05

The next logical step in the patient definition process was to examine the patient's process flow within the clinic. With support from the medical experts, seven distinct processes in the patient-physician encounter were identified (see Figure 4.3). They are:

- registration
- check-in
- pre-examination
- examination
- post-examination
- exit interview
- check-out

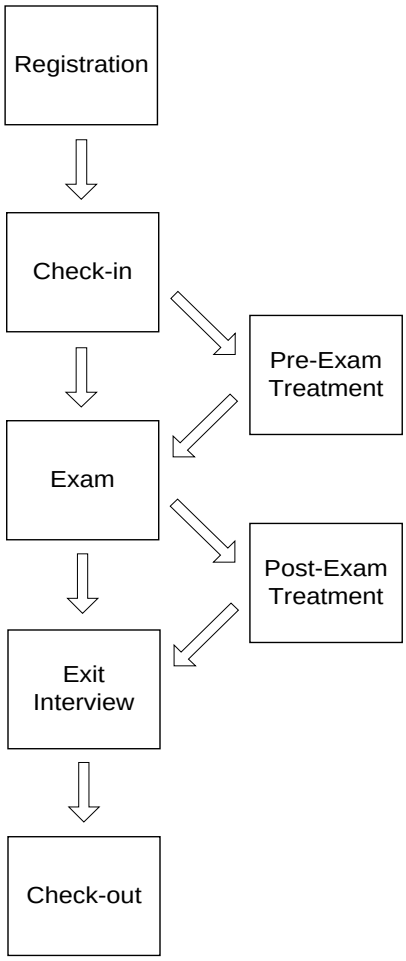


Figure 4.3: Diagram of Patient Service Flow

Registration is the time a patient spends interacting with a clerical staff person prior to treatment. *Check-in* is the time spent with a medical staff member collecting initial medical information prior to an examination. A *pre-examination* describes the time spent by a patient with a medical staff member in an examination room or specialty room collecting more extensive medical information prior to an examination. An *examination* is the time spent with a medical staff member either undergoing medical services used to diagnose an ailment or undergoing treatment for an ailment. A *post-examination* is similar to a pre-examination, covering the time spent by a patient with a medical staff member collecting additional medical information after an examination. An

exit interview is the time the patient spends with a medical staff member for final consultation and diagnoses. *Check-out* is the time spent interacting with a clerical staff person prior to exiting the clinic. The only required processes for each patient are registration, at least one type of examination, and check-out.

With an understanding of the medical processes and the patient categories, a form was developed for each patient category to assist the medical experts in identifying the key variables associated with a clinic visit for each such patient. The following variables were deemed important to adequately model each patient category:

- probability of occurrence
- distribution of scheduling lead time
  (i.e., number of days between a patient's telephone call and the appointment date)
- distribution of cost and revenue
- scheduling rule (e.g., appointment must be in the morning hours)
- probability of undergoing a process (e.g., pre-exam, examination, post-exam)
- probability of requiring a particular minimum level of staff skill for each process
  (e.g., probability of 0.50 that a patient requires at least a PA/NP for an examination)
- distribution of the time to undergo a process

The precise definitions of the variables associated with the patient categories proved to be a formidable task. The data collection effort required to obtain the needed patient information was deemed both too costly and too time-consuming. Limited data collection was performed at the aforementioned clinic in Christiansburg, Virginia, USA, though existing data sources and the medical experts' clinical knowledge were the primary sources of information. For example, anecdotal evidence from the data collection effort suggested that the time to undergo a medical process could be modeled

using the triangular distribution. Since a sufficiently large amount of data was not available to statistically support this conjecture, the medical experts estimated the minimum, maximum, and modal times for each process. In this manner, a triangular distribution was built for each patient category in each process with each medical staff type (see Appendix A). These distributions are typically positively skewed in reality, which is captured in the value sets for the minimum, maximum, and modal times. In this case and others, the medical experts relied upon their own clinical experiences and published medical information.

Table 4.1 provides the probability of occurrence for each patient category as derived by the medical experts. Note that this is the probability that a patient wishing to schedule an appointment is from a particular patient category, not the observed model occurrence. The actual observed fraction of patients from each category in the model is affected by no-show rates, walk-in patient arrival rates, and pre-visit probabilities. A complete listing of the generic patient population demographics can be found in Appendix A. The determination of the patient population demographics is an important and non-trivial task required to accurately model a specific clinic. If that population is unknown or cannot be derived, the patient population defined in Appendix A may serve as a generic representation of family practice clinic patients. However, the modeler must understand that even slight changes in patient population can drastically affect clinic output performance measures (Swisher et al. 1997).

The last type of patient requiring definition was the walk-in patient. Walk-in patients are drawn from the overall patient population and arrive at the clinic throughout the day. Limited information from observation at the Christiansburg clinic suggested that

an exponential arrival rate for walk-ins would be appropriate. The default rate used in the model is one walk-in per 6,750 seconds (four walk-ins per 7.5 hours), though this may be redefined by the user to more accurately model a specific clinic. The acceptance-rejection technique (Law and Kelton 1991), or thinning, was used to ensure that walk-ins only arrived at the clinic during business hours. Walk-ins who are scheduled to arrive during clinic hours are accepted, while those scheduled to arrive outside of clinic hours are destroyed (rejected) after scheduling the next walk-in arrival. The model also reschedules the arrival of walk-ins scheduled to arrive during the clinic's lunch hour to the end of the lunch hour. In this manner, the realistic occurrence of a patient waiting for service until the clinic reopens after lunch is represented in the model.

Table 4.2: Patient Probability of Arriving with a Companion

Number of Companions	Probability of Occurrence
0	0.70
1	0.20
2	0.09
3	0.01

Although a comprehensive definition of patient types had been developed, one additional class of humans remained for the model to be complete: the companion. A companion is a person who accompanies a patient to the clinic (e.g., a patient's husband, wife, parent, child). A patient may arrive with 0, 1, 2, or 3 companions. The number of companions per patient is randomly distributed. Table 4.2 displays the probabilities associated with companion generation. Note that these probabilities were derived from the Christiansburg clinic observation. Although companions do not utilize the clinic's medical resources, they do utilize its waiting room space. Failure to include companions

in the simulation model could provide misleading results for the appropriate size of a clinic's waiting room.

4.4 Information Center and Scheduling Development

The information center consists of a user-defined number of operators who answer incoming telephone calls. A portion (25%) of these calls is to ask informational questions (e.g., billing, insurance). The remaining calls are patients wishing to schedule an appointment in a network clinic. The operator determines the appropriate clinic and schedules an appointment for the patient based upon the patient's needs. The center accepts calls twenty-four hours per day, seven days per week.

The arrival of calls to the information center is modeled as a nonhomogeneous Poisson process. Calls arrive at a greater rate during the morning and afternoon hours than in the evening and night hours. Calls also arrive more frequently on weekdays than on weekends (see Table 4.3). Note that all call arrival rates are user-defined inputs. Arrival thinning (Lewis and Shedler 1979) is used to generate the calls. Employing this method, the model generates calls at the maximum rate throughout the day and simply accepts calls with a probability based upon the call rate for the given time period. For example, if a particular clinic's maximum call rate is 1 call per 650 seconds and the current call arrival rate is 1 call per 1000 seconds, the model will accept calls with probability 0.65 ((1/1000)/(1/650)). During any time period when the call arrival rate is at its maximum, all calls are accepted. This arrival thinning scheme was readily implemented using OOP by assigning each call a state attribute of *thinned* or *accepted*.

Thinned calls are destroyed, while accepted calls are received by the operators at the information center.

Table 4.3: Call Interarrival Times by Time of Day

Description	Time Period	Mean Interarrival Time (seconds)
Weekday Morning	8:00 AM – 12:00 PM	650
Weekday Afternoon	12:00 PM – 6:00 PM	650
Weekday Evening	6:00 PM – 10:00 PM	1,000
Weekday Night	10:00 PM – 8:00 AM	3,000
Weekend Day	8:00 AM – 6:00 PM	2,500
Weekend Evening	6:00 PM – 10:00 PM	3,500
Weekend Night	10:00 PM – 8:00 AM	5,000

Upon the arrival of a patient scheduling call, the information center's operators must follow a particular set of scheduling rules for each specific member clinic. The medical experts' domain knowledge was valuable in the derivation of such rules for the simulation model. They suggested that family practice clinics typically follow similar operating hours. Based upon their experience, the model's clinic accepts scheduled appointments from 9:00 AM until 4:15 PM in fifteen minute increments. Each physician in the clinic has two available appointments for each fifteen minute period. The medical experts suggested that each physician leave one of their two appointment slots unavailable for scheduling (blocked) at the end of each hour. Many physicians use this practice to accommodate walk-in patients and account for any schedule fluctuations. In addition, the clinic schedules no patients from 11:30 AM until 1:00 PM so that the physician and medical staff may take a lunch break upon completion of treating the morning's patients.

Three patient types require particular attention for appointment scheduling in the model: new patients, walk-in patients, and clinic appointments. New patients typically require an extensive amount of a physician's time (thus their category position of 4), hence most family practice clinics schedule at least two appointment slots for a new patient appointment. In the simulation model, a new patient requires 30 minutes of appointment time (i.e., two consecutive 15 minute appointment slots). In addition, the medical experts' experience suggested that each physician in a clinic typically imposes a daily maximum number of new patients. That is, a physician will specify that only a certain number of new patients be scheduled on a particular day. This new patient maximum may vary from day to day because of expected patient load or physician preference. To accommodate this, the simulation model specifies a maximum number of new patients for each clinic physician (distributed discrete uniform from 0 to 4).

In contrast to new patients, walk-in patients require no extra appointment time, they simply require an open slot. Walk-ins, then, must typically wait for an open appointment upon entering the clinic (i.e., an appointment time not previously filled or a slot at the end of an hour). However, a walk-in may take the place of a scheduled patient if the scheduled patient is more than 5 minutes late for an appointment. Such "bumped" scheduled patients are then simply fit in as the physician becomes available.

While formulating the model's scheduling design, the medical experts identified a group of patients that came to be called *clinic appointments*. Clinic appointments are those patients the clinic's scheduler knows in advance do not require the service of a physician. For instance, a patient may come in weekly simply for a blood pressure check. The person scheduling this patient is aware that he/she will not need to see the physician

and informally pencils the patient in on the schedule without actually filling an appointment slot. To handle these patients, the simulation model reserves a number of clinic appointments (one per clinic physician) for every fifteen minute period.

Figure 4.4 provides an overview of the architecture employed in VSE to model the clinic's appointment book. The appointment book consists of a series of nested object lists. The first list contains information pertaining to each model day and contains as many elements as the modeler defines in the *Constants* panel (see Chapter 3) for the variable LAST_MODEL_DAY. Each day object is composed of 60 time slot objects, two slots for each of the 30 appointment times during the day (9:00 AM to 4:15 PM). Each time slot object is then composed of a physician list of size two times the number of physicians defined by the user in the *Input Data* window.

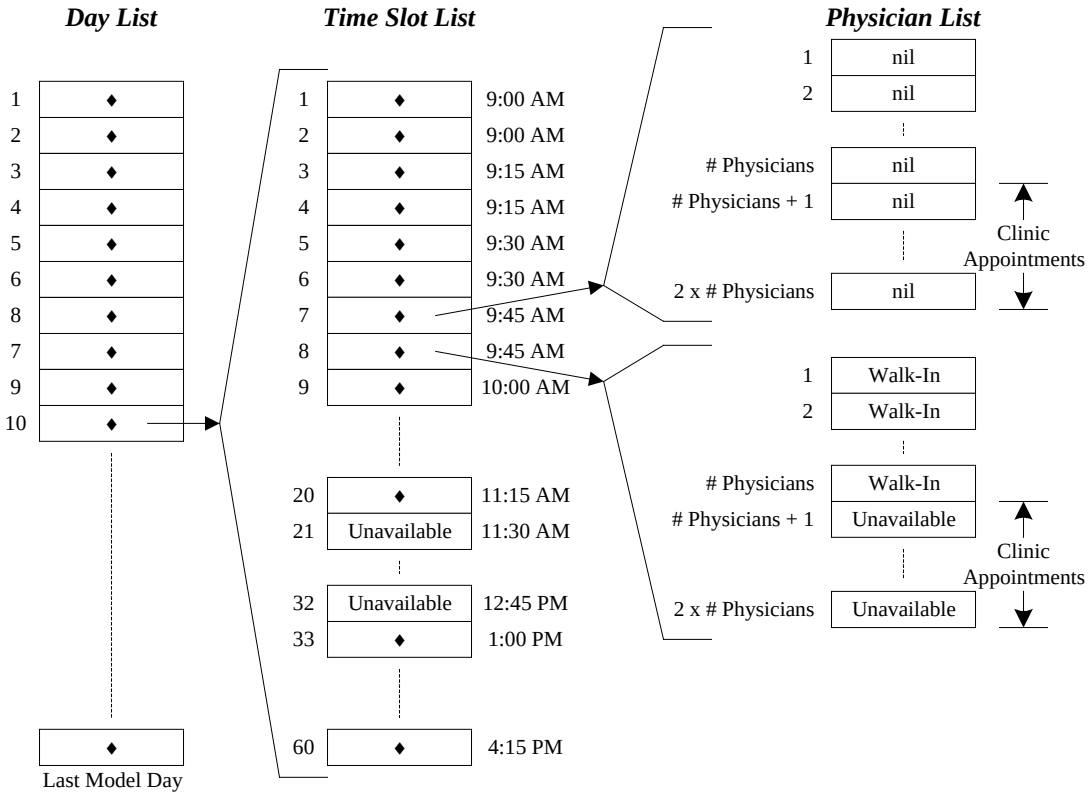


Figure 4.4: The Clinic's Appointment Book Architecture

The actual scheduled appointment information is contained in the physician list. An undefined (nil) element in the physician list means that element is available for scheduling. At creation, all objects in the physician list are defined as nil. Certain objects are then defined with the string *Appointment Unavailable* to meet the clinic's scheduling needs. For instance, all time slots during the clinic's lunch period are defined in this manner since no patient is to be scheduled during those times. For the remaining time slots, each physician list element numbered less than or equal to the number of clinic physicians is available for scheduling patients. The elements numbered greater than the number of physicians are reserved for clinic appointments only. Note that for even-numbered time slots the clinic appointment elements are defined as *Appointment Unavailable* so that only one clinic appointment per physician is available every fifteen minutes. Note also that every eighth time slot (the end of every hour) reserves the elements of the physician list numbered less than or equal to the number of physicians for walk-in appointments. Since these slots are unavailable for scheduling and therefore cannot be nil, they are defined with the string *Walk-in Slot*.

The set of rules followed by an information center operator to search for and place a patient in an open (nil) appointment slot is based upon an attribute of the particular patient to be scheduled. This attribute is referred to as the patient's *scheduling rule*. Three scheduling rules are used in the model:

1. specific scheduling,
2. sequential scheduling, and
3. random scheduling.

The *specific scheduling rule* handles those patients who have a specific time preference for an appointment (e.g., a 1:00 PM appointment). The scheduling procedure begins by examining the two time slots corresponding to the given specific appointment time (e.g., slots 33 and 34) on the initial search day as determined by the patient's scheduling lead time. Based upon the patient's physician requirements (i.e., specific physician, any available physician, clinic appointment), the scheduling routine checks for a nil physician list object in either time slot. If no appointment is available for the initial search day at the given specific time, the scheduling routine next examines proximal days. That is, it checks one day after the initial day at the specific time, then one day prior to the initial day at the specific time. If no appointment is found on either of those days, the specific scheduling rule assumes that the patient's day of week preference overrides the preference for initial search day proximity. Therefore, the procedure next examines the day seven days following the initial search day. If there is still no appointment found, proximity to the original day becomes the driving search factor once more and the routine begins sequentially searching each day forward from two days after the initial search day. Figure 4.5 depicts this search pattern (note the arc numbers define the sequence of the search pattern).

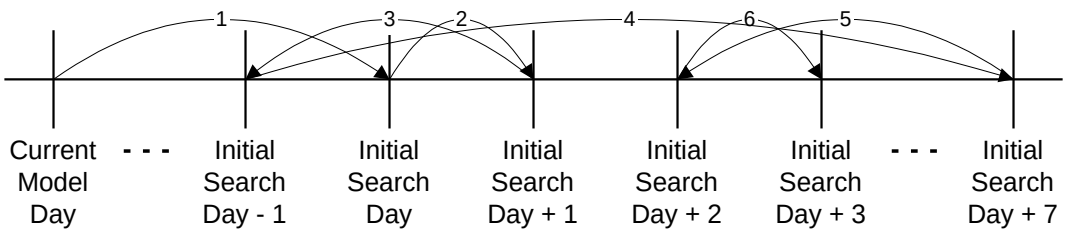


Figure 4.5: Specific Scheduling Rule Day Search Pattern

The *sequential scheduling rule* is used for those patients who may have a time of day preference (e.g., morning appointment, afternoon appointment), but do not have a specific time preference. The procedure searches a given set of time slots on a particular day based upon the patient's time of day preference. If the patient prefers a morning appointment, the appointment search begins at 9:00 AM (i.e., slot 1) and ends at 11:15 AM (i.e., slot 20) on the search day. Conversely, if the patient prefers an afternoon appointment, the appointment search begins at 1:00 PM (i.e., slot 33) and ends at 4:15 PM (i.e., slot 60) on the search day. If there is no patient preference, the search runs from 9:00 AM to 4:15 PM. Like specific scheduling, only those elements of the physician list pertaining to the patient's physician requirements are examined. In contrast to the specific scheduling rule, there is never an assumption that day of week preference overrides preference for proximity to the initial search day in multiple day searching. The pattern used by the sequential scheduling rule when an appointment cannot be found on a given day is depicted in Figure 4.6.

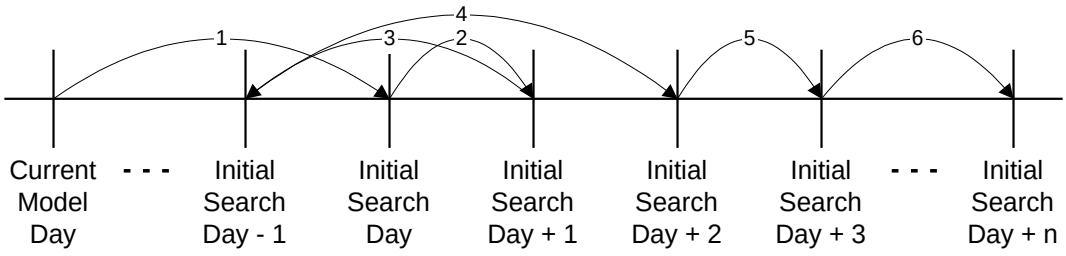


Figure 4.6: Sequential/Random Scheduling Rule Day Search Pattern

Like the sequential scheduling rule, the *random scheduling rule* applies to patients who have only a time of day preference (i.e., AM or PM), but not a specific time preference. The difference between the two procedures is that the random scheduling rule

randomly selects the daily search start slot and search direction. Of the 60 time slots, 43 are potential start slots for the random scheduling rule (the unavailable slots at the end of an hour and slots during lunch are excluded). Each of the potential slots has equal probability ($p = 1/43$) of being selected as the starting search slot. The ending search slot is determined by the search direction selected. A forward search ends with slot 60 (i.e., 4:15 PM), while a reverse search ends with slot 1 (i.e., 9:00 AM). Each direction has probability 0.50 of being selected. For example, the procedure may select a starting search slot of 18 (11:00 AM) and a search direction of reverse. This would mean that the scheduling routine would begin by searching time slot 18 for an available appointment and if no appointment is found, move backwards to slot 17, then 16, and so on until it reaches slot 1. If the routine cannot find an appointment on the first day searched, it follows the same multiple day search pattern as the sequential rule (see Figure 4.6). That is, proximity to the initial search day is always the most important search criteria when an appointment cannot be found on the initial search day.

