2006

Multi-criteria decision making in outpatient scheduling

Jana Iezzi
University of South Florida

Multi-Criteria Decision Making in Outpatient Scheduling

by

Jana Iezzi

A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Science in Engineering Management
Department of Industrial and Management Systems Engineering
College of Engineering
University of South Florida

Major Professor: José L. Zayas-Castro, Ph.D.
Michael Weng, Ph.D.
Kingsley Reeves, Ph.D.
Grisselle Centeno, Ph.D.

Date of Approval:
October 30, 2006

Keywords: healthcare, clinic, waiting time, eigenvector method, simulation

Table of Contents

List of Tables

List of Figures

Multi-Criteria Decision Making in Outpatient Scheduling

Jana Iezzi

ABSTRACT

The healthcare industry has found itself in need of improvement, both financially and with respect to patient satisfaction. Hospital ambulatory patients are seen in outpatient departments (OPDs) located in the hospital. 83.3 million visits were made to these departments in 2002. A survey of outpatients listed affordability, waiting time and coordination of care as their measures of quality. Many sources of patient waiting time exist including: poor coordination of information, inefficient scheduling, inaccurate time estimation and others. Well-designed and executed patient scheduling has the potential to remedy some of these problems.

To properly schedule patients, variability in demand must be addressed. Patients may cancel appointments, arrive late and arrive without appointments. Therefore, daily decisions must be made to handle these conditions. We address this problem based on a Multi-attribute Decision Making (MADM) approach. Decision models are developed using the Simple Additive Weighting (SAW) method to address scheduling decisions for late-arrival and walk-in patients and the operational decision of calling back patients from the waiting room.

The models are developed as part of a case study at H. Lee Moffitt Cancer Center. The models are tested in a single-clinic computer simulation against the current clinic

system decision process with respect to various performance measures: waiting time, number of patients seen, clinic close time, and room and practitioner utilization.

The proposed decision models (PPM and AAM) successfully made walk-in and late patient scheduling decisions as well as modified the sequence in which patients were called back. When there was no reduction in number of patients, our models performed the same as the current system. The contributions of this research include identifying, defining and weighting of relevant decision making criteria at H. Lee Moffitt. Our decision models guaranteed all of the defined criteria are included every time a walk-in or late patient decision must be made. Based on the findings, implementation of the PPM and AAM with no reduction in number of patients would improve scheduling and operational decisions while not affecting clinic output measures.

Using criteria to restrict the number of late and walk-in patients, on average, the clinic closed between 36.20 minutes and 47.95 minutes earlier. Waiting time was also discussed. However, practitioner and room utilization suffered. The tradeoff among number of patients seen, resource utilization, waiting time and clinic close time should be considered but cannot be fully assessed solely on the information gathered in this research.

As a case study of H. Lee Moffitt Cancer Center, the decision models successfully incorporated all relevant patient criteria without adversely affecting the clinic system. Future research is needed to better understand what factors will impact system measures and expand the decision models to other outpatient clinic settings.

Chapter One

Introduction

The United States healthcare industry, consisting of almost 5,800 hospitals in 2002, is a complex industry utilizing a considerable amount of resources. In that same year, the US national healthcare expenditures totaled more than $1.5 trillion. This was a 9.3% increase from 2001. The US allocates a larger portion of its gross domestic product (GDP) to health than any other major industrialized country; 14.9% of the GDP was spent on health in 2002. Of the $1.5 trillion spent that year, 31% was hospital care expenditures and 22% physician services. Community hospital expenses increased at an average annual rate of 8% between 2000 and 2002 (Health, United States, 2004).

There are a variety of methods for providing healthcare services in the US, of which ambulatory medical care is dominant. Ambulatory care is medical services provided as an outpatient. Services can include diagnosis, treatment and rehabilitation. Hospital ambulatory patients are seen in outpatient departments (OPDs) and represent 9% of all ambulatory care in the US. This is a substantial amount considering 83.3 million visits were made to hospital OPDs in 2002. Clinics are a type of OPD where ambulatory medical care is provided under the supervision of a physician. Clinics providing only ancillary services, such as radiology, are not included in the OPD survey (Hing and Middleton, 2004).

OPD visits have multiple characteristics, making them complicated in nature. The provider who sees the patient, the type of visit, continuity of care and the continued treatment of patients over time are all traits. The majority of patients will see a physician (i.e., staff physician, resident/intern or other physician) at their visit, approximately 80.4%. However, the number of visits to residents/interns decreased by half between 1992 and 2002. This may be attributed to the 47% increase in OPD visits involving midlevel providers (physician assistants or nurse practitioners) (Hing and Middleton, 2004). Healthcare services now have a mixture of providers, also referred to as practitioners, to coordinate for patient visits.

OPD visits may be classified in two ways: episode of care and the type of visit. The episode of care distinguishes whether the patient has an initial or follow-up visit. Injury-related, diagnostic and screening, counseling/education and medical therapy are all types of visits for which a patient may be seen (Hing and Middleton, 2004). Both the episode of care and the visit type contribute to the variability in healthcare service time.

Another contributing factor to OPD service is continuity of care. Continuity of care is defined as follows (Hing and Middleton, 2004).

“A goal of healthcare achieved through an interdisciplinary process involving patients, families, healthcare professionals and providers in the management of a coordinated plan of care. Based on the changing needs and available resources, the process optimizes outcomes in the health status of patients. It may involve professionals from many different disciplines within multiple systems”.

OPDs must operate within a hospital system, coordinating time and resources to provide quality care to patients. The dynamics of a hospital system add another level of complexity to OPD services.