Upon determination of an appointment time via one of the scheduling rules, the patient is assigned an actual clinic arrival time. The clinic arrival time is normally distributed ($\mu = 0$ seconds, $\sigma = 250$ seconds) about the patient's scheduled appointment time, so a patient is equally likely to be early as he/she is to be late for an appointment. Note that μ and σ may be redefined by the model user to better depict a specific clinic.

Chapter 5

Verification, Validation, and Testing

Simulation model verification, validation, and testing (VV&T) plays an important role in any simulation study. VV&T is the structured process of increasing one's confidence in a model, thereby providing a basis for confidence in a modeling study's results. Model verification substantiates that the model has been properly transformed from one form to another (e.g., from a flowchart to an executable program). Balci (1995) describes verification as building the model *right*. Model validation, on the other hand, substantiates that the model behaves with sufficient accuracy in light of the study's objectives. Balci (1995) describes validation as building the *right* model. Model testing is the process of revealing errors in a model. Testing procedures may be designed to perform either model verification or model validation. It is important to note that since a model is by definition an abstraction of a system, perfect representation cannot be expected (Balci 1995). Hence, a model is unlikely to ever be deemed absolutely verified or absolutely validated. The goal of VV&T, then, is to increase confidence in a model, not to ensure *absolute* model accuracy (Robinson 1997).

Throughout the development and implementation of the clinical simulation model, several VV&T techniques were employed. These techniques may be categorized as either informal, static, or dynamic VV&T techniques (Balci 1998). Each category is explored in the ensuing sections.

5.1 Informal VV&T Techniques

Informal VV&T techniques are among the most commonly used in discrete-event simulation modeling studies. Though they do not rely on stringent mathematical formalism, well-structured informal VV&T techniques applied under formal guidelines can be very effective (Balci 1998). Examples of informal VV&T techniques employed in the clinical modeling effort include audits, reviews, walkthroughs, desk checking, face validation, and the Turing test.

During model development, weekly modeling meetings served as either audits, reviews, or walkthroughs depending on the meeting's stated objective and those persons in attendance. Audits are used to assess how adequately the modeling study is conducted with respect to established plans, policies, procedures, standards, and guidelines (Balci 1998). As the model was constructed, review and oversight by Biopop's medical experts, members of Biopop's Information Systems group, upper Biopop management, and external simulation experts was documented to provide an appropriate audit trail for the substantiation of model accuracy. Similarly, structured walkthroughs involving Biopop Information Systems representation and the medical experts were conducted to assess model accuracy during development. As opposed to walkthroughs, reviews are intended to ensure that tolerable levels of quality are being attained through a structured

documentation and evaluation process (Balci 1998). A majority of early modeling meetings involving the medical experts and Biopop management can be classified as reviews.

Throughout the model development lifecycle, extensive desk checking (self-inspection) was performed. The use of a second Biopop operations research analyst was especially helpful in assuring that the model code was correct, complete, consistent, and clear. Early stages of model development also took advantage of a great deal of face validation in which project team members subjectively use estimates and intuition to judge whether the model and its output are reasonable (Balci 1998). The medical experts and external simulation experts were often asked to provide subjective feedback as to model behavior. Their input led either to reformulation and more face validation or to more structured reviews such as the Turing test.

Turing tests are based upon structured evaluation of a system by expert knowledge. The experts are presented with output data from both an actual system and a simulated system under the same input conditions and asked to differentiate between the two. If they succeed, they are asked to specifically enumerate the differences, thereby providing valuable feedback to the modeler. If the experts do not succeed, the modeler's confidence in the model's validity is increased (Balci 1998). For the clinical model, Biopop's team of medical experts were presented with output (e.g., patient demographics and throughput, medical staff utilization) from the simulation model and output from an actual clinic (the aforementioned Christiansburg clinic) under the same input conditions. The experts were unable to distinguish between the two data sets, thereby significantly increasing confidence in the model's validity.

5.2 Static VV&T Techniques

Static VV&T techniques are concerned with assessing the accuracy of a model based upon characteristics of the static model design and source code. Static techniques do not require machine execution of the model, but may take advantage of automated tools including the simulation language compiler itself (Balci 1998). Examples of static VV&T techniques employed in the clinical modeling effort include syntax analysis, calling structure analysis, traceability assessment, and fault/failure analysis.

Syntax analysis is carried out by the simulation language compiler to ensure that the mechanics of the language are applied correctly (Balci 1998). VSE's compiler provides feedback to the modeler in the form of errors and warnings. For example, an unreferenced local variable would be presented to the modeler as a warning while a failure to define a referenced model variable would be presented as an error. Each error or warning is accompanied by a description describing the logical problem and presents the offending code to the modeler for correction. Although a model which compiles without any errors or warnings may still not accurately represent the intended system (i.e., model validation), it does serve as an necessary step in the model verification process. In other words, the absence of errors and warnings is a necessary, but *not* sufficient condition for model verification.

Calling structure analysis assesses model accuracy by identifying who calls whom and who is called by whom. The who may be a procedure, subroutine, function, method, or submodel within the model (Balci 1998). Because of the object-oriented nature of the clinical model, calling structure analysis was performed by analyzing message passing between model objects. During model building, care was taken to ensure that each

method includes comments describing what other method might call it. For instance, careful analysis of the messages passed to the clinic to alter the mean interarrival time between phone calls to the information center based upon time of day ensured proper construction of a nonhomogeneous Poisson process (see Chapter 4). In another case, calling structure analysis revealed a method which required alteration when the boolean variable USE_HOLIDAYS was added to the model so that users were given the choice of whether to utilize clinic holidays.

Traceability assessment is used to match, on a one-to-one basis, the elements of one form of the model to another (Balci 1998). For example, Biopop's original requirement specification for the simulation model called for a family practice clinic with user-defined staffing and facility size and an information center with a user-defined number of operators. Matching such elements on a one-to-one basis ensured that the simulation model captured all of the required functionality as defined in the logical model. As model design reviews led to revision of the logical model, the simulation model was again reviewed for a one-to-one match. This process was repeated iteratively as the design process progressed to ensure that the simulation model contained *all* of the elements specified in the logical design.

Fault/Failure analysis examines the model input-output transformation design specification to determine how the model *might* logically fail. Examination of the model's design specification is used to identify possible points of failure along with potential failure conditions (Balci 1998). This technique is meant to identify model defects prior to the application of dynamic VV&T techniques. In the clinical model, fault/failure analysis identified a logic problem wherein a patient waiting for treatment in

an examination room could potentially wait indefinitely without being seen by a medical staff member. The identification of this potential problem resulted not only in the addition of code to prevent the error, but in code to check for the error during model execution (i.e., dynamic VV&T).

5.3 Dynamic VV&T Techniques

Dynamic VV&T techniques require model execution and are intended to evaluate the model based on its execution behavior (Balci 1998). Examples of dynamic VV&T techniques employed in the clinical modeling effort include debugging, fault/failure insertion testing, assertion checking, object flow testing, visualization/animation, functional testing, and special input testing.

The four step iterative process of debugging as described by Balci (1998) was an important part of the dynamic VV&T process. In the first step, the model is tested revealing the presence of errors. In step two, the modeler determines the cause of the errors and in step three determines the model changes necessary to correct the errors. In step four, the actual model changes are made and the process returns to step one to ensure that the corrections did not introduce new errors. Adhering to this iterative process ensured that each bug in the model was documented and addressed in the same manner.

Fault/Failure insertion testing is the technique of inserting a fault (incorrect model component) or a failure (incorrect behavior of a model component) into a model and observing whether the model produces the expected invalid behavior (Balci 1998). In the clinical model, fault insertion was used to ensure that the model failed when the user improperly specified input parameters (e.g., a clinic with 0 physicians) and to test the

functionality of assertion statements (see below). Note that VSE's design greatly facilitated such improper input parameter testing. By changing model parameters in the *Input Data* window and the *Constants* panel (see Chapter 3), the modeler can quickly insert a fault and assess its effect.

```
set actualArrivalTime to [[VSEModel clinic] scheduleApptTimeFor:newPreVisitPatient];
assert actualArrivalTime > currentTimeInSeconds with msg "Arrival is in the past";
```

Figure 5.1: Excerpt from Model Code – Use of Assertions

An assertion is a logical statement that should hold true during the execution of the simulation model (Balci 1998). By design, VSE allows the modeler to insert specific assertion checks within each object method. This allows the model to constantly monitor critical state variables to ensure that their values are not infeasible. For example, when a patient wishes to schedule an appointment in the model, a method (i.e., a piece of code specific to a model object) is called that returns the patient's clinic arrival time based upon the patient's needs and the clinic's availability. An assertion in this method ensures that the returned appointment time is not less than the current time in the model, therefore a patient is never scheduled to arrive in the past (see Figure 5.1). Upon failure of an assertion in VSE, the model run is terminated and the user-defined descriptor of the problem is displayed (e.g., "Arrival is in the past" for the previous example). The clinical model takes advantage of assertion statements in all model methods identified as potential failure points in the fault/failure analysis (see Section 5.2). The use of

assertions in the clinical model not only helps to verify that the model is functioning within its acceptable domain, but it also serves to document the intentions of the modeler.

Although the use of assertions can be extremely beneficial in model verification and validation, it is important to note that assertion checking degrades model performance because of the additional computational resources required. Balci (1998) suggests that when execution performance is critical, the modeler should consider commenting out, but not deleting, the assertion statements after initial model testing. By commenting out the assertions instead of deleting them, they remain accessible for maintenance testing and as permanent documentation of the model's acceptable operating characteristics, but do not degrade model execution. For the clinical modeling effort, it was decided that the importance of using assertion checking outweighed any performance degradation, so all model runs presented herein take advantage of the assertion statements.

Object-flow testing assesses model accuracy by tracing the lifecycle of an object during model execution (Balci 1998). Object-flow testing was aided by both VSE's visual nature and its implementation of the object-oriented paradigm. Tracing the life of an object in VSE is simplified by VSE's object inspector. VSE gives the modeler the capability of inspecting any model object during model execution. The user simply selects an object to inspect and observes it throughout its model lifecycle. Figure 5.2 shows VSE's object inspection capabilities for tracing the lifecycle of a clinic patient. Note that all of a patient's attributes are displayed in a scrollable list for the user to browse as the patient moves through the model.

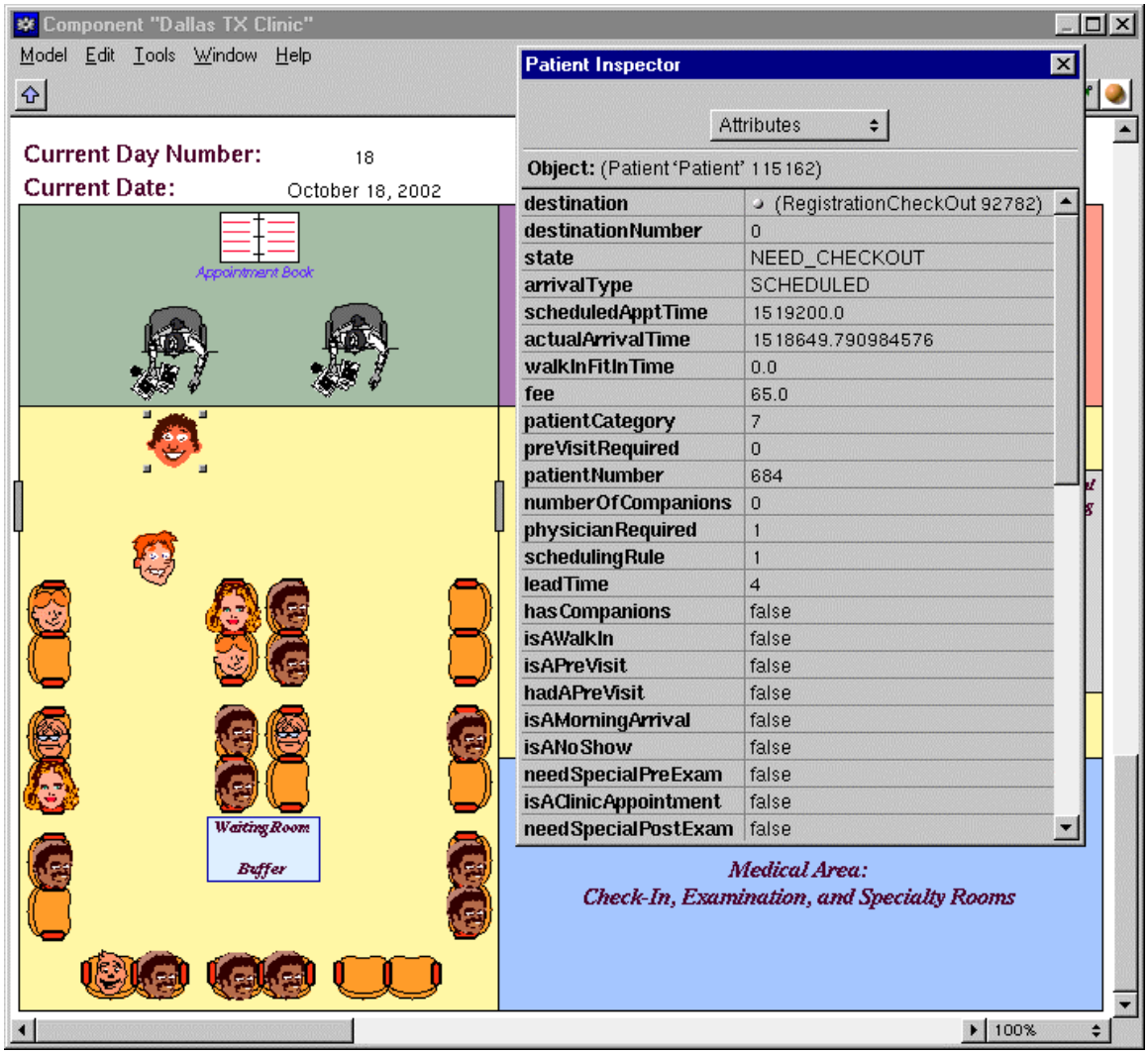


Figure 5.2: VSE's Object Inspection Capabilities

In general, the visual nature of the model was an aid in the VV&T process. Visualization/animation in simulation can greatly assist in model VV&T (Sargent 1992) by allowing the modeler to actually observe (i.e., see) inconsistent behavior. For example, should a patient appear in the medical staff area of the clinic, one would instantly know there is a flaw in the model. Simply comparing the visualization of the model execution to a real system may also help the modeler identify any discrepancies between the two (Balci 1998). However useful visualization may be for uncovering

model errors, it does not guarantee model correctness (Paul 1989) and should be used cautiously in making claims of model veracity and validity.

Functional testing is used to assess the accuracy of a model based upon its outputs, given a specific set of inputs (Balci 1998). Although it is impossible to test all input-output combinations, the simulation model was tested with a large variety of input parameter variations. For example, the model was tested with a wide range of incoming telephone call rates to the information center. For those runs in which the call rate was low (i.e., very few calls were placed), clinic output performance measures like clinic overtime and medical staff utilization were also low. Conversely, for those runs in which many calls were placed, clinic overtime and medical staff utilization were much greater. Likewise, special input testing assesses model accuracy by subjecting the model to a variety of inputs. One form of special input testing, extreme input testing, tests the model with its user-defined input parameters at only their minimum values, maximum values, or an arbitrary mixture of minimum and maximum values (Balci 1998). Testing the clinical model with maximal inputs revealed an error in the model logic for the handling of an excessive number of patients in the clinic's waiting room. After following the iterative debugging process, testing with maximal values was again performed. These experiments revealed no logical errors in the waiting room and produced values in the expected range for the clinic's output performance measures.

5.4 VV&T Conclusions

A wide variety of VV&T techniques were applied to the clinical simulation model throughout its development. From management and expert oversight to varied input

testing, the VV&T techniques employed increased confidence in the model. The only obviously absent VV&T techniques are statistical techniques (e.g., nonparametric goodness of fit tests, multivariate ANOVA). Unfortunately, no statistical tests could be performed to compare model output to reality due to a lack of data. Although the clinic observation in Christiansburg, Virginia, USA provided some real-world data, there was insufficient data to statistically determine the underlying patient population demographics and other key model input distributions.

Based upon the results of the VV&T techniques utilized in testing the clinical model, it appears to provide a sufficiently valid representation of the clinical environment for the research presented herein. Obviously, more extensive statistical testing would need to be performed to be confident in the model's representation of a specific real-world clinic.

Chapter 6

Output Analysis

The simulation model described in Chapters 3, 4, and 5 is a general tool for decision-making in a family practice outpatient clinic. This chapter focuses on the analysis of the model's output for its application to a specific goal: optimizing the staffing and facility size for a two-physician family practice clinic. Two-physician family practice clinics are of particular interest due to their prevalence, especially among those clinics that do not have an existing network or hospital affiliation (i.e., clinics that are potential Queston clients). The objective of this specific application of the simulation model, then, is to determine the optimal clinic configuration in terms of the number of medical assistants, nurses, PA/NPs, check-in rooms, specialty rooms, and examination rooms for a two-physician family practice outpatient clinic. For simplicity, the number of registration windows in the clinic will be fixed at two and the patient population distributions given in Appendix A will be used for experimentation. Clinic configuration optimality will be defined in terms of a *clinic effectiveness* measure derived in this chapter. In addition, this

chapter addresses initialization bias control, application of the method of batch means, and factor (input parameter) screening strategies.

6.1 Clinic Effectiveness Measurement

The optimal clinic configuration, from the perspective of the clinic owner or administrator, should simultaneously maximize clinic profit, patient satisfaction, and staff satisfaction. However, determining an optimal staffing and facility size is complicated by the often conflicting nature of these objectives. For example, a clinic configuration that maximizes clinic profit may create excessive patient waiting times, thereby decreasing patient satisfaction. On the other hand, minimizing patient waiting times may result in unacceptable reductions in overall clinic profit. Moreover, simulation optimization techniques applicable to the clinical model are challenged when more than one performance measure defines optimality (i.e., multivariate output analysis). Specifically, ranking and selection (R&S) and multiple comparison procedures (MCPs), two widely-used methods for optimizing simulation models with discrete input parameters, are almost always formulated as univariate performance measure optimization problems (Bechhofer et al. 1995). Not only does multivariate analysis complicate simulation optimization, but it may overwhelm the medical decision-maker who would prefer a simple, concise, and intuitive measurement of a clinic's overall effectiveness. For these reasons, it is not sufficient to select a single output measure for optimization from among the many output performance measures collected from the clinical model. Therefore, a univariate measure composed of multiple attributes (i.e., multiple output performance measures) must be constructed for use both as an aid in simulation optimization and as a

means for providing information to decision-makers through a single, simple measurement. Since this univariate measure evaluates how effective a particular clinic configuration is in simultaneously satisfying the conflicting objectives of both its medical staff and its patients, it will be referred to as the *clinic effectiveness (CE) measure*.

The field of decision analysis, and more specifically multiattribute utility (MAU) theory, studies the construction of scalar measures composed of multiple attributes (Keeney and Raiffa 1993, Winterfeldt and Edwards 1986). MAU theory provides a structured process for identifying important performance measures and appropriately weighting them so that the alternative (e.g., model configuration) that performs most effectively on the overall weighted measure is selected (Morrice et al. 1998). Although the CE measure developed herein is not actually a utility measure by definition (since it is not converted to a 0 to 1 scale), its process of development closely parallels MAU performance measure development. Just as in the MAU process, the goal of developing the CE measure is to identify the performance measures of importance, convert them to a common scale, and weight them accordingly to obtain a single value. To provide an intuitive unit of measurement, the CE measure is constructed on a monetary scale (i.e., dollars/clinic day) instead of the 0-1 scale used in traditional MAU measures.

As previously stated, three high-level measurements are of utmost importance in evaluating clinic performance:

1. clinic profit (i.e., clinic revenue minus clinic expenses),
2. patient satisfaction, and
3. medical staff satisfaction.

Quantitatively, *clinic profit* is the simplest of these measures to derive and capture. Clinic revenue is driven by the fees generated from the medical services provided to each patient. Table 6.1 provides, by patient category, the fee per patient collected in the simulation model. These fees were derived by examining the average national Medicare reimbursement rate (Health Care Financing Administration 1996) for each AMA-defined level of care as described in Chapter 4. The appropriate patient fee is added to the CE measure when each patient checks out of (exits) the clinic.

Table 6.1: Patient Fees by Category

Patient Category	Fee/Visit
1 A	$20.00
1 B	$35.00
1 C	$20.00
2	$30.00
2 PV	$30.00
3	$40.00
3 PV	$40.00
4 A	$60.00
4 B	$65.00
5	$100.00

Clinic expenses are driven by both payroll and non-payroll items. Table 6.2 lists the salaries used for the clinical model. These figures represent the regional (southeastern USA) average salary for each type of medical staff member (Vander Schaaff and Akers 1997). Note that it is assumed that all staff (except PA/NPs) are paid 1.5 times their salary for overtime. PA/NPs are treated as salaried employees and hence do not receive overtime pay. Non-payroll clinic expenses can be broken down into professional expenses and facility rent. Professional expenses include office supplies, medical supplies and equipment, and liability insurance. Table 6.3 lists the values used within the

simulation model for professional expenses and facility rent on a per physician basis. Note that rent is not a fixed value for all clinics, but is determined by a clinic's size. A fixed base facility rent fee plus a fee per examination room is charged. Both professional expenses and facility rent expenses were derived from a regional survey conducted by a Biopop affiliate, Resolve Medical Marketing, Inc. (Vander Schaaff and Akers 1997). Note that all clinic expenses decrement the CE measure on a daily basis.

Table 6.2: Medical Staff Salaries

Medical Staff Member	Daily Salary	Overtime Pay
Clerk	$59.00	$11.00/hour
Technician	$99.00	$18.00/hour
Medical Assistant	$99.00	$18.00/hour
Nurse	$158.00	$30.00/hour
PA/NP	$198.00	N/A

Table 6.3: Non-Payroll Clinic Expenses

Expense	Amount
Professional Expenses	$284/day/physician
Base Facility Rent	$57/day/clinic
Examination Room Rent	$19/day/room

The subjective nature of both patient and medical staff satisfaction makes each difficult to evaluate. Many researchers have addressed the assessment of patient satisfaction in healthcare. Factors involving a patient's perception of the provider's competence and overall personality are often identified as significant in determining a patient's satisfaction (Mittal and Baldasare 1996, Mummalaneni and Gopalakrishna 1995, Taylor and Cronin 1994, Mowen et al. 1993). Obviously, such factors cannot be assessed via a simulation model. However, the same research consistently identifies patient waiting as a highly significant factor in overall patient satisfaction. Therefore, patient

waiting time can be considered an acceptable *quantitative identifier* of the *qualitative concept* of patient satisfaction. For model experimentation, a penalty of $10/hour for patient waiting is used to decrement the CE measure. To avoid unnecessarily penalizing the clinic, the patient waiting penalty is only imposed for patient visits totaling more than 15 minutes and in which the ratio of patient waiting time to total patient time in the clinic is greater than 0.30. This is based upon research which suggests that patients are most dissatisfied with waiting that they feel is unjust (Mowen et al. 1993) and will tolerate a limited amount of waiting for medical service. Using the same reasoning, patients who must stand in the waiting room decrease the CE measure by an additional $10/hour (i.e., $20/hour total). Likewise, any companion that must stand reduces the CE measure by $20/hour. Note, however, that *seated* waiting by a companion does not penalize the CE measure since a companion arrives to the clinic expecting to wait while the patient he/she is accompanying is treated. Therefore, only when a companion's waiting is made uncomfortable (i.e., standing) is the CE measure penalized. The patient satisfaction measures (along with the physician satisfaction measures) and their associated values are provided in Table 6.4.

Satisfaction of the medical staff within a clinic is also an extremely subjective measure to define and quantify. Assuming the physician has a stake in the clinic's profit (as is typically the case), his/her satisfaction can partly be measured by the clinic's financial success. In addition, it can be assumed that the physician also values any personal time he/she has during the work day (e.g., a lunch break) at a rate commiserate with his/her salary. When that time is interrupted by increased workload, the physician's satisfaction is decreased. Since the physician's satisfaction is paramount, a penalty of

$50/hour (see Table 6.4) is charged against the CE measure for any physician lunch break lasting less than one hour. Likewise, the other members of the clinic's medical staff likely are dissatisfied by excessive levels of clinic overtime requiring them to sacrifice their personal time. Given that their dissatisfaction is balanced against the overtime compensation that they receive, only the dollars paid for medical staff overtime are decremented from the CE measure.

Table 6.4: Patient and Physician Satisfaction Penalties

Satisfaction Penalty	Amount
Patient Waiting	$10/hour
Patient Standing	$10/hour
Companion Standing	$20/hour
Physician Missed Lunch	$50/hour

Using the attributes presented in Tables 6.1, 6.2, 6.3, and 6.4, the CE measure is incremented and decremented throughout each simulated clinic day and the daily total recorded. The daily CE value represents, on a dollar scale, the relative effectiveness of a clinic on a given day. High daily CE values indicate days in which the tradeoff between satisfaction (patient and physician) and clinic profit has been effectively balanced. Adjusting the rates at which the CE measure is incremented and decremented (e.g., increasing patient fees or decreasing patient waiting penalties) defines the relative worth a clinic owner or administrator places on the attributes which define the CE measure. The research presented herein is based upon the values provided in the preceding tables (Tables 6.1 through 6.4). Note that different conclusions may be drawn based on specific attribute weightings derived from a particular clinic's owner or administrator.

6.2 Initialization Bias Control

In steady-state discrete-event simulation studies, the initial conditions typically bias the steady-state output performance measure estimator (Cash et al. 1992). The CE measure in the clinical simulation optimization study exhibits this behavior, known as *initialization bias*. The identification and control of such initialization bias is crucial to gaining the appropriate insights from a model. Several methods are available for dealing with initialization bias. One such method is to initialize the simulation in a manner more representative of the long-run conditions (Banks et al. 1996). However, this method requires knowledge of the steady-state conditions of the actual system being modeled, and is therefore often infeasible in simulation studies because of the data collection effort required. Another alternative is to simply accept the presence of initialization bias and attempt to overwhelm its effects by using very long simulation model runs (Yücesan 1993). Once again, this is typically not feasible because of the length of simulated time required to negate the initial effects and the difficulty in determining the appropriate simulation run length. The most common approach is to initialize the simulation in some convenient manner and allow an arbitrary "warm-up" period before retaining steady-state data for analysis. This is the method employed in the clinical simulation study.

There are no widely accepted, proven, or objective methods for determining the point at which to begin collecting steady-state data (Banks et al. 1996). Banks et al. (1996) recommend the use of ensemble average plots across several simulation replications to establish a *truncation point*. This method, albeit subjective, can be an effective means of detecting initialization bias. Alternatively, Schruben et al. (1983), Vassilacopoulos (1989), and Yücesan (1993) structure the problem within a hypothesis

testing framework. For the clinical simulation model, each of these methods was applied to a set of 30 independently-seeded replications of a baseline model, with each replication run for 15 simulated months. The baseline model input parameters represent a typical clinic configuration for a two-physician family practice clinic (see Table 6.5).

Table 6.5: Baseline Model Input Parameters

Input Parameter	Input Value
Number of Physicians	2
Number of PA/NPs	2
Number of Nurses	2
Number of Medical Assistants	1
Number of Registration Windows	2
Number of Check-In Rooms	2
Number of Examination Rooms	6
Number of Specialty Rooms	1

The initial set of 30 replications of the baseline model was made with the boolean variable USE_HOLIDAYS (see Chapter 3) set to true. That is, the clinic was closed on the days listed in Table 3.1 for each replication. The graphs of the daily CE measure (see Appendix B) show that the use of holidays dramatically affects the steady-state behavior of the model. A holiday creates an influx of patients on the days immediately surrounding it, thereby creating "spikes" in the CE measure. These spikes create a system which never reaches a steady state. Because of the bias introduced by the use of holidays, the 30 replications were repeated with the boolean variable USE_HOLIDAYS set to false. That is, the simulated clinic observed no holidays. The daily CE measure outputs from the second set of replications display an initial transient period followed by a clear steady-state period (see Appendix C for graphs). Therefore, the removal of holidays results in daily CE observations representative of the clinic's steady-state behavior.

Although excluding holidays removes an element of reality from the model, their inclusion would force the analysis of a purely transient process. Hence, for the purposes of steady-state analysis of the CE measure, holidays are neither used in the determination of the truncation point nor any subsequent model runs.

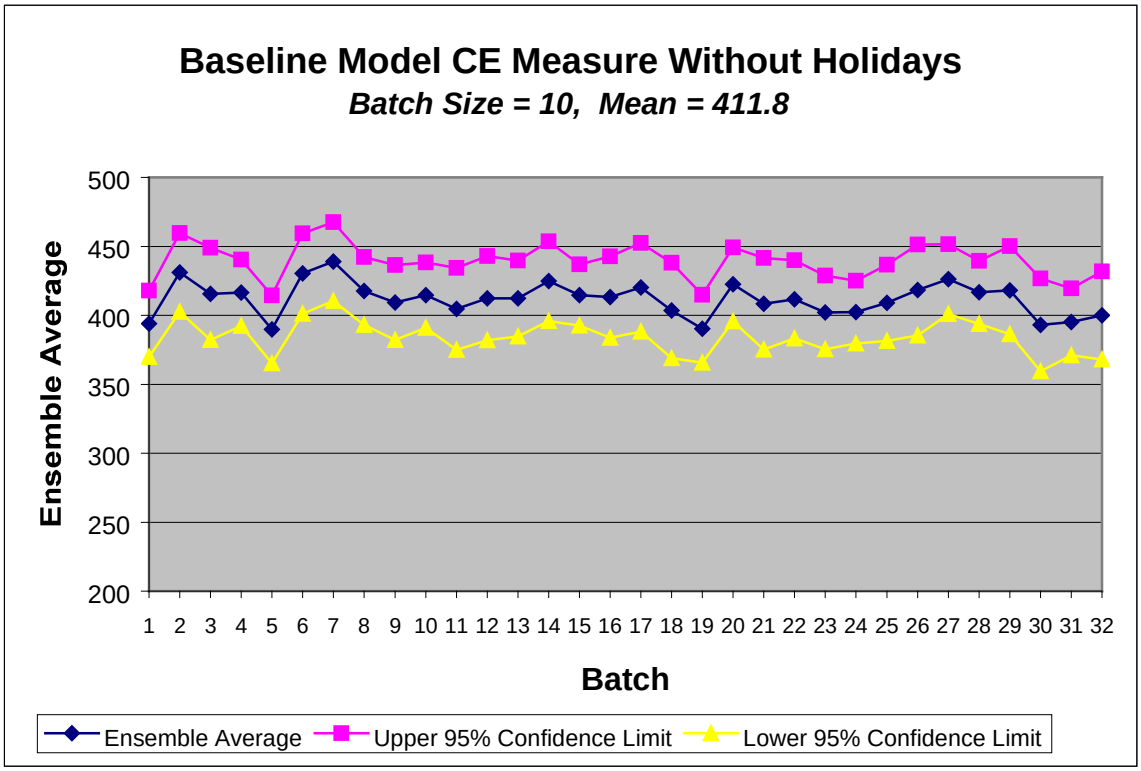


Figure 6.1: Batched CE Measure Excluding the First Seven Observations

The simulation model using no holidays and run for 15 simulated months yields 327 clinic days, thereby producing 327 CE observations. Batching these observations into groups of 10 (see Section 6.3) produces 32 total batches and requires 7 observations be discarded. Since the initial observations are likely to be biased by the simulation model's initial conditions, the first 7 observations were discarded. Figure 6.1 displays the ensemble average for each of these 32 batches and the associated 95% confidence

interval. Visual inspection of the ensemble averages, as advocated by Banks et al. (1996), shows the batched CE measure to be steady-state throughout. Therefore, a truncation point of 7 observations would be appropriate for the CE measure output data. However, since Schmeiser (1982) advocates the use of no more than 30 batches when applying the method of batch means (as will be discussed in Section 6.3), a truncation point of 27 observations is a more suitable choice.

The optimal test proposed by Schruben et al. (1983) formulates the problem of detecting the presence of initialization bias as a hypothesis test. In general, the optimal test seeks to determine if the mean of an output process remains unchanged throughout a run. If so, the null hypothesis is rejected. More specifically, the null hypothesis may either be that no negative initialization bias exists in the observation sequence, no positive initialization bias exists in the observation sequence, or no initialization bias exists in the observation sequence. In the absence of prior knowledge about the observation sequence, the third option should be selected. Using the batched CE data as previously described (see Figure 6.1), the hypothesis of no initialization bias was tested using the optimal test. Calculation of the (approximately *t* distributed) test statistic when testing all 32 batches yields a p-value of 0.2045 (calculated as two times the one-sided p-value), meaning one would only reject the null hypothesis if the test's significance level is greater than 0.2045. In comparison, if one were to delete the first two batches and test the remaining 30, the test yields a p-value of 0.1575. Based on the Schruben et al. (1983) optimal test, then, a truncation point of either 7 or 27 observations would be appropriate.

Vassilacopoulos (1989) also formulates a test for initialization bias in terms of a hypothesis test. This test, known as the rank test, is based on a standardized sequence of

linear combinations of the ranks of a simulation's observations. Although this test does not perform quite as well as the more conservative Schruben et al. (1983) optimal test, the rank test is easier to implement since it does not require the estimation of the variance of the stochastic sequence being evaluated (Ma and Kochhar 1993). Like the optimal test, the rank test may be used to test any of three null hypotheses: no negative initialization bias, no positive initialization bias, or no initialization bias. Testing the hypothesis of no initialization bias in the batched CE measure output sequence, the two-sided test statistic for the rank test yields a p-value of 0.5216 for all 32 batches and 0.4546 for the last 30 batches. Again, a truncation point of either 7 or 27 observations would be appropriate based upon the rank test.

The final and most robust initialization bias test applied to the batched CE data was Yücesan's randomization test (1993). This test first requires the output data to be batched into b groups with negligible autocorrelation (see Section 6.3). Next, the batches are partitioned into two groups in an iterative fashion, starting with only the first batch mean in the first group and the remaining b-1 batch means in the second group, followed by the first two batch means in the first group and the remaining b-2 batch means in the second, and so on. At each iteration, the grand means of each group are compared. If the difference between the grand means is significantly different from zero, the null hypothesis of no initialization bias is rejected. The iterations continue until the null hypothesis cannot be rejected, at which point the truncation point is set. The actual C++ code used to implement this procedure is provided in Appendix D. Testing all 32 batches of the CE measure, the procedure terminates at the first iteration (indicating no initialization bias) and provides a p-value of 0.2116. Deleting the first two batches and

testing the remaining 30 batches yields a p-value of 0.6657 for terminating the test on the first iteration. Like the two preceding tests, a truncation point of 7 or 27 would be appropriate based upon the randomization test. Unlike the other tests which show a slight preference for using all 32 batches (truncation point of 7), the Yücesan test shows a distinct preference for using only the last 30 batches (truncation point of 27). Table 6.6 provides the p-values for all three hypothesis testing methods.

Table 6.6: Comparison of Initialization Bias Tests

Initialization Bias Test	Truncation Point = 7 p-value	Truncation Point = 27 p-value
Schruben et. al	0.1575	0.2045
Vassilacopoulos	0.5216	0.4545
Yücesan	0.2116	0.6657

Based upon the graphical representation of the batched CE data and the initialization bias tests employed, a truncation point of either 7 or 27 observations is acceptable. Since the most robust of the bias testing procedures clearly favors a truncation point of 27 observations and because of Schmeiser's batch number rule (Schmeiser 1982) as will be discussed in the ensuing section, the first 27 daily CE output observations will be deleted for all further output analysis.

6.3 Method of Batch Means

The method of batch means is frequently used to estimate the steady state mean and/or variance of a simulation output measure (Alexopoulos and Seila 1996). Batch means is an attractive technique because it allows the simulation analyst to avoid making an excessive number of replications, each of which must discard data due to initialization

bias, to obtain a valid steady-state mean and/or variance point estimator. The standard approach to the method of batch means is to divide the steady-state output from a single replication into contiguous batches whose means are treated as independent observations. Given an output series $X_1, \ldots, X_n$ of a simulation run, k batches of size $b = n/k$ are formed.

The chief problem with the application of batch means in practice is the choice of the batch size, b. If b is set too small, the batch means may be highly correlated, frequently resulting in a confidence interval with coverage below the user-specified level. Conversely, a batch size set too large will likely produce very few batches, presenting problems when an assumption of normality via the central limit theorem is required (Alexopoulos and Seila 1996). Unfortunately, there is no widely accepted or simple method for choosing the appropriate batch size (Banks et al. 1996, Schmeiser and Song 1996).

Despite the lack of an accepted, convenient method for determining an appropriate batch size, the research literature does provide some guidelines. Perhaps the most cited research on batch size selection is Schmeiser's 1982 study of the effects of batch size on simulation output analysis. He found little benefit in creating more than $k = 30$ batches, even if independence can be attained by doing so. In addition, he found that selecting $k < 10$ produced unacceptable variability in the width of the confidence interval on the mean. Therefore, he suggests that using between 10 and 30 batches is reasonable for most simulation studies. As alluded to previously, this serves to support the selection of observation 27 as the truncation point in Section 6.2.

Although there is typically autocorrelation (serial correlation) between batch means at all lags, the lag-1 autocorrelation is commonly studied to assess dependence

between batches (Banks et al. 1996). When the lag-1 autocorrelation is nearly 0, then the batch means may be treated as independent. This approach is based upon the assumption that the autocorrelation in most stochastic processes decreases as the lag increases. Therefore, all lag autocorrelations should be smaller (in absolute value) than the lag-1 autocorrelation. However, the analyst must be careful in estimating the lag-1 autocorrelation because of bias in the autocorrelation estimator. Box et al. (1978) suggest that the autocorrelation estimator not be used on less than 50 data points. Therefore, the recommended procedure is to estimate the autocorrelation with a large number of batch means (i.e., more than 50) and when it is approximately zero, assume that it will be even smaller once the data is rebatched to between 10 and 30 batches (Banks et al. 1996). Note that the more correlated the data, the larger the final batch size, *b*, will need to be (Bratley et al. 1987).

Following the recommended procedure as described above, the steady-state data for each of the 30 baseline replications was batched into $k = 60$ groups of size $b = 5$. The lag-1 autocorrelation (r_1) was estimated for each replicate. The overall mean for r_1 is very near zero (-0.0366) and produces the following confidence intervals:

$$\text{99\% Confidence Interval: } -0.1094 \le \mu_{r1} \le 0.0362 \qquad (1)$$

$$\text{95\% Confidence Interval: } -0.0907 \le \mu_{r1} \le 0.0174 \qquad (2)$$

$$\text{90\% Confidence Interval: } -0.0815 \le \mu_{r1} \le 0.0082 \qquad (3)$$

$$\text{85\% Confidence Interval: } -0.0757 \le \mu_{r1} \le 0.0024 \qquad (4)$$

Since the overall mean is close to zero and (1), (2), (3), and (4) all include zero, the lag-1 autocorrelation for batch size $b = 5$ can be considered approximately equal to

zero with sufficient confidence. Therefore, rebatching the data into $k = 30$ groups of $b = 10$ observations provides approximately independent batches with which to conduct further output analysis on the model's CE measure. In addition, $b = 10$ also provides a batch size that is a multiple of the number of clinic days per week (i.e., 5), and therefore should smooth the cyclic weekly patient demand pattern (i.e., more patients on Mondays and Fridays and fewer during the middle of the week). This smoothing can be observed by the steady-state nature of the batched CE outputs ($b = 10$) as presented in Section 6.2.

6.4 Factor Screening

Prior to analyzing a complex model's response to changes in several input parameters, it is often beneficial to know which input parameters have little effect on the output measure of interest. Factor screening methods are useful in identifying which factors (i.e., input parameters) are important and which are irrelevant and may be fixed at some reasonable value and ignored in further analysis. A popular and straightforward method for factor screening is fractional factorial design.

Fractional factorial designs provide a means for obtaining good estimates of the main effects and some higher-order interactions of altering k factors (input parameters) without the computational burden required by a complete factorial (i.e., 2^k) design (Law and Kelton 1991). The main effect of a factor is defined as the average change in response of some output performance measure when the factor is changed from one level (i.e., input parameter value) to another. Likewise, n-way interactions describe the average change in response of an output performance measure when n of the factors are at their higher-valued level (known as the + level). Computational efficiency in estimating the

main effects and interactions is gained because a 2^{k-p} fractional factorial design requires the simulation be run only for a certain subset of the 2^k possible design points. Since $(½)^p$ of the possible 2^k factor combinations are actually run, the fractional factorial design is referred to as a half fraction when $p = 1$. Obviously, a large value of p is beneficial from a computational standpoint, however it may also fail to produce an adequate amount of useful information (i.e., valid main effect and interaction estimates) for analysis.

One important consideration in constructing fractional factorial designs is confounding. Confounding occurs when the algebraic expressions for two or more effects or interactions are exactly the same. For instance, in a 2^{6-1} half fraction, the experiments can be designed such that the formulas for the main effect e_6 and the three-way interaction effect e_{123} are identical. In this case, it said that the main effect of factor 6 is confounded with the three-way interaction of factors 1, 2, and 3. This means that the common expression for e_6 and e_{123} is an unbiased estimator for the sum of their expected values (i.e., $E(e_6) + E(e_{123})$). Very often, higher-order interactions, like three-way interactions, are negligible. In the above example, this would result in e_6 being a nearly unbiased estimator of $E(e_6)$. However, when two-way interactions and main effects are confounded with one another, the assumption that the two-way interaction is nearly zero becomes less plausible. In general, the larger the value of p for a fractional factorial design, the more pervasive the problem of confounding (Law and Kelton 1991).

The manner in which a fractional factorial design is constructed is dependent upon the resolution of the particular design. Resolution is a convenient manner for defining the level at which factors are confounded with one another. To illustrate, a resolution VI design provides unconfounded main effects with two-way interactions ($1 + 2 < 6$), but

three-way interactions that are confounded with one another ($3 + 3 \geq 6$). In discrete-event simulation studies, there could be at least two-way interactions, hence a resolution greater than IV is necessary (Law and Kelton 1991).

Using the above information, a resolution VI half fraction was designed to analyze the clinic model's input parameters in an effort to screen factors. Table 6.7 provides the factors (input parameters) and their levels used in the half fraction. The complete design is provided in Appendix E.

Table 6.7: Factors (Input Parameters) and Their Levels for Screening

Factor	Description	-	+
1	Number of PA/NPs	2	3
2	Number of Nurses	2	3
3	Number of Medical Assistants	2	3
4	Number of Check-In Rooms	2	4
5	Number of Exam Rooms	4	8
6	Number of Specialty Rooms	1	2

Table 6.8 provides the results of the half fraction design in terms of main effects, two-way interactions, and three-way interactions. Note that the three-way interactions are all negligible (also note the confounding pattern for three-way interactions). Examination of the main effects shows that the main effect of factor 4, the number of check-in rooms, is negligible. Its two-way interaction with the other factors is also negligible. Therefore, the number of check-in rooms can be safely screened from further analysis and will be fixed at two for all future experiments. Additionally, the main effect for factor 6, the number of specialty rooms, shows that moving from 1 to 2 rooms decreases the average CE by approximately $100. Since, at least one specialty room is required for further

experimentation, this factor can be screened and set to 1 for all future experiments, resulting in a higher average CE.

Table 6.8: Fractional Factorial Design Main Effects and Interactions

Main Effects	
e_1	-166.90
e_2	-146.08
e_3	-94.21
e_4	1.43
e_5	31.77
e_6	-100.56

Two-Way Interactions	
e_{12}	-7.28
e_{13}	-3.79
e_{14}	0.74
e_{15}	-10.75
e_{16}	0.07
e_{23}	-3.13
e_{24}	-0.06
e_{25}	-4.25
e_{26}	0.91
e_{34}	0.54
e_{35}	-2.08
e_{36}	0.54
e_{45}	0.35
e_{46}	-1.59
e_{56}	0.45

Three-Way Interactions	
e_{123}	2.76
e_{124}	-0.44
e_{125}	1.89
e_{126}	-0.04
e_{134}	-0.11
e_{135}	1.07
e_{136}	0.03
e_{145}	-0.54
e_{146}	0.17
e_{156}	0.49
e_{234}	0.49
e_{235}	0.17
e_{236}	-0.54
e_{245}	0.03
e_{246}	1.07
e_{256}	-0.11
e_{345}	-0.04
e_{346}	1.89
e_{356}	-0.44
e_{456}	2.76

Through analysis of a fractional factorial design, two factors (input parameters), the number of check-in rooms and the number of specialty rooms, were screened. This factor screening greatly reduces the complexity of the model for further analysis. By reducing the number of factors from 6 to 4, the number of simulation experiments required to make a full 2^k factorial design is reduced by a factor of 4 (from 64 to 16), making 2^k designs an attractive means for identifying potential clinic configurations for

comparison using a discrete-parameter simulation optimization technique (e.g., simultaneous ranking, selection, and multiple comparisons).

Chapter 7

Model Experimentation and Optimization

The clinic effectiveness (CE) measure derived in Chapter 6 provides a quantitative means for comparing alternative clinic configurations in terms of staffing (i.e., number of medical assistants, nurses, and NP/PAs) and facility size (i.e., number of check-in rooms, examination rooms, and specialty rooms). Having effectively controlled the initialization bias present in the CE measure, determined an appropriate batch size for grouping the output CE observations, and screened those input parameters which have little or no effect upon the output CE measure, a simulation optimization technique may be applied to determine the optimal clinic configuration. This chapter focuses on the selection and application of such a simulation optimization technique, Nelson and Matejcik's (1995) simultaneous ranking, selection, and multiple comparisons with the best procedure.

7.1 Ranking, Selection, and Multiple Comparisons

The most common goal of discrete-event simulation models is to choose the best system design from among a set of competing alternatives where best is used in regard to the

output performance measure deemed most important by the experimenter. Two simulation optimization techniques, ranking and selection (R&S) and multiple comparison procedures (MCPs), are applicable and have been widely used when the number of designs to be compared is both discrete and small (i.e., 2 to 20). The particular method that is applicable is dependent upon the type of comparison desired by the analyst and the properties of the simulation output data. Jacobson and Schruben (1989), Fu (1994), and Jacobson et al. (1999) provide extensive reviews of simulation optimization techniques including, but not limited to, R&S and MCPs.

R&S procedures are statistical methods specifically developed to select the best system or a subset that contains the best system design from a set of k competing alternatives (Goldsman and Nelson 1994). In general, these methods ensure the probability of a correct selection at or above some user-specified level. MCPs specify the use of certain pairwise comparisons to make inferences in the form of confidence intervals (Fu 1994) about relationships among all designs. In short, R&S provides the experimenter with the best system design while MCPs provide information about the relationships among the designs (e.g., how much better the best design is in comparison to the alternatives).

In the ensuing sections, a brief overview of each method and a more comprehensive overview of combined R&S-MCP procedures are provided. Several excellent sources for more extensive treatments of R&S and MCPs exist. A thorough survey of the development of R&S and MCPs is given by Swisher and Jacobson (1999) and summarized in Table 7.1. Goldsman and Nelson (1994, 1998) provide comprehensive state-of-the-art reviews of ranking, selection, and multiple comparison

procedures in simulation. Where possible, they attempt to unify the R&S and MCP perspectives. Bechhofer et al. (1995) provide a detailed text on R&S along with practical hints for practitioners. Likewise, Hsu (1996) provides a detailed text on the theory and application of MCPs.

Table 7.1: Key Dates and Contributions in R&S and MCPs

Date	Author(s)	Contribution
1953	Tukey	Origin of MCA
1954	Bechhofer	Origin of Indifference Zone (IZ) R&S Procedures
1955	Dunnett	Origin of MCC
1956	Gupta	Origin of Subset Selection (SS) R&S Procedures
1975	Dudewicz & Dalal	Elimination of Variance Constraints for IZ R&S
1978	Dudewicz & Taneja	Multivariate R&S Formulation
1984	Gupta & Hsu	First Reference to R&S, MCP Unification
1984	Hsu	Origin of MCB
1985	Koenig & Law	Extension of IZ R&S Procedures
1989	Sullivan & Wilson	Elimination of Variance Constraints for SS R&S
1991	Yang & Nelson	Control Variates and CRN for MCA, MCB, MCC
1993	Matejcik & Nelson	Establishes Connection Between IZ R&S and MCB
1994	Goldsman & Nelson	Unification of R&S and MCP Perspectives
1995	Nelson & Matejcik	Procedures for Simultaneous R&S and MCB

The following notation will be used in Section 7.1: Let Y_{ij} represent the jth simulation output (replication or batch mean) of the parameter of interest from the ith design alternative, for $i = 1, 2, \ldots, k$ and $j = 1, 2, \ldots, n$. Let $\mu_i = E[Y_{ij}]$ denote the expected value of an output from the ith design alternative and let $\sigma_i^2 = \text{Var}[Y_{ij}]$ denote its variance. Let $\mu_{[1]} \leq \mu_{[2]} \leq \ldots \leq \mu_{[k]}$ denote the ordered but unknown expected values for the outputs of the k alternatives. Let $\mathbf{Y}_j = (Y_{1j}, Y_{2j}, \ldots, Y_{kj})'$ be the $k \times 1$ vector of outputs across all design alternatives for output j and assume that $\mathbf{Y}_1, \mathbf{Y}_2, \ldots$ are independent and identically distributed (i.i.d.) with multivariate normal distribution $\mathbf{Y}_j \sim N(\mu, \Sigma)$ where μ is the unknown mean vector, $\mu = (\mu_1, \mu_2, \ldots, \mu_k)'$, and Σ is the unknown variance-covariance matrix. In addition, the use of the subscript "$\cdot$" indicates averaging with

respect to that subscript. For example, the average design alternative output performance measure value across all replications (or batch means) is denoted by $\overline{Y}_{i\cdot} = \sum_{j=1}^{n} Y_{ij} / n$.

7.1.1 Ranking and Selection (R&S)

Ranking and selection is a commonly prescribed method for selecting the best system from among a set of competing alternatives. A majority of the research on R&S can be classified into two general approaches: indifference zone selection and subset selection. The goal of indifference zone selection is to select the population with the largest mean (or smallest mean for minimization problems) for some population statistic from a set of *k* normal populations. This population is referred to as the "best." Typically, an experimenter will take a certain number of observations from each population (Y_{ij}) and select the best population using statistics from these observations. Since the observations are realizations of random variables, it is possible that the experimenter will not select the best population. However, if the best population is selected, the experimenter is then said to have made the correct selection (CS).

In addition, an experimenter may be indifferent (at some level) in the selection of a population when two populations are nearly the same. That is, if $\mu_{[k]} - \mu_{[k-1]}$ is very small, then the experimenter may view the populations as essentially the same and not have a preference between the two. To quantify this, define δ, the indifference zone. If $\mu_{[k]} - \mu_{[k-1]} < \delta$, the experimenter is said to be indifferent to choosing $\mu_{[k]}$ or $\mu_{[k-1]}$. Define the probability of correct selection as $P\{CS\} = P\{\mu_{[k]} > \mu_{[i]}, \forall\, i \neq k \mid \mu_{[k]} - \mu_{[i]} \geq \delta\} \geq P^*$

where $\{\delta, P^*\}$ are pre-specified by the experimenter. Since $P\{CS\} = 1/k$ could be achieved by simply choosing a population at random, $1/k < P^* < 1$ is required.

The original indifference zone R&S procedure proposed by Bechhofer (1954) assumes unknown means, $\mu_1, \ldots, \mu_k$, and *known*, *common* variance, σ^2, for all i populations ($i = 1, \ldots, k$). Note that this procedure is a *single-stage* procedure. That is, the total number of observations required, N, is determined *a priori* by the experimenter's choice of $\{\delta, P^*\}$. When a simulation analyst is modeling a system that does not physically exist, it is often impossible to know the performance measure's variance. In addition, modeling an existing system still may not allow the analyst to know the performance measure's variance because of the potentially high cost or practical infeasibility of data collection. Moreover, even when the variance is known, ensuring common variance across system configurations may be difficult. For these reasons, modern indifference zone R&S procedures typically require *neither equal nor known* variances.

The derivation of modern indifference zone procedures can be traced to Dudewicz and Dalal (1975). They present a two-stage procedure in which the experimenter chooses δ, P^*, and n_0 where n_0 is the number of observations to be made during the first stage of the procedure. The first stage variances are then used to determine the number of second stage observations required. A weighted average of the first and second stage sample means is then used to select the best system (i.e., the system with the largest weighted average). Dudewicz (1976) presents the same procedure with applications to simulation. Rinott (1978) shows how the number of samples to be taken in the second stage of

Dudewicz and Dalal (1975) can be modified to require fewer observations (in some cases) with a greater P{CS}.

In contrast to indifference zone procedures, Gupta (1956) presents a procedure for producing a subset of *random size* that contains the best system, with user-specified probability P^* without the specification of an indifference zone (i.e., $\delta = 0$). This procedure and others like it are known as subset selection R&S procedures. Like the original indifference zone R&S procedures, the original subset selection procedures required *equal and known* variances among system alternatives. For this reason, subset selection R&S procedures have rarely been applied to discrete-event simulation. However, Sullivan and Wilson (1989) present a procedure that allows *unknown and unequal* variance, as well as the specification of an indifference zone.

Although Sullivan and Wilson's (1989) R&S procedure makes subset selection more attractive for simulation, indifference zone procedures are still the more popular of the two. In most cases, an analyst wishes to determine the best system, not identify a subset containing the best (Ho et al. 1992). In addition, for those situations in which the analyst wishes to identify a subset containing the best, specialized indifference zone procedures allow the *a priori* specification of the subset's size (Koenig and Law 1985). Although the allowance of unequal and unknown variance makes indifference zone R&S procedures attractive for simulation optimization, they typically do not exploit the variance reduction technique known as common random numbers (CRN). Indifference zone R&S procedures also do not provide any inference about systems other than the system selected as the best (Nelson and Matejcik 1995).

7.1.2 Multiple Comparison Procedures (MCPs)

In contrast to R&S procedures in which the goal is to make a decision, the goal of MCPs is to identify the differences between systems' performance (not guarantee a decision). Four general classes of MCPs have been developed: paired-*t*, Bonferroni, all-pairwise comparisons; all-pairwise multiple comparisons (MCA); multiple comparisons with a control (MCC); and multiple comparisons with the best (MCB).

Fu (1994) refers to the paired-*t*, Bonferroni, all-pairwise approach as the brute force approach to multiple comparisons. In this approach, one simply examines all possible pairwise confidence intervals for system designs. Here, there will be $k(k\text{-}1)/2$ confidence intervals constructed. Due to the Bonferroni inequality, each confidence interval must be made at level $(1\text{-}\alpha)/[k(k\text{-}1)/2]$ in order to have a confidence interval of at least $(1\text{-}\alpha)$ for all intervals together. Clearly, for any more than 10 alternatives, the width of the individual confidence intervals becomes quite large. Unfortunately, unless there is a clear winner among the systems (i.e., a system with the confidence interval for the difference with all other pairs that is strictly positive), one gains little inference from this procedure.

MCA has its origins in Tukey (1953) and is similar to the brute-force method, except that instead of constructing separate confidence intervals and using Bonferroni to determine an overall confidence bound, a simultaneous set of confidence intervals at an overall $(1\text{-}\alpha)$ level is formed. Like the previous method, MCA requires $k(k\text{-}1)/2$ confidence intervals be constructed. In contrast to the brute force method, MCA obtains an overall simultaneous confidence level with the same confidence half-widths for each

pairwise comparison, while the brute-force method obtains a different confidence half-width for each pairwise comparison and uses Bonferroni to establish a bound on the overall confidence. Yang and Nelson (1991) provide a revision for MCA which allows the use of control variates and CRN.

There are times when an experimenter wishes to compare a set of alternatives to a pre-defined control. The construction of (*k*-1) simultaneous confidence intervals in comparison to a fixed control is attributed to Dunnett (1955) and is known as MCC. This method is particularly useful when one wishes to compare design alternatives to the current design (Bratley et al. 1987). Yang and Nelson (1991) provide a revision for MCC which allows the use of control variates and CRN while Bofinger and Lewis (1992) expand traditional MCC procedures by describing two-stage MCC procedures.

MCB is by far the most widely used of the multiple comparison methodologies. MCB procedures have their origin in Hsu (1984) and Hsu and Nelson (1988). MCB's intent is similar to that of R&S procedures: determine the best system from a set of alternatives. MCB attacks this problem by forming simultaneous confidence intervals on the parameters $\mu_i - \max_{j \neq i} \mu_j$ for $i = 1, 2, \ldots, k$. These (k-1) confidence intervals bound the difference between the expected performance of each system and the best of the others. To apply MCB in discrete-event simulation, the simulation runs must be independently seeded and the simulation output must be normally distributed or averaged so that the estimators used are (approximately) normally distributed. Yang and Nelson (1991) present modifications to the MCB procedure that incorporate two variance reduction techniques (CRN and control variates). Their results suggest that using variance reduction can lead to correct selections with higher probabilities.

7.1.3 Combined Procedures

Recently, there has been an effort to unify the fields of R&S and MCPs. The first reference to such a movement is Gupta and Hsu (1984). They propose a methodology for simultaneously executing R&S and MCB. Matejcik and Nelson (1993, 1995) establish a fundamental connection between indifference zone procedures and MCB. The idea of combining indifference zone approaches with MCB is appealing to the simulation analyst. Such an approach not only selects the best system with pre-specified confidence, but it provides inferences about the relationships between systems which may facilitate decision-making based on secondary criteria that are not reflected in the performance measure selected.

Nelson and Matejcik (1995) show that most indifference zone procedures can simultaneously provide MCB confidence intervals with the width of the intervals (whisker length) corresponding to the indifference zone. Therefore, both indifference zone selection and MCB inference can be derived from the same experiment with a pre-specified MCB whisker length, $w = \delta$. They describe four R&S-MCB procedures which depend on having normally distributed data, but do not require known or equal variance:

1. Rinott's Procedure (Procedure *R*),
2. Dudewicz and Dalal's Procedure (Procedure *DD*),
3. Clark and Yang's Procedure (Procedure *CY*), and
4. Nelson and Matejcik's Procedure (Procedure *NM*).

Procedure *R* is an extension of Rinott's (1978) two-stage indifference zone R&S procedure as described in Section 7.1.1. It requires n_0 (where n_0 is the first-stage sample size) i.i.d. samples from each of the *k independently-simulated* systems. The marginal

sample variance for each system is then computed and used to determine the final sample size for each system, N_i (for i = 1, 2, …, k). After taking $N_i - n_0$ additional i.i.d. observations from each of the k systems, independent of the first-stage samples and independent of the other second-stage samples, the system with the largest overall sample mean is selected as best. In addition, MCB confidence intervals on $\mu_i - \max_{j \neq i} \mu_j$ are formed. Likewise, Procedure *DD* (based on Dudewicz and Dalal 1975) is performed in the same manner with the only difference being in the calculation of the sample means. While Procedures *R* and *DD* provide both R&S selection and MCB inference, their requirement for independence among all observations precludes the use of CRN. The total sample size required to obtain the desired confidence level is dependent on the sample variances of the systems. In particular, the larger the sample variance, the more replications (or batch means) required. For this reason, simultaneous R&S-MCB procedures that exploit CRN should require fewer total observations to obtain the same confidence level.

Procedure *CY* is based upon Clark and Yang's (1986) indifference zone R&S procedure. As one of the few R&S procedures that allows CRN, Clark and Yang (1986) use the Bonferroni inequality to account for the dependence induced by CRN. It is therefore a conservative procedure that typically prescribes more total observations than are actually necessary to make a correct selection. Like Procedure *R*, Procedure *CY* is performed in two stages. In the first stage, i.i.d. samples from each of the k systems are taken *using CRN across systems*. The sample variances of the differences are then used to compute the final sample size, N (note that N does not vary across systems for Procedure *CY*). After taking the remaining $N - n_0$ i.i.d. observations, again using CRN

across systems, the system with the largest sample mean is selected as best and the MCB confidence intervals are formed.

Nelson and Matejcik (1995) find that Procedure *CY* can be effective in reducing the total number of samples required to make a correct selection in comparison with Procedures *R* and *DD*. However, they also note that the benefit gained from using Procedure *CY* is diminished when the number of systems to be compared, *k*, is large. This is because the conservatism of the procedure from the Bonferroni inequality increases as *k* increases and, at some point, overwhelms the benefit induced by CRN. To overcome this problem, they present Procedure *NM*.

Procedure *NM* is motivated by Nelson's (1993) robust MCB procedure. This procedure assumes that the unknown variance-covariance matrix, Σ, exhibits a structure known as *sphericity*. Specifically, the sphericity structure takes the form:

$$\Sigma = \begin{pmatrix} 2\psi_1 + \tau^2 & \psi_1 + \psi_2 & \cdots & \psi_1 + \psi_r \\ \psi_2 + \psi_1 & 2\psi_2 + \tau^2 & \cdots & \psi_2 + \psi_r \\ & & \ddots & \\ \psi_r + \psi_1 & \psi_r + \psi_2 & \cdots & 2\psi_r + \tau^2 \end{pmatrix}$$

where $\tau^2 > \sqrt{k\sum_{i=1}^{k}\psi_i^2} - \sum_{i=1}^{k}\psi_i$ so that Σ is guaranteed to be positive definite (Nelson and Matejcik 1995). Sphericity implies that $\mathrm{Var}[Y_{ij} - Y_{lj}] = 2\tau^2$ for all $i \neq l$. This means that the variances of all pairwise differences across systems are equal, even though the marginal variances and covariances may be unequal. Sphericity generalizes *compound symmetry* (Nelson and Matejcik 1995), which takes the form:

$$\Sigma = \sigma^2 \begin{pmatrix} 1 & \rho & \cdots & \rho \\ \rho & 1 & \cdots & \rho \\ & & \ddots & \\ \rho & \rho & \cdots & 1 \end{pmatrix}$$

Several researchers have proposed that compound symmetry accounts for the variance reduction effects of CRN (see Tew and Wilson 1994, Nozari et al. 1987, and Schruben and Margolin 1978 for more details). Procedure *NM* is valid when Σ satisfies sphericity, however Nelson and Matejcik (1995) show it to be extremely robust to departures from sphericity. The procedure is as follows:

1. Specify w ($w = \delta$), α, and n_0. Let $g = T^{(1-\alpha)}_{k-1,(k-1)(n_0-1),0.50}$, where $T^{(1-\alpha)}_{k-1,(k-1)(n_0-1),0.50}$ is the $(1-\alpha)$-quantile of the maximum of a multivariate t random variable with k-1 dimensions, $(k-1)(n_0-1)$ degrees of freedom, and common correlation 0.50.

2. Take i.i.d. samples $Y_{i1}, Y_{i2}, ..., Y_{in_0}$ from each of the k competing systems *using CRN across systems*.

3. Compute the sample variance of the difference under the condition of sphericity as:

$$S^2 = \frac{2\sum_{i=1}^{k}\sum_{j=1}^{n_0}(Y_{ij} - \bar{Y}_{i\cdot} - \bar{Y}_{\cdot j} + \bar{Y}_{\cdot\cdot})^2}{(k-1)(n-1)}$$

4. Compute the final required sample size (constant for all k alternatives) as:

$$N = \max\{n_o, \lceil (gS/w)^2 \rceil\}$$

5. Take $N - n_0$ additional i.i.d. observations from each system, using CRN across systems.

6. Compute the overall sample means for each system as:

$$\bar{\bar{Y}}_{i\cdot} = \frac{1}{N}\sum_{j=1}^{N} Y_{ij} \quad \text{for } i = 1, 2, \ldots, k$$

7. Select the system with the largest $\overline{\overline{Y}}_{i\cdot}$ as the best alternative.

8. Simultaneously, form the MCB confidence intervals as:

$$\mu_i - \max_{j \neq i} \mu_j \in [-(\overline{\overline{Y}}_{i\cdot} - \max_{j \neq i} \overline{\overline{Y}}_{j\cdot} - w)^-, (\overline{\overline{Y}}_{i\cdot} - \max_{j \neq i} \overline{\overline{Y}}_{j\cdot} + w)^+] \text{ for } i = 1, 2, \ldots, k$$

where $-x^- = \min\{0, x\}$ and $x^+ = \max\{0, x\}$

Note that the value of $T^{(1-\alpha)}_{k-1,(k-1)(n_0-1),0.50}$ in Step 1 of Procedure *NM* can be derived from Table 4 of Hochberg and Tamhane (1987) or Table B.3 of Bechhofer et al. (1995). For values that fall outside of the tables, the FORTRAN program of Dunnett (1989) may be used.

Nelson and Matejcik (1995) report results that suggest that Procedure *NM* is superior to Procedures *R*, *DD*, and *CY* in terms of the total observations required to obtain the desired confidence level. Procedure *NM*'s only potential drawback is that the assumption of sphericity may not be exactly or even approximately satisfied in many situations (Nelson and Matejcik 1995). To evaluate the procedure's robustness to departures from sphericity, Nelson and Matejcik (1995) performed an empirical study. They found that when the desired P{CS} = 0.95, the actual probability attained ranged from 0.88 to 1.0 with a mean of 0.94. Provided the assumption of the data's normality is not significantly violated, this performance suggests that the procedure is sufficiently robust for use in practice. They suggest that the analyst consider slightly inflating the nominal coverage probability (e.g., use 0.97 when 0.95 is desired) to ensure adequate coverage. They also conclude that even when slightly inflating the nominal coverage probability, Procedure *NM* should still outperform Procedure *CY* in terms of the required sample size.

7.2 Application of Procedure *NM* to CE Optimization

Combined R&S-MCB procedures are more attractive for use in simulation optimization than using either R&S or MCB individually since combined procedures provide both R&S selection and MCB inference with little or no additional computational overhead. The power of these procedures lies in their ability to provide the analyst with both the optimal configuration with pre-specified confidence (R&S) and inferences about that configuration's superiority (MCB). Procedure *NM* (Nelson and Matejcik 1995) is the most efficient of the existing combined procedures. For this reason, it was selected as the simulation optimization technique to apply to the determination of the optimal clinic configuration (i.e., the configuration with the largest mean daily CE) from among a group of competing alternative configurations.

Table 7.2: Comparison of Tests for Normality

Normality Test	p-Value
Anderson-Darling	0.6829
Kolmogorov-Smirnov	> 0.15
Shapiro-Wilk W	0.8100

The first step in applying Procedure *NM* is to ensure that the output data used is normally distributed. To this end, the sample means of each batch from the 30 baseline model replications (see Section 6.2) were tested for normality. Three tests for normality were applied (using Analyse-It for Microsoft Excel v1.32): Anderson-Darling modified for use with unknown population mean and variance (D'Agostino and Stephens 1986), Kolmogorov-Smirnov modified for use with unknown population mean and variance (D'Agostino and Stephens 1986), and Shapiro-Wilk W (Royston 1992). The results of

these tests (see Table 7.2) show large p-values, suggesting that the null hypothesis of normally distributed data would not be rejected at any reasonable confidence level.

Table 7.3: Clinic Configurations to be Compared with Procedure *NM*

Config.	No. of PA/NPs	No. of Nurses	No. of Medical Assistants	No. of Check-In Rooms	No. of Exam Rooms	No. of Specialty Rooms
1	2	2	1	2	5	1
2	2	1	1	2	6	1
3	2	2	0	2	6	1
4	2	2	1	2	6	1
5	3	1	0	2	6	1
6	3	1	1	2	6	1
7	2	1	1	2	7	1
8	2	2	0	2	7	1
9	2	2	1	2	7	1
10	3	1	0	2	7	1
11	3	1	1	2	7	1
12	2	1	1	2	8	1
13	2	2	0	2	8	1
14	2	2	1	2	8	1
15	2	1	1	2	9	1
16	2	2	0	2	9	1
17	2	1	1	2	10	1

As suggested in Section 6.4, the identification of potentially optimal clinic configurations was performed by iteratively examining the main effects, two-way interactions, and three-way interactions of 2^k factorial designs (see Appendix F for details). After each iteration, a new local search space of clinic configurations was selected and explored in the improving directions until there was no evidence of further improvement. Using CRN across clinic configurations, a simulation run of length 15 months was made for each clinic configuration (i.e., each 2^k factorial design point). Each simulation run produced 327 observations where the first 27 observations were deleted

and the remaining 300 observations were grouped into batches of size b = 10. The maximum observed CE sample mean from the factorial designs was 402.75. A 95% confidence interval on the maximum observed CE mean yielded a lower bound of 369.11. Of the remaining ninety-three unique clinic configurations simulated, only sixteen other clinic configurations produced CE sample means greater than 369.11. Therefore, these seventeen clinic configurations (see Table 7.3) were selected as the set of potentially optimal configurations for investigation with Procedure *NM*.

Procedure *NM* allows the specification of an indifference zone (which also specifies the MCB whisker length, w). A value of $\delta = w = 10$ was used to select the optimal clinic configuration from among the seventeen competing alternatives. Based upon the definition of the CE measure used for experimentation (see Section 6.1), this value is equivalent to a total of 30 minutes of additional patient waiting per physician per day (i.e., the $10/hour patient waiting penalty divided among two physicians). Since each physician averages approximately 35 patients per day in the clinic, this would amount to less than 1 minute of additional waiting per patient.

Since a P{CS} = (1 - α) = 0.95 is desired, a more conservative value of $\alpha = 0.03$ will be used, as suggested by Nelson and Matejcik (1995). Given $n_0 = 30$, $w = \delta = 10$, and $\alpha = 0.03$, $g = T_{16,464,0.50}^{(0.97)} = 2.7910$ (as derived from Dunnett's 1989 procedure). The sample variance under the condition of sphericity, S^2, is 882.80 and $N = \max\{30, \lceil (gS/w)^2 \rceil\} = 69$. Therefore, 39 ($N - n_0$) additional observations were generated for each of the seventeen clinic configurations by simulating 417 clinic days (27 deleted observations + 390 usable observations) using CRN across configurations and forming 39

batches of size $b = 10$. Using the formulas provided in Section 7.3, the overall sample means and MCB intervals were then formed (see Table 7.4).

Table 7.4: Overall Sample Means and MCB Results for Procedure *NM*

Configuration	$\bar{\bar{Y}}_{i\cdot}$	Lower MCB Limit	$\bar{\bar{Y}}_{i\cdot} - \min_{j \neq i} \bar{\bar{Y}}_{j\cdot}$	Upper MCB Limit
1	388.17	-28.00	-18.00	0
2	392.41	-23.76	-13.76	0
3	394.18	-21.99	-11.99	0
4	406.17	-9.76	0.24	10.24
5	380.70	-35.47	-25.47	0
6	386.07	-30.10	-20.10	0
7	405.93	-10.24	-0.24	9.76
8	398.74	-17.43	-7.43	2.57
9	405.32	-10.85	-0.85	9.15
10	382.72	-33.45	-23.45	0
11	381.11	-35.06	-25.06	0
12	401.98	-14.19	-4.19	5.81
13	392.53	-23.65	-13.65	0
14	392.07	-24.10	-14.10	0
15	393.78	-22.39	-12.39	0
16	378.67	-37.50	-27.50	0
17	378.28	-37.90	-27.90	0

Procedure *NM* selects configuration 4, with $\bar{\bar{Y}}_{4\cdot} = 406.17$, as the best clinic configuration. From a R&S perspective, this means that with probability greater than or equal to 0.97, configuration 4 has mean μ_4 within $\delta = 10$ of the configuration with the true largest mean, $\mu_{[1]}$. Examination of the MCB intervals provides inferences on the (assumed) superiority of configuration 4. Interestingly, four other configurations (7, 8, 9, and 12) have MCB intervals that contain 0. This means, from an MCB perspective, there is no one clearly superior configuration. Configurations 4, 7, 8, 9 and 12 are all clearly superior to the remaining systems whose upper MCB bound is 0, however there is no

clear winner among them. Note that had one configuration possessed a lower MCB bound of 0, while the rest were upper-bounded by 0, then that configuration would have been selected as best by MCB.

One of the benefits of using a combined R&S-MCB procedure is that the analyst gains inferences on systems other than the best, which may lead to the selection of an inferior system (if it is not inferior by much) based on some secondary criteria not reflected in the performance measure of interest (Matejcik and Nelson 1993). Although profit is a component of the performance measure used (CE measure), no real inference on clinic profit can be made from examining the CE measure. Therefore, a decision-maker would likely be interested in examining clinic profit as a measure separate from the CE measure for the five configurations whose MCB interval covers zero. Table 7.5 provides the mean daily clinic profit (without any service penalties) for each of the five configurations.

Table 7.5: Mean Daily Clinic Profit for the Five Best Configurations

Configuration	Mean Daily Profit ($)
4	851.92
7	990.78
8	931.89
9	833.88
12	972.08

Note that configuration 7 produces approximately $140 per day more clinic profit than the configuration selected as the best (configuration 4). In addition, configuration 7's overall sample mean is less than 25 cents less than configuration 4's overall sample mean (see Table 7.4). In short, the MCB inference provided by Procedure *NM* would lead the clinical decision-maker to choose configuration 7, despite the fact that

configuration 4 was selected as the best by Procedure *NM*'s R&S result. If only a R&S approach had been used to evaluate the clinic configurations, the clinical decision-maker would have selected an excellent configuration in terms of CE. However, that choice may cost the clinic $140 per day in profit compared to an equally good (from an MCB perspective) choice. In this case, the value of the application of a combined R&S-MCB procedure is obvious.

Chapter 8

Results and Conclusions

The research presented herein provides a general means for evaluating the overall effectiveness of family practice outpatient healthcare clinics via discrete-event simulation. The simulation model itself is built in an intuitive, visual manner to facilitate understanding by the often non-technical clinic decision-maker (e.g., physician, office manager). All of the statistical distributions defining the simulation model clinic's operational characteristics may be altered to fit the needs of a particular real-world clinic. In addition, a multiattribute performance measure, referred to as the clinic effectiveness (CE) measure, is presented. The weighting of each of the attributes composing the CE measure can be modified to suit the preferences of a particular clinic's decision-maker. An example of determining the optimal clinic configuration for a hypothetical clinic using the CE measure and a simulation optimization technique due to Nelson and Matejcik (1995) is presented to provide the reader a context for this work. This chapter describes some of the implications of the simulation study's results and discusses possible directions for future research.

8.1 Implications of the Simulation Study's Results

At a high level, the implications of the results of this simulation study can be described as:

- the importance of PA/NPs to the family practice healthcare clinic
- the dilemma of trading clinic profit for patient and physician satisfaction
- the potential for higher priced, more patient-focused clinics (i.e., designer clinics)

Although not necessarily obvious through examination of the results presented in Section 7.2, the PA/NP plays an important role in the effectiveness of a family practice healthcare clinic. PA/NPs are the most skilled non-physician medical staff member in a clinic. As such, they can treat a much wider variety of patient ailments as compared to nurses or medical assistants. Examination of the 2^k factorial designs (see Appendix F) shows that when a two-physician clinic has only one PA/NP, the mean daily CE suffers tremendously. In contrast, the addition of a PA/NP consistently tends to add value (in terms of mean daily CE) to a clinic configuration despite the nearly $200 per day additional salary cost (see Table 6.2). Note that all seventeen clinic configurations having the largest mean CEs (see Table 7.3) have either two or three PA/NPs. Even when the addition of a PA/NP does not increase the mean daily CE, it typically does not decrease it by much. For instance, compare clinic configurations 7 and 11. The values for each configuration's input parameters are identical except for the number of PA/NPs; configuration 7 has 2 PA/NPs while configuration 11 has 3 PA/NPs (see Table 7.3). Note that configuration 7 was selected as the optimal clinic configuration for the hypothetical two-physician clinic (see Section 7.2). One would expect the addition of a PA/NP to the optimal clinic configuration to amount to overstaffing and as such decrease the mean CE

significantly. However, configuration 11's mean CE is only approximately $25 lower than configuration 4's mean CE (see Table 7.4). This case is noteworthy because configuration 7 is not a poor design that is simply benefiting from the addition of another medical staff member. Therefore, the value of using PA/NPs can be seen even in the best of situations. Other experiments (Ad Hoc Designs 2 and 3 in Appendix F) show that even when the same total salary expenditure can provide the clinic with two additional staff members (i.e., 4 medical assistants instead of 2 PA/NPs), a smaller staff composed of only PA/NPs is significantly better.

Another important implication of this work is the dilemma faced by the clinic's decision-maker in trading clinic profit for patient and physician satisfaction. The results of Section 7.2 illustrate that two clinic configurations with practically identical CE performance can yield significantly different clinic profits. Determining the appropriate tradeoff between profit and satisfaction is therefore a difficult task. When placing more emphasis on clinic profit, the decision-maker must have thoroughly evaluated his/her clinic's position in the local healthcare market. In a market saturated with numerous clinics, the patient may simply choose to go to a different clinic if dissatisfied. Over time, even small differences in a clinic's service level as compared to its competitors may cause significant patient loyalty erosion, thereby decreasing clinic profit in the long run. On the other hand, a clinic in a market with little or no competition may be able to afford to sacrifice patient satisfaction in lieu of clinic profit. In either case, failure to maintain an adequate level of physician satisfaction may lead to the departure of the physician and potentially of his/her patients.

The dilemma faced by the clinic's decision-maker in trading clinic profit for patient satisfaction points to the possibility of the creation of a niche market for *designer clinics*. That is, some patients, particularly those that greatly value their time, may be willing to pay a premium for highly patient-focused care. Clinics providing such a service would be heavily staffed with skilled medical professionals (i.e., physicians and PA/NPs) with very few lower-skilled staff members and have ample physical space. These clinics would cater to a limited number of patients and charge more than the typical clinic for their services. Those able to afford to use one of these designer clinics would derive value from the fast, reliable care they receive. In a sense, some such clinics already exist in the United States. For instance, Mayo Clinic in Minnesota, Florida, and Arizona and Lahey Clinic in Massachusetts are well known for the high-quality care they provide. Such care comes at a price, though, and many health insurance plans fail to cover all of the services offered by Mayo and Lahey. Therefore, only those patients that derive enough benefit to justify the cost of patronizing such clinics seek treatment there.

The designer clinic concept may also provide a model for partially-socialized healthcare. Obviously, in a socialized healthcare system there must be competent, quality care available for all persons. However, those who derive great value from the convenience afforded by a designer clinic may be willing to pay for that convenience even when they could receive free care elsewhere. Such a healthcare system may be constructed so that designer clinics are privately held and administered, while other clinics are government-owned and operated. Those unable or unwilling to pay the high prices charged at designer clinics would receive free care at public clinics, while those patronizing the designer clinics would pay a fee (not reimbursed by a government or

insurance organization). The clear pitfall to such a scheme is the potential for a quality-of-care schism to develop between the haves (i.e., the affluent) and the have-nots (i.e., the poor). Such schisms have already forced the recent reform of socialized health plans in several nations, including Canada. Perhaps limiting the scope of fee-for-service healthcare in a partially-socialized healthcare system could mitigate such problems. For example, the government could allow fee-for-service arrangements only in the most general of care-giving situations, like family practice clinics. Not allowing privatization of specialty clinics or hospitals may prevent the affluent from monopolizing specialized medical skills.

8.2 Future Research

Aside from further investigation of the issues discussed in Section 8.1, a great deal of potential research specific to the discrete-event simulation model exists. On an individual clinic basis, investigation of real-world clinics using the CE measure would be beneficial. Such studies could not only assist clinics in optimizing their operations, but would also provide insight into the CE measure's sensitivity to the different values decision-makers place on the attributes of which it is composed. Furthermore, more real-world interaction with medical decision-makers may lead to revisions of the attributes composing the CE measure (i.e., addition or deletion of attributes).

From the clinical network operator perspective there is also great potential for further research. Expansion of the simulation model to allow the easy instantiation of multiple clinics is an outstanding issue. Fortunately, VSE's object-oriented structure should facilitate this process. Given a multi-clinic model, exploration of staffing policies

at the network operator's centralized information center would be advantageous. In addition, future researchers should consider the clinical network application of an idea typically applied to manufacturing systems, namely load balancing. It is possible that clinics may gain efficiencies simply by balancing patient load between clinics within some common region. The determination of when to send patients to a clinic other than their standard clinic and the definition of an acceptable travel distance between clinics could prove both interesting and challenging.

In a world of high-quality, efficient service operations, healthcare consumers expect no less from their physicians. Efficient healthcare in the 21st century will be vital to the success of outpatient clinics. This ensures that the optimization of both patient satisfaction and overall clinic profit will be a hot area of study for future researchers. This specific work provides a structured starting point for such research. Discrete-event simulation's applicability to research in the clinical environment is evidenced by the work presented in this thesis. Simulation not only gives the clinical decision-maker a means for balancing the patient's satisfaction with overall clinic profit, but visual simulation also provides an intuitive reference for the non-technical decision-maker. In short, discrete-event simulation provides the operations research analyst with a powerful tool for improving the patient-physician encounter in the coming century.

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Appendix A

Patient Distribution Definition

	Patient Category									
	1A	**1B**	**1C**	**2**	**2PV**	**3**	**3PV**	**4A**	**4B**	**5**
Probability of Occurrence:	0.10	0.13	0.05	0.30	0.2*	0.28	0.2*	0.04	0.05	0.05
Scheduling Lead Time Min (days):	0	2	2	2	2	4	4	5	2	5
Scheduling Lead Time Mode (days):	1	3	3	5	5	5	5	10	5	8
Scheduling Lead Time Max (days):	3	5	4	7	7	7	7	15	7	10
Probability of No Show:	0.05	0.07	0.05	0.2	0.2	0.2	0.2	0.33	0.05	0.05
Revenue Mean:	$20	$35	$20	$30	$30	$40	$40	$60	$65	$100
Patient Scheduling Rule (%)†:	100 All	100 All	100 All	50 All	100 All	100 All	0 All	0 All	100 All	0 All
	0 AM	0 AM	0 AM	25 AM	0 AM	0 AM	100 AM	0 AM	0 AM	50 AM
	0 PM	0 PM	0 PM	25 PM	0 PM	0 PM	0 PM	100 PM	0 PM	50 PM

* Probability that patient category will need a pre-visit, not of model occurrence.

† AM denotes sequential rule with morning preference, PM denotes sequential rule with afternoon preference, and All denotes sequential rule with no AM/PM preference.

	1A	**1B**	**1C**	**2**	**2PV**	**3**	**3PV**	**4A**	**4B**	**5**
Probability of having **Registration**:	1	1	1	1	1	1	1	1	1	1
with Clerical Staff:	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
minimum time (min.):	1	2	3	3	3	3	3	5	5	5
mode time (min.):	2	3	4	4	4	4	4	7	7	8
maximum time (min.):	3	4	5	5	5	5	5	10	10	10

	1A	**1B**	**1C**	**2**	**2PV**	**3**	**3PV**	**4A**	**4B**	**5**
Probability of having **Check-In**:	1	1	0	1	0.2	1	0.2	1	1	1
with a Medical Assistant:	75%	15%	0%	65%	10%	65%	10%	30%	30%	15%
minimum time (min.):	2	2	0	2	2	2	2	2	2	2
mode time (min.):	4	4	0	4	4	4	4	4	4	5
maximum time (min.):	10	10	0	10	10	10	10	10	10	10
with a Nurse:	20%	80%	0%	30%	90%	30%	90%	65%	65%	75%
minimum time (min.):	2	2	0	2	2	2	2	2	2	2
mode time (min.):	4	4	0	4	4	4	4	4	4	5
maximum time (min.):	10	10	0	10	10	10	10	10	10	10
with a PA/NP:	5%	5%	0%	5%	0%	5%	0%	5%	5%	10%
minimum time (min.):	2	2	0	2	0	2	0	2	2	2
mode time (min.):	4	4	0	4	0	4	0	4	4	5
maximum time (min.):	10	10	0	10	0	10	0	10	10	10
with a Physician:	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
minimum time (min.):	0	0	0	0	0	0	0	0	0	0
mode time (min.):	0	0	0	0	0	0	0	0	0	0
maximum time (min.):	0	0	0	0	0	0	0	0	0	0

	1A	1B	1C	2	2PV	3	3PV	4A	4B	5
Probability of having **Pre-Exam**:	0	0	0	0.05	1	0.95	1	0.8	0.8	0.5
with a Technician:	0%	0%	0%	0%	0%	0%	0%	20%	20%	10%
minimum time (min.):	0	0	0	0	0	0	0	6	6	6
mode time (min.):	0	0	0	0	0	0	0	8	8	8
maximum time (min.):	0	0	0	0	0	0	0	12	12	12
with a Medical Assistant:	0%	0%	0%	80%	80%	30%	80%	20%	20%	10%
minimum time (min.):	0	0	0	3	3	3	3	6	6	6
mode time (min.):	0	0	0	5	5	5	5	8	8	8
maximum time (min.):	0	0	0	15	20	20	20	12	12	12
with a Nurse:	0%	0%	0%	10%	20%	60%	20%	50%	50%	50%
minimum time (min.):	0	0	0	3	3	3	3	6	6	6
mode time (min.):	0	0	0	4	4	4	4	8	8	8
maximum time (min.):	0	0	0	10	10	10	10	12	12	12
with a PA/NP:	0%	0%	0%	10%	0%	10%	0%	10%	10%	20%
minimum time (min.):	0	0	0	3	0	3	0	6	6	6
mode time (min.):	0	0	0	4	0	4	0	8	8	8
maximum time (min.):	0	0	0	10	0	10	0	12	12	12
with a Physician:	0%	0%	0%	0%	0%	0%	0%	0%	0%	10%
minimum time (min.):	0	0	0	0	0	0	0	0	0	6
mode time (min.):	0	0	0	0	0	0	0	0	0	8
maximum time (min.):	0	0	0	0	0	0	0	0	0	12

	1A	1B	1C	2	2PV	3	3PV	4A	4B	5
Probability of having **Exam:**	0	0.3	0	1	0	1	0	1	1	1
with a Medical Assistant:	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
minimum time (min.):	0	0	0	0	0	0	0	0	0	0
mode time (min.):	0	0	0	0	0	0	0	0	0	0
maximum time (min.):	0	0	0	0	0	0	0	0	0	0
with a Nurse:	0%	85%	0%	0%	0%	0%	0%	0%	0%	0%
minimum time (min.):	0	5	0	0	0	0	0	0	0	0
mode time (min.):	0	7	0	0	0	0	0	0	0	0
maximum time (min.):	0	8	0	0	0	0	0	0	0	0
with a PA/NP:	0%	15%	0%	20%	0%	60%	0%	50%	50%	20%
minimum time (min.):	0	5	0	4	0	6	0	8	8	10
mode time (min.):	0	7	0	6	0	8	0	10	10	15
maximum time (min.):	0	8	0	10	0	11	0	20	20	30
with a Physician:	0%	0%	0%	80%	0%	40%	0%	50%	50%	80%
minimum time (min.):	0	0	0	4	0	6	0	8	8	10
mode time (min.):	0	0	0	6	0	8	0	10	10	15
maximum time (min.):	0	0	0	10	0	11	0	20	20	30

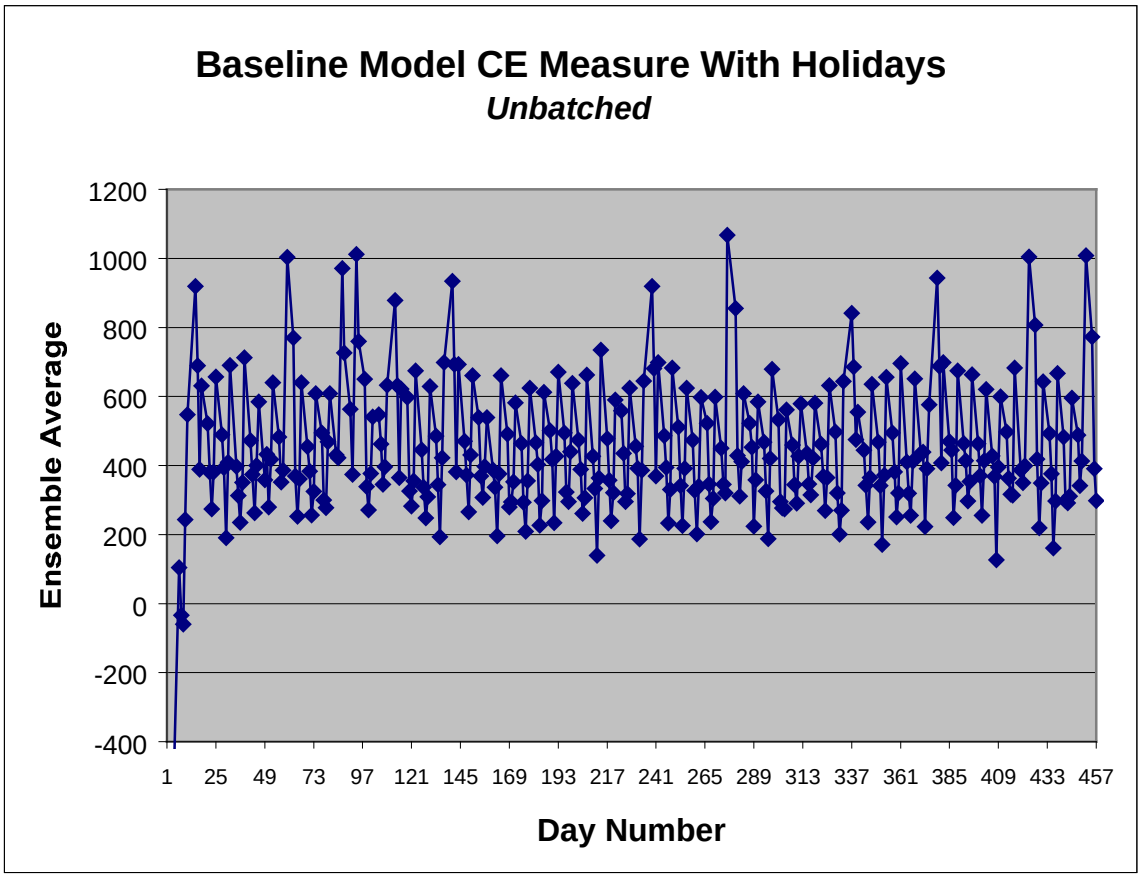
	1A	1B	1C	2	2PV	3	3PV	4A	4B	5
Probability of having **Post Exam**:	0	0	0.5	0.8	0	1	0	0.2	0.2	0.8
with a Technician:	0%	0%	5%	0%	0%	0%	0%	20%	20%	20%
minimum time (min.):	0	0	3	0	0	0	0	6	6	6
mode time (min.):	0	0	4	0	0	0	0	7	7	7
maximum time (min.):	0	0	5	0	0	0	0	10	10	10
with a Medical Assistant:	0%	0%	5%	80%	0%	0%	0%	20%	20%	20%
minimum time (min.):	0	0	3	3	0	0	0	6	6	6
mode time (min.):	0	0	4	5	0	0	0	7	7	7
maximum time (min.):	0	0	5	20	0	0	0	10	10	10
with a Nurse:	0%	0%	80%	20%	0%	70%	0%	30%	30%	30%
minimum time (min.):	0	0	5	3	0	3	0	5	5	6
mode time (min.):	0	0	8	4	0	5	0	6	6	7
maximum time (min.):	0	0	10	10	0	15	0	8	8	10
with a PA/NP:	0%	0%	10%	0%	0%	30%	0%	15%	15%	15%
minimum time (min.):	0	0	8	0	0	3	0	5	5	6
mode time (min.):	0	0	10	0	0	4	0	6	6	7
maximum time (min.):	0	0	15	0	0	10	0	8	8	10
with a Physician:	0%	0%	0%	0%	0%	0%	0%	15%	15%	15%
minimum time (min.):	0	0	0	0	0	0	0	3	3	6
mode time (min.):	0	0	0	0	0	0	0	4	4	7
maximum time (min.):	0	0	0	0	0	0	0	6	6	10

	1A	1B	1C	2	2PV	3	3PV	4A	4B	5
Probability of having **Exit Interview**:	0	0	1	1	0	1	0	1	1	1
with a Medical Assistant:	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
minimum time (min.):	0	0	0	0	0	0	0	0	0	0
mode time (min.):	0	0	0	0	0	0	0	0	0	0
maximum time (min.):	0	0	0	0	0	0	0	0	0	0
with a Nurse:	0%	0%	50%	5%	0%	10%	0%	5%	5%	0%
minimum time (min.):	0	0	2	3	0	3	0	3	3	0
mode time (min.):	0	0	3	4	0	4	0	5	5	0
maximum time (min.):	0	0	5	5	0	5	0	8	8	0
with a PA/NP:	0%	0%	25%	15%	0%	10%	0%	5%	5%	5%
minimum time (min.):	0	0	2	3	0	3	0	3	3	4
mode time (min.):	0	0	3	4	0	4	0	5	5	6
maximum time (min.):	0	0	5	5	0	5	0	8	8	9
with a Physician:	0%	0%	25%	80%	0%	80%	0%	90%	90%	95%
minimum time (min.):	0	0	2	3	0	3	0	5	5	5
mode time (min.):	0	0	3	5	0	5	0	7	7	9
maximum time (min.):	0	0	5	8	0	8	0	10	10	15

	1A	1B	1C	2	2PV	3	3PV	4A	4B	5
Probability of having **Check-Out**:	1	1	1	1	1	1	1	1	1	1
with Clerical Staff:	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
minimum time (min.):	2	2	2	4	4	3	2	4	4	2
mode time (min.):	3	3	3	5	5	4	4	5	5	4
maximum time (min.):	4	4	4	6	6	5	5	6	6	5

Appendix B

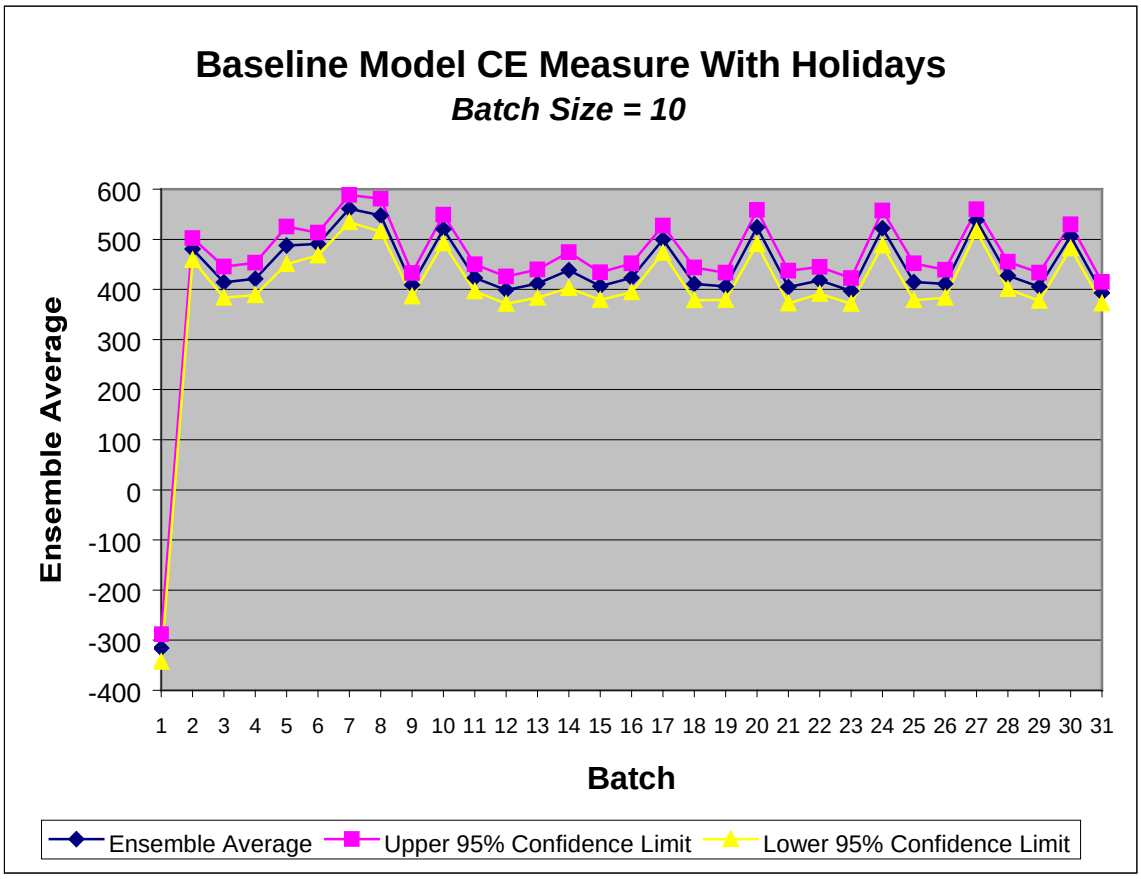
CE Graphs for Baseline Model With Holidays



The above figure represents the *unbatched* daily outputs of the CE measure for 30 replications of the baseline model. In each replication the simulated clinic is closed on the holidays listed in Table 3.1 (i.e., the boolean variable USE_HOLIDAYS is true), resulting in 315 total observations.

For the data represented above, the overall mean is 428.11, the minimum observed value is -1569.70, the maximum observed value is 1067.73, and the standard deviation is 428.11.

Holidays occur on days 14 (Columbus Day 2002), 59 (Thanksgiving Day 2002), 86 (Christmas Day 2002), 93 (New Year's Day 2003), 112 (Martin Luther King Day 2003), 140 (President's Day 2003), 238 (Memorial Day 2003), 277 (Independence Day 2003), 336 (Labor Day 2003), 378(Columbus Day 2003), 423 (Thanksgiving Day 2003), and 451 (Christmas Day 2003). Note that every CE observation greater than 800.00 corresponds to a day surrounding a holiday.

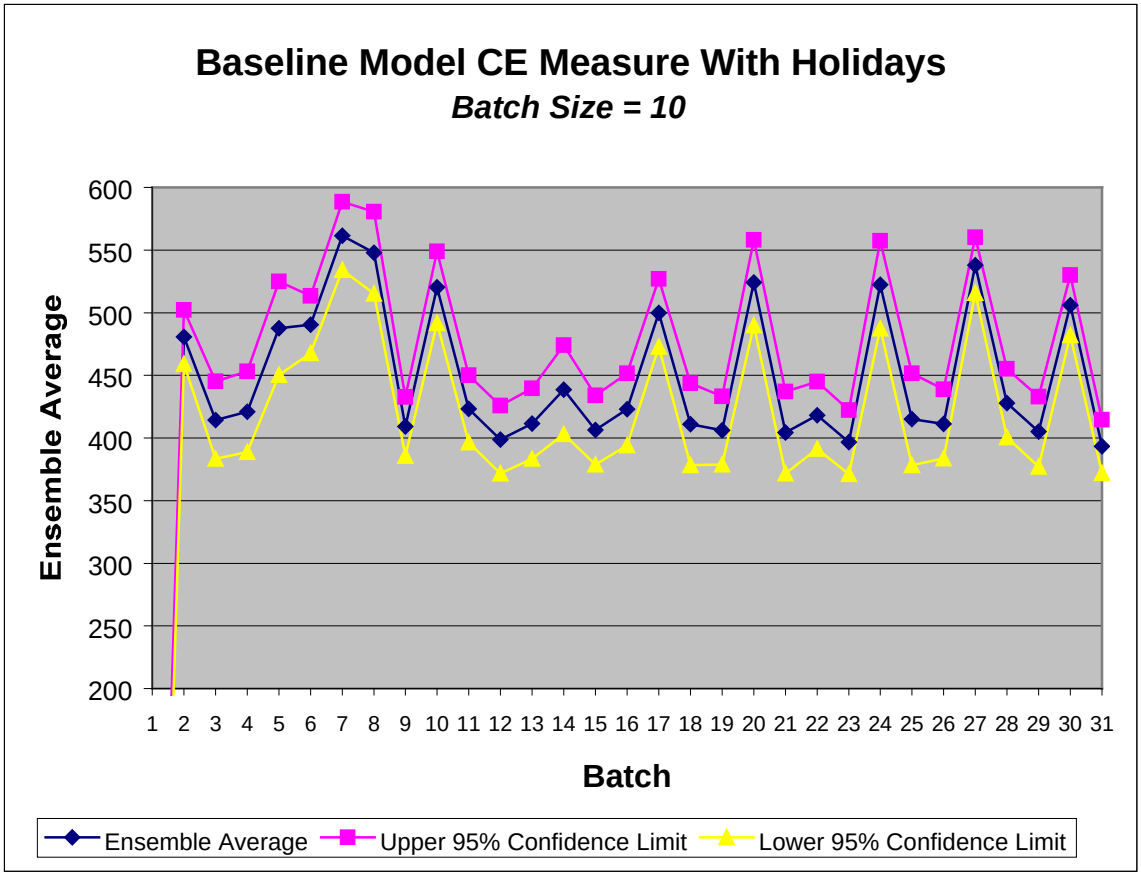


The above figure represents the *batched* daily outputs of the CE measure for 30 replications of the baseline model. The 95% confidence bounds on the mean of each batch are also presented. In each replication the simulated clinic is closed on the holidays listed in Table 3.1 (i.e., the boolean variable USE_HOLIDAYS is true), resulting in 315 total observations. These observations have been batched into 31 contiguous groups of size 10 (with the *last* 5 of the 315 observations discarded).

For the data represented above, the overall mean is 425.72, the minimum observed value is -315.72, the maximum observed value is 561.34, and the standard deviation is 147.45.

Holidays fall within batches 1 (Columbus Day 2002), 5 (Thanksgiving Day 2002), 6 (Christmas Day 2003), 7 (New Year's Day 2003), 8 (Martin Luther King Day 2003), 10 (President's Day 2003), 17 (Memorial Day 2003), 20 (Independence Day 2003), 24 (Labor Day 2003), 27 (Columbus Day 2003), and 30 (Thanksgiving Day 2003). Note that each of these batches (excluding the negatively-biased batch 1) has a mean exceeding 485.00.

For a more clear presentation of this data, see the ensuing figure.



The above figure represents the *batched* daily outputs of the CE measure for 30 replications of the baseline model. The 95% confidence bounds on the mean of each batch are also presented. In each replication the simulated clinic is closed on the holidays listed in Table 3.1 (i.e., the boolean variable USE_HOLIDAYS is true), resulting in 315 total observations. These observations have been batched into 31 contiguous groups of size 10 (with the *last* 5 of the 315 observations discarded).

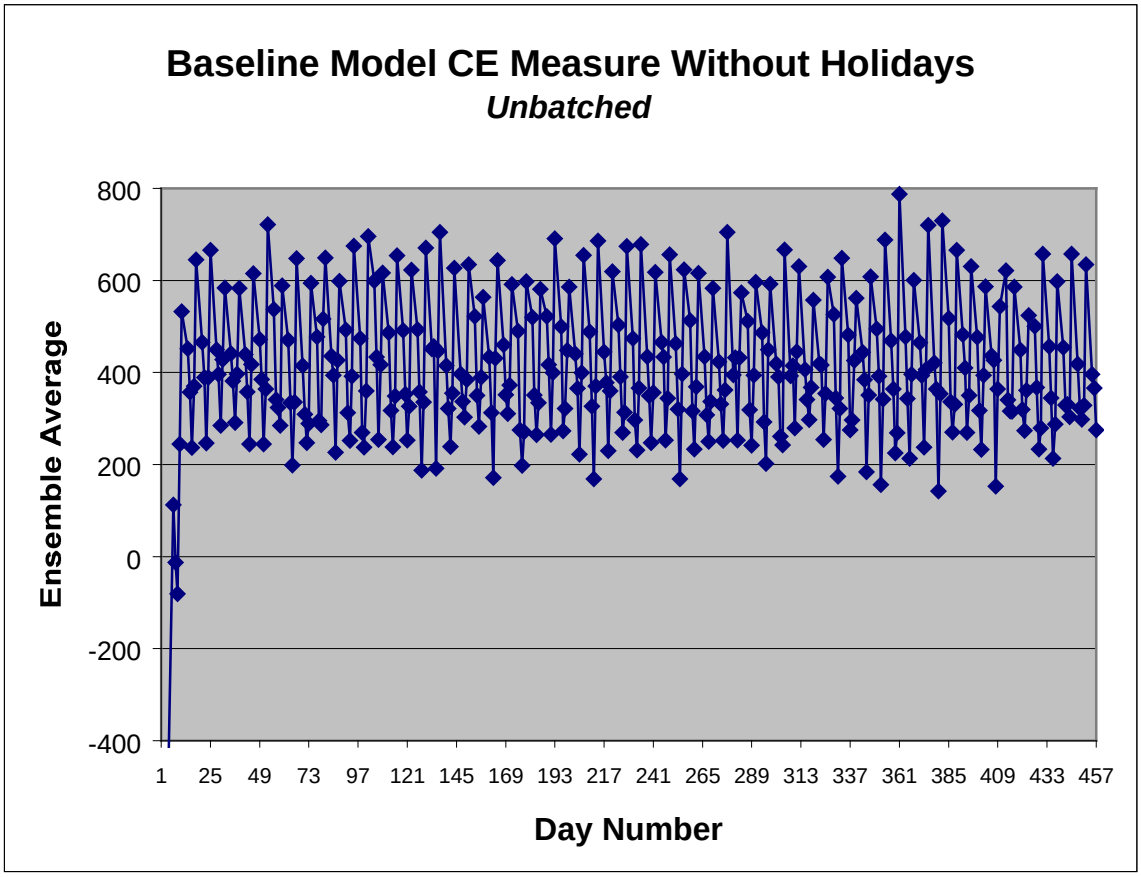
For the data represented above, the overall mean is 425.72, the minimum observed value is -315.72, the maximum observed value is 561.34, and the standard deviation is 147.45.

Holidays fall within batches 1 (Columbus Day 2002), 5 (Thanksgiving Day 2002), 6 (Christmas Day 2003), 7 (New Year's Day 2003), 8 (Martin Luther King Day 2003), 10 (President's Day 2003), 17 (Memorial Day 2003), 20 (Independence Day 2003), 24 (Labor Day 2003), 27 (Columbus Day 2003), and 30 (Thanksgiving Day 2003). Note that each of these batches (excluding the negatively-biased batch 1) has a mean exceeding 485.00.

Note that this figure presents the same data as the previous figure, except that the CE ensemble average scale is reduced for a more clear presentation.

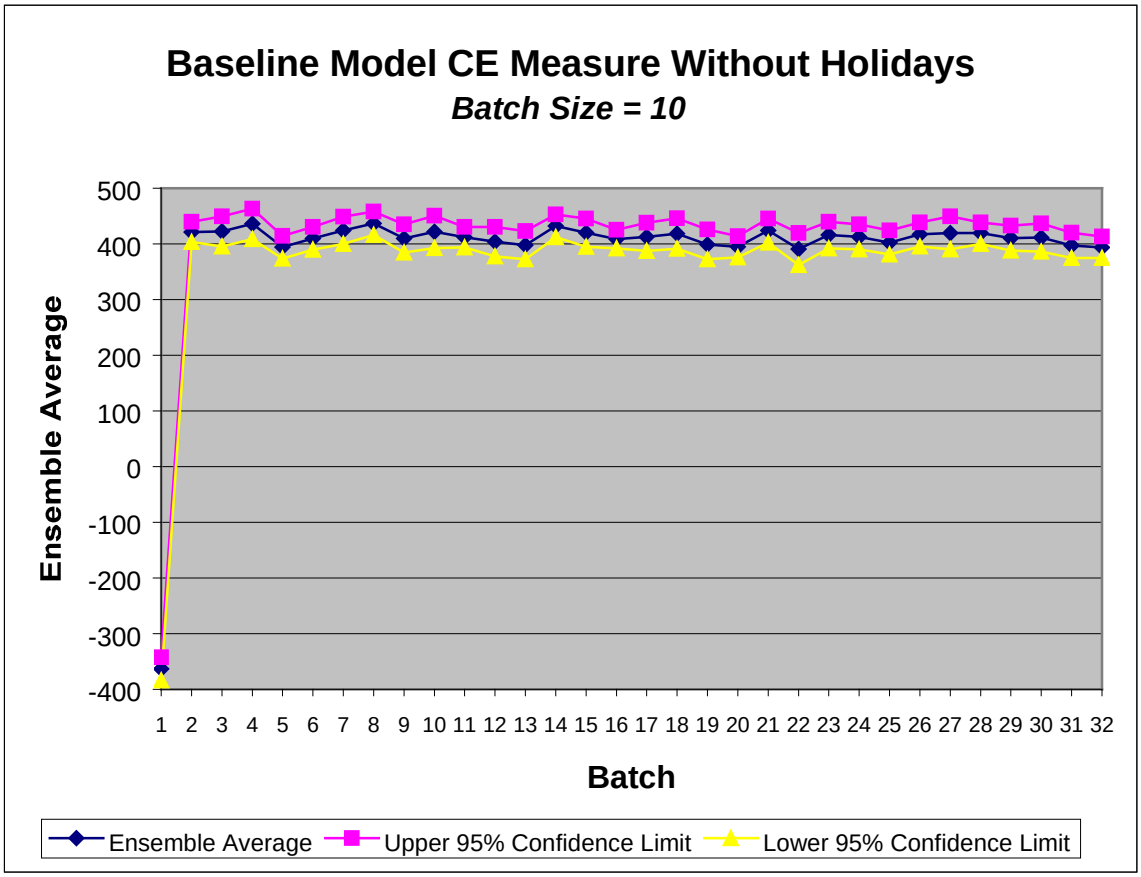
Appendix C

CE Graphs for Baseline Model Without Holidays



The above figure represents the *unbatched* daily outputs of the CE measure for 30 replications of the baseline model. Holidays are *not* used in these replications (i.e., the boolean variable USE_HOLIDAYS is false), resulting in 327 total observations.

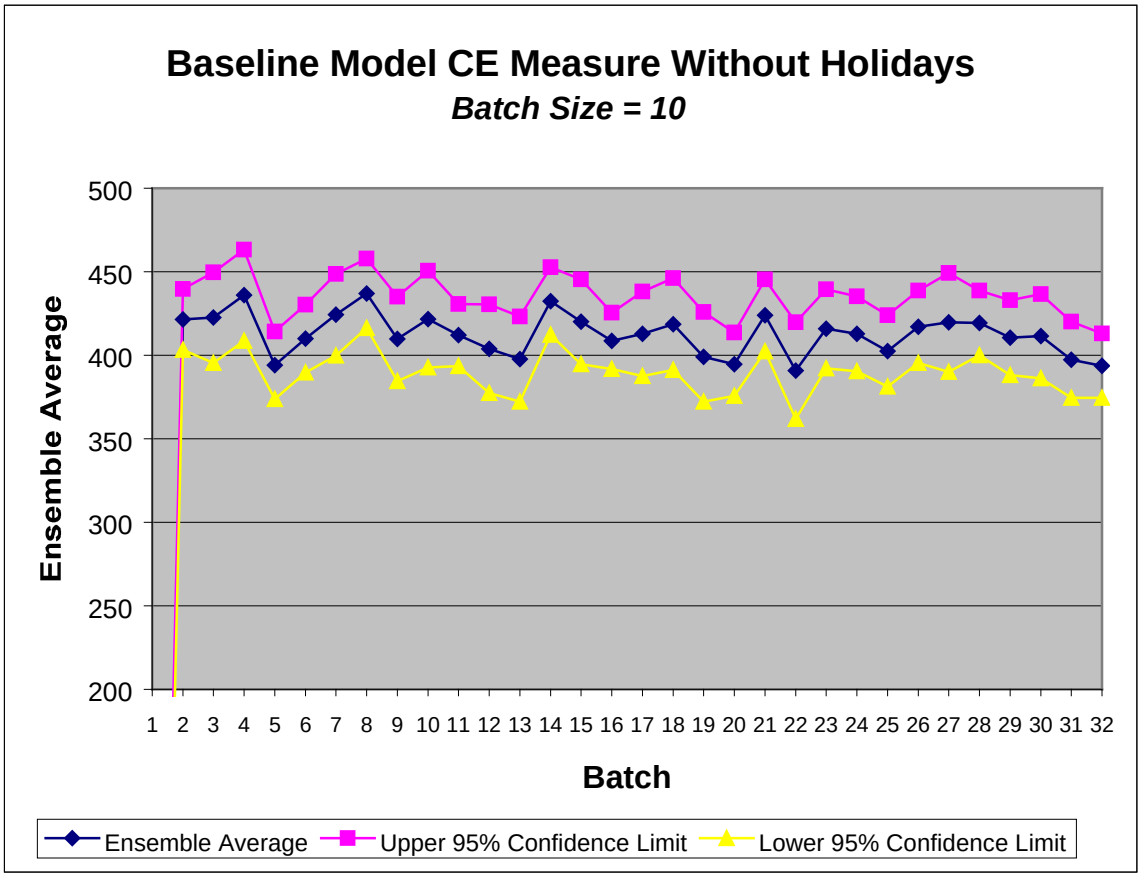
For the data represented above, the overall mean is 388.07, the minimum observed value is -1569.70, the maximum observed value is 787.44, and the standard deviation is 233.20.



The above figure represents the *batched* daily outputs of the CE measure for 30 replications of the baseline model. The 95% confidence bounds on the mean of each batch are also presented. Holidays are *not* used in these replications (i.e., the boolean variable USE_HOLIDAYS is false), resulting in 327 total observations. These observations have been batched into 32 contiguous groups of size 10 (with the *last* 7 of the 327 observations discarded).

For the data represented above, the overall mean is 388.37, the minimum observed value is -363.44, the maximum observed value is 437.00, and the standard deviation is 137.72.

For a more clear presentation of this data, see the ensuing figure.



The above figure represents the *batched* daily outputs of the CE measure for 30 replications of the baseline model. The 95% confidence bounds on the mean of each batch are also presented. Holidays are *not* used in these replications (i.e., the boolean variable USE_HOLIDAYS is false), resulting in 327 total observations. These observations have been batched into 32 contiguous groups of size 10 (with the *last* 7 of the 327 observations discarded).

For the data represented above, the overall mean is 388.37, the minimum observed value is -363.44, the maximum observed value is 437.00, and the standard deviation is 137.72.

Note that this figure presents the same data as the previous figure, except that the CE ensemble average scale is reduced for a more clear presentation.

Appendix D

C++ Code for Yücesan Initialization Bias Test

```
/*              ******************************************
                *                                        *
                *      Yücesan Test for Initialization Bias      *
                *                                        *
                ******************************************

This program tests the batched output across 30 replications of the clinic model.  For each
replication, the first seven observations have been discarded and the remaining 320
observations have been grouped into batches of size 10.  The values making up the array
B, then, are the means across all replications for each of the 32 batches.  Note that this
data has already been tested for negligible autocorrelation.
*/

#include<iostream.h>
#include<math.h>
#include<stdio.h>
#include<stdlib.h>

FILE *output;

// Main Algorithm
int main()
{
        // Define and initialize variables
        unsigned int    seed=0              /* random number seed */;

        int             k=1,                /* iteration number */
                        num_batches=0,      /* total number of batches in array B */
                        del_size=0,         /* number of initial batches to ignore */
                        b=0,                /* number of batches to be examined */
                        G1_size=0,          /* size of group 1 of array Z */
                        G2_size=0,          /* size of group 2 of array Z */
                        s=0,                /* batch number to be shuffled */
                        shuffle=0,          /* number of shuffles counter */
                        m=0,                /* for counter */
                        j=0;                /* for counter */

        double          alpha=0,            /* type I error level */
                        sig_level=0,        /* computed significance level */
                        actual_stat=0,      /* unshuffled data test statistic */
                        pseudo_stat=0,      /* shuffled data pseudo test statistic */
                        G1_sum=0,           /* sum of elements of group 1 of array Z */
                        G1_mean=0,          /* sample mean for group 1 of array Z */
                        G2_sum=0,           /* sum of elements of group 2 of array Z */
                        G2_mean=0,          /* sample mean for group 2 of array Z */
```

```
                G1_Sh_sum=0,        /* sum of shuffled group 1 */
                G1_Sh_mean=0,       /* sample mean for shuffled group 1 */
                G2_Sh_sum=0,        /* sum of shuffled group 2 */
                G2_Sh_mean=0,       /* sample mean for shuffled group 2 */
                temp=0,             /* temporary storage for shuffling */
                urv=0,              /* uniform random variate */
                NS=0,               /* number of shuffles per iteration */
                nge=0;              /* pseudo larger than actual counter */

double          Z[33],              /* array of used batch means from array B */
                Z_Sh[33];           /* shuffled array of batch means */

double          B[33] =         {    0.000000000000,
                                   393.862769106667,
                                   431.099614746667,
                                   415.547464126667,
                                   416.421696560000,
                                   389.693064636667,
                                   430.360267013333,
                                   438.956055270000,
                                   417.595392610000,
                                   409.253025096667,
                                   414.575617663333,
                                   404.536104916667,
                                   412.353819536667,
                                   412.275716836667,
                                   424.732867180000,
                                   414.695378786667,
                                   413.218980550000,
                                   420.252395773333,
                                   403.398919706667,
                                   390.318323960000,
                                   422.401272520000,
                                   408.356414513333,
                                   411.543668523333,
                                   402.139179086667,
                                   402.252306420000,
                                   409.041808906667,
                                   418.277278163333,
                                   426.215523140000,
                                   416.622775693333,
                                   418.150857433333,
                                   392.949511696667,
                                   395.161910490000,
                                   399.901713143333};
```

```
// Collect initial data from user
cout << "\nInput the total number of batches to examine: ";
cin >> num_batches;
cout << "\nInput the number of batches to delete: ";
cin >> del_size;
cout << "\nInput the number of shuffles (NS) for the randomization test: ";
cin >> NS;
cout << "\nInput the Type I error level (alpha): ";
cin >> alpha;
cout << "\nInput the initial seed for the random number generator: ";
cin >> seed;

// Seed the pseudorandom number stream
srand(seed);

// Calculate the actual number of batches to be used
b = num_batches - del_size;

// Open file and write header data
output=fopen("yucesanout.txt","a");
fprintf(output,"\n~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~");
fprintf(output,"\nTotal Batches = %u\nNumber Deleted = %u",
num_batches,del_size);
fprintf(output,"\nBatches Examined = %u\nShuffles per Iteration = %.0f",b,NS);
fprintf(output,"\nAlpha = %.6f\nInitial PRNG Seed = %u",alpha,seed);

// Fill Z and shuffled Z from B
for (m=1;m<=b;++m)
{
        Z[m] = B[del_size+m];
        Z_Sh[m] = Z[m];
}

// Find initial G1 mean
G1_sum = Z[1];
G1_size = 1;
G1_mean = G1_sum/G1_size;

// Find initial G2 mean
for (m=G1_size+1;m<=b;++m)
        G2_sum += Z[m];
G2_size = b-G1_size;
G2_mean = G2_sum/G2_size;
```

```
do //while k<b
{
	// Begin Randomization Test
	nge = 0;
	shuffle = 1;
	actual_stat = fabs(G1_mean-G2_mean);

	do //while shuffle <=NS
	{
		// Completely shuffle the data set
		for (j=1;j<=b-1;++j)
		{
			urv=(double)rand()/RAND_MAX;
			s=urv*(b-j+1)+j;
			if (urv == 1.0) s = b;
			if (s>32)
				fprintf(output,"\n ERROR! - s>32 - Consult Code");
			if (s<1)
				fprintf(output,"\n ERROR! - s<1 - Consult Code");
			temp=Z_Sh[s];
			Z_Sh[s]=Z_Sh[j];
			Z_Sh[j]=temp;
		}

		// Find the shuffled means and calculate pseudo stat
		G1_Sh_sum = 0.0;
		for (j=1;j<=G1_size;++j)
			G1_Sh_sum +=Z_Sh[j];
		G1_Sh_mean=G1_Sh_sum/G1_size;

		G2_Sh_sum = 0.0;
		for (j=G1_size+1;j<=b;++j)
			G2_Sh_sum +=Z_Sh[j];
		G2_Sh_mean=G2_Sh_sum/G2_size;

		pseudo_stat = fabs(G1_Sh_mean-G2_Sh_mean);

		// Increment nge if pseudo stat >= actual stat
		if (pseudo_stat >= actual_stat)
			++nge;

		++shuffle;

		} while (shuffle <= NS);
```

```
                // Calculate the significance level
                sig_level = (nge+1)/(NS+1);

                // Write data for current iteration to file
                fprintf(output,"\nFor Iteration (k) %u:",k);
                fprintf(output,"\n\tThe actual test statistic is: %.6f",actual_stat);
                fprintf(output,"\n\tThe significance level (nge+1/NS+1) is: %.6f",
                sig_level);

                // Break out of the do loop if H0 is not rejected
                if (sig_level > alpha)
                        break;

                // End Randomization Test

                // H0 rejected - Alter batches
                ++G1_size;
                G1_sum += Z[G1_size];
                G1_mean = G1_sum/G1_size;

                G2_sum -= Z[G1_size];
                --G2_size;
                G2_mean = G2_sum/G2_size;

                ++k;

        } while (k<b);

        //Write concluding information to the screen
        cout << "\n\nThe terminating iteration is: " << k;
        cout << "\nThe significance level is: " << sig_level;
        cout << "\nSee the file yucesanout.txt for solution details.\n\n";

        return 0;
}
```

Appendix E

Fractional Factorial Design

Factor	Description	-	+
1	Number of PA/NPs	2	3
2	Number of Nurses	2	3
3	Number of Medical Assistants	2	3
4	Number of Check-In Rooms	2	4
5	Number of Exam Rooms	4	8
6	Number of Specialty Rooms	1	2

Design Point	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Mean CE Response
1	-	-	-	-	-	-	261.015
4	+	+	-	-	-	-	-30.598
6	+	-	+	-	-	-	22.795
7	-	+	+	-	-	-	38.594
10	+	-	-	+	-	-	124.242
11	-	+	-	+	-	-	134.199
13	-	-	+	+	-	-	180.288
16	+	+	+	+	-	-	-125.260
18	+	-	-	-	+	-	144.024
19	-	+	-	-	+	-	171.582
21	-	-	+	-	+	-	223.129
24	+	+	+	-	+	-	-112.067
25	-	-	-	+	+	-	314.273
28	+	+	-	+	+	-	-9.227
30	+	-	+	+	+	-	48.730
31	-	+	+	+	+	-	75.348
34	+	-	-	-	-	+	18.954
35	-	+	-	-	-	+	34.533
37	-	-	+	-	-	+	79.192
40	+	+	+	-	-	+	-227.526
41	-	-	-	+	-	+	157.718
44	+	+	-	+	-	+	-130.298
46	+	-	+	+	-	+	-75.662
47	-	+	+	+	-	+	-59.698
49	-	-	-	-	+	+	211.605
52	+	+	-	-	+	+	-109.515
54	+	-	+	-	+	+	-54.031
55	-	+	+	-	+	+	-26.475
58	+	-	-	+	+	+	45.097
59	-	+	-	+	+	+	72.659
61	-	-	+	+	+	+	123.860
64	+	+	+	+	+	+	-208.257

Appendix F

2^k Factorial Designs

2^k Designs – Set 1

Factor	Description	-	+
1	Number of PA/NPs	1	2
2	Number of Nurses	0	2
3	Number of Medical Assistants	0	2
4	Number of Check-In Rooms	2	2
5	Number of Exam Rooms	8	12
6	Number of Specialty Rooms	1	1

Design Point	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Mean CE Response
1	-	-	-	Fixed	-	Fixed	-7546.57
2	+	-	-	Fixed	-	Fixed	-1678.98
3	-	+	-	Fixed	-	Fixed	-72.69
4	+	+	-	Fixed	-	Fixed	381.93
5	-	-	+	Fixed	-	Fixed	-2736.03
6	+	-	+	Fixed	-	Fixed	151.71
7	-	+	+	Fixed	-	Fixed	274.60
8	+	+	+	Fixed	-	Fixed	312.70
9	-	-	-	Fixed	+	Fixed	-7293.17
10	+	-	-	Fixed	+	Fixed	-1416.63
11	-	+	-	Fixed	+	Fixed	-59.67
12	+	+	-	Fixed	+	Fixed	318.88
13	-	-	+	Fixed	+	Fixed	-2654.64
14	+	-	+	Fixed	+	Fixed	125.19
15	-	+	+	Fixed	+	Fixed	225.33
16	+	+	+	Fixed	+	Fixed	235.40

Main Effects	
e_1	2286.63
e_2	3083.20
e_3	1662.64
e_5	49.25

Two-Way Interactions	
e_{12}	-516.57
e_{13}	-214.42
e_{15}	-6.35
e_{23}	-385.69
e_{25}	-23.35
e_{35}	-16.80

Three-Way Interactions	
e_{123}	165.36
e_{125}	-0.16
e_{135}	-2.15
e_{235}	12.01

2^k Designs – Set 2

Factor	Description	-	+
1	Number of PA/NPs	2	3
2	Number of Nurses	1	2
3	Number of Medical Assistants	0	1
4	Number of Check-In Rooms	2	2
5	Number of Exam Rooms	10	14
6	Number of Specialty Rooms	1	1

Design Point	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Mean CE Response
1	-	-	-	Fixed	-	Fixed	92.44
2	+	-	-	Fixed	-	Fixed	333.31
3	-	+	-	Fixed	-	Fixed	355.78
4	+	+	-	Fixed	-	Fixed	274.69
5	-	-	+	Fixed	-	Fixed	370.60
6	+	-	+	Fixed	-	Fixed	323.93
7	-	+	+	Fixed	-	Fixed	350.68
8	+	+	+	Fixed	-	Fixed	199.41
9	-	-	-	Fixed	+	Fixed	44.68
10	+	-	-	Fixed	+	Fixed	261.23
11	-	+	-	Fixed	+	Fixed	281.09
12	+	+	-	Fixed	+	Fixed	196.44
13	-	-	+	Fixed	+	Fixed	297.06
14	+	-	+	Fixed	+	Fixed	246.47
15	-	+	+	Fixed	+	Fixed	273.53
16	+	+	+	Fixed	+	Fixed	122.27

Main Effects	
e_1	-13.51
e_2	10.52
e_3	43.04
e_5	-72.26

Two-Way Interactions	
e_{12}	-25.89
e_{13}	-21.61
e_{15}	-0.99
e_{23}	-20.89
e_{25}	-1.14
e_{35}	-1.02

Three-Way Interactions	
e_{123}	13.06
e_{125}	0.77
e_{135}	0.75
e_{235}	0.93

2^k Designs – Set 3

Factor	Description	-	+
1	Number of PA/NPs	2	3
2	Number of Nurses	2	3
3	Number of Medical Assistants	1	2
4	Number of Check-In Rooms	2	2
5	Number of Exam Rooms	6	10
6	Number of Specialty Rooms	1	1

Design Point	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Mean CE Response
1	-	-	-	Fixed	-	Fixed	402.75
2	+	-	-	Fixed	-	Fixed	263.56
3	-	+	-	Fixed	-	Fixed	286.87
4	+	+	-	Fixed	-	Fixed	112.71
5	-	-	+	Fixed	-	Fixed	334.21
6	+	-	+	Fixed	-	Fixed	172.28
7	-	+	+	Fixed	-	Fixed	197.12
8	+	+	+	Fixed	-	Fixed	15.17
9	-	-	-	Fixed	+	Fixed	350.68
10	+	-	-	Fixed	+	Fixed	199.41
11	-	+	-	Fixed	+	Fixed	226.34
12	+	+	-	Fixed	+	Fixed	48.75
13	-	-	+	Fixed	+	Fixed	274.75
14	+	-	+	Fixed	+	Fixed	104.89
15	-	+	+	Fixed	+	Fixed	133.65
16	+	+	+	Fixed	+	Fixed	-48.91

Main Effects	
e_1	-167.31
e_2	-141.35
e_3	-88.49
e_5	-61.89

Two-Way Interactions	
e_{12}	-2.94
e_{13}	-1.69
e_{15}	-0.75
e_{23}	-1.48
e_{25}	-0.28
e_{35}	-0.43

Three-Way Interactions	
e_{123}	0.89
e_{125}	0.50
e_{135}	0.22
e_{235}	0.24

2^k Designs – Set 4

Factor	Description	-	+
1	Number of PA/NPs	2	3
2	Number of Nurses	1	2
3	Number of Medical Assistants	0	1
4	Number of Check-In Rooms	2	2
5	Number of Exam Rooms	5	7
6	Number of Specialty Rooms	1	1

Design Point	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Mean CE Response
1	-	-	-	Fixed	-	Fixed	-14.09
2	+	-	-	Fixed	-	Fixed	341.69
3	-	+	-	Fixed	-	Fixed	351.38
4	+	+	-	Fixed	-	Fixed	317.35
5	-	-	+	Fixed	-	Fixed	351.54
6	+	-	+	Fixed	-	Fixed	366.72
7	-	+	+	Fixed	-	Fixed	377.43
8	+	+	+	Fixed	-	Fixed	252.00
9	-	-	-	Fixed	+	Fixed	70.83
10	+	-	-	Fixed	+	Fixed	375.28
11	-	+	-	Fixed	+	Fixed	386.21
12	+	+	-	Fixed	+	Fixed	326.07
13	-	-	+	Fixed	+	Fixed	395.41
14	+	-	+	Fixed	+	Fixed	375.74
15	-	+	+	Fixed	+	Fixed	400.13
16	+	+	+	Fixed	+	Fixed	254.69

Main Effects	
e_1	36.34
e_2	50.27
e_3	77.37
e_5	30.04

Two-Way Interactions	
e_{12}	-31.90
e_{13}	-26.29
e_{15}	-4.13
e_{23}	-25.39
e_{25}	-3.20
e_{35}	-2.62

Three-Way Interactions	
e_{123}	15.25
e_{125}	1.25
e_{135}	0.71
e_{235}	1.48

2^k Designs – Set 5

Factor	Description	-	+
1	Number of PA/NPs	2	3
2	Number of Nurses	1	2
3	Number of Medical Assistants	0	1
4	Number of Check-In Rooms	2	2
5	Number of Exam Rooms	6	8
6	Number of Specialty Rooms	1	1

Design Point	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Mean CE Response
1	-	-	-	Fixed	-	Fixed	36.67
2	+	-	-	Fixed	-	Fixed	370.80
3	-	+	-	Fixed	-	Fixed	384.19
4	+	+	-	Fixed	-	Fixed	334.02
5	-	-	+	Fixed	-	Fixed	385.19
6	+	-	+	Fixed	-	Fixed	381.14
7	-	+	+	Fixed	-	Fixed	402.75
8	+	+	+	Fixed	-	Fixed	263.56
9	-	-	-	Fixed	+	Fixed	86.17
10	+	-	-	Fixed	+	Fixed	367.09
11	-	+	-	Fixed	+	Fixed	381.93
12	+	+	-	Fixed	+	Fixed	310.74
13	-	-	+	Fixed	+	Fixed	391.04
14	+	-	+	Fixed	+	Fixed	359.95
15	-	+	+	Fixed	+	Fixed	386.06
16	+	+	+	Fixed	+	Fixed	237.37

Main Effects	
e_1	21.33
e_2	40.32
e_3	66.93
e_5	-4.74

Two-Way Interactions	
e_{12}	-30.91
e_{13}	-25.52
e_{15}	-3.46
e_{23}	-24.30
e_{25}	-3.09
e_{35}	-2.45

Three-Way Interactions	
e_{123}	15.12
e_{125}	1.55
e_{135}	1.18
e_{235}	1.37

2^k Designs – Set 6

Factor	Description	-	+
1	Number of PA/NPs	2	3
2	Number of Nurses	1	2
3	Number of Medical Assistants	0	1
4	Number of Check-In Rooms	2	2
5	Number of Exam Rooms	9	10
6	Number of Specialty Rooms	1	1

Design Point	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Mean CE Response
1	-	-	-	Fixed	-	Fixed	91.54
2	+	-	-	Fixed	-	Fixed	349.34
3	-	+	-	Fixed	-	Fixed	370.34
4	+	+	-	Fixed	-	Fixed	293.69
5	-	-	+	Fixed	-	Fixed	384.22
6	+	-	+	Fixed	-	Fixed	342.88
7	-	+	+	Fixed	-	Fixed	367.88
8	+	+	+	Fixed	-	Fixed	219.24
9	-	-	-	Fixed	+	Fixed	92.44
10	+	-	-	Fixed	+	Fixed	333.31
11	-	+	-	Fixed	+	Fixed	355.78
12	+	+	-	Fixed	+	Fixed	274.69
13	-	-	+	Fixed	+	Fixed	370.60
14	+	-	+	Fixed	+	Fixed	323.93
15	-	+	+	Fixed	+	Fixed	350.68
16	+	+	+	Fixed	+	Fixed	199.41

Main Effects	
e_1	-5.87
e_2	17.93
e_3	49.72
e_5	-14.79

Two-Way Interactions	
e_{12}	-27.13
e_{13}	-22.78
e_{15}	0.92
e_{23}	-22.26
e_{25}	-0.72
e_{35}	-0.65

Three-Way Interactions	
e_{123}	13.89
e_{125}	0.47
e_{135}	0.42
e_{235}	0.44

Ad Hoc Designs

Factor	Description
1	Number of PA/NPs
2	Number of Nurses
3	Number of Medical Assistants
4	Number of Check-In Rooms
5	Number of Exam Rooms
6	Number of Specialty Rooms

Design Point	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Mean CE Response
1	1	1	4	2	6	1	-93.61
2	2	0	4	2	6	1	47.89
3	4	0	0	2	6	1	330.44
4	4	0	1	2	6	1	345.56
5	4	1	1	2	6	1	229.06
6	5	0	0	2	6	1	265.59
7	2	1	3	2	6	1	342.36
8	2	1	4	2	6	1	253.70
9	2	2	0	2	11	1	336.09
10	2	1	1	2	11	1	354.60
11	3	1	1	2	11	1	304.20
12	2	2	1	2	11	1	331.98

VITA

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