Healthcare providers often treat a patient recurrently. OPDs assess the need for continued care after each visit. The patient may be asked to return to the same OPD or be referred to another. In 2002, 63.3 % of all OPD visits were told to return by appointment and 12.7% referred to another physician or clinic. It is possible for one OPD visit to have multiple follow-up options (Hing and Middleton, 2004). The scheduling of patient visits is another difficulty faced by healthcare services.

In addition to tackling the preexisting difficulties faced by healthcare services (variability of services, coordination of multiple resources etc.), the healthcare industry is under pressure for improvement. These pressures arise from two areas: financial necessity and patient satisfaction. Hospitals that are unable to make their OPDs more cost-effective are finding themselves in a financially undesirable position. Healthcare services need to reduce costs for their patients and improve quality (Cayirli and Veral 2003, Rohleder and Klassen 2002). Rising healthcare costs and dissatisfaction with quality has made productivity improvements critical to survival in this industry (Ho and Lau, 1992). The issue of quality is important to consider from the patient perspective. Patients are the customers of healthcare services and their satisfaction is also vital to success. Patients listed affordability, waiting time and coordination of care as measures of quality (Sofaer and Firminger, 2005). Waiting time in particular is a common complaint among patients. A lack of coordination exists between the scheduled appointment time and the time a patient is actually seen by the provider. Patient waiting time and waiting room congestion are two elements of quality, which can assess the appointment time and time called to see the provider discrepancy (Robinson and Chen 2003, Cayirli and Veral 2003).

Many sources of patient waiting time exist. It can be caused by poor coordination of information, inefficient scheduling of resources, inaccurate time estimation or others. Well-designed and executed patient scheduling has the potential to remedy these problems. A well-designed patient schedule is a necessary start, but is not enough to effectively see patients and utilize resources. Since clinic patients cancel appointments, arrive late and arrive without appointments, daily decisions must be made to handle these conditions. Much work has been done in the area of schedule construction, which is explained further in Chapter 2. This research, however, addresses scheduling operations. Our goal is to accommodate variable patient demand and conditions, allowing patients to be seen as close to appointment time as possible. We suggest two models for operational decisions to improve scheduling, a patient priority and a scheduling assignment model. Establishing patient priority has been explored to some extent in the literature. Three levels of priority are assigned in Rising, Baron and Averill (1973) to emergency, previously scheduled and walk-in patients, listed in decreasing order. Our work is more extensive, considering key factors that influence patient priority and the relative importance of each. The appointment assignment model addresses late-arrival and walk-in patient same-day appointment assignments. This is different than the patient scheduling literature, which typically schedules all patients and in advance. Both models are dynamic, changing with the conditions of the system. Our models are explained further in the next section.

1.1 Patient Priority and Appointment Assignment Models for Outpatient Scheduling Decisions

We propose two models, a Patient Priority Model (PPM) and an Appointment Assignment Model (AAM), designed to help outpatient clinic staff make the best same-day patient scheduling decisions by using a score. Same-day scheduling is the scheduling of patients, who do not have a preexisting appointment that day or have missed his/her appointment. Specifically, the following two scenarios are addressed.

At a given point in time, there are patients waiting to be seen in a clinic. Changes occur to the existing state of the clinic waiting room under two conditions:

1. A walk-in or late arrival patient arrives at the clinic. A decision must be made as to whether or not the patient can be accepted into the clinic that day. If the patient is accepted, then an approximate time for the patient to be seen by the practitioner must be assigned. This time is referred to as his / her appointment time. If the patient is not accepted, they are sent home.
2. A practitioner becomes available. A decision must be made as to which waiting patient is seen next. In this research, practitioner refers to those individuals with whom patients schedule appointments (e.g., medical doctor, surgeon, nurse practitioner etc.).

The models consider factors found to influence routine patient scheduling decisions in outpatient clinics. Staff interviews and patient shadowing is used to determine the factors. This is a Multi-Attribute Decision Making problem, a sub-set of Multi-Criteria Decision Making, which is associated with multiple attributes, also referred to as goals or decision criteria (Triantaphyllou, 2000).

Relative weights are established for each factor through the eigenvector method, used in the Analytic Hierarchy Process. Relative values of each factor are also incorporated. The weights and values are used to determine a priority score for each patient at a given point in time in the PPM, while a similar score is used to select an appointment assignment time in the AAM.

In this research, we will assume deterministic data and a single decision maker (DM). Decisions will be made only using the information available at that point in time. The factors are representative of an outpatient clinic within a hospital.

1.2 Research Objective

Our objective is to provide decision making models that will assist daily clinic scheduling decisions with respect to same-day scheduled patients by:

1. Data collection of the process through patient shadowing and time study
2. Identification of key decision making factors
3. Determination of factor levels
4. Administration of survey to clinic staff
5. Computation of relative weights and values for each factor
6. Validate models through a single-clinic computer simulation

The goal of our models is to effectively accommodate late-arrival and walk-in patients considering waiting time, resource utilization, overtime and the total number of patients seen each day.

1.3 Organization of Paper

The remainder of this thesis is organized in six chapters. Chapter 2 reviews the healthcare modeling and scheduling literature with an emphasis on outpatient scheduling. Multi-criteria decision making is also discussed. In Chapter 3, the problem statement and research approach is presented. Results of the relative weights and development of the models is shown in Chapter 4. Simulation logic and results are presented in Chapters 5 and 6 respectively. Conclusion and future work are discussed in Chapter 7.

Chapter Two

Literature Review

Research has been developing in all areas of healthcare including: diagnosis, treatment and operations. This thesis is concerned with the later. We will review the use of modeling techniques in the healthcare industry and then more specifically, scheduling. Decision-making and its application to healthcare is also discussed. This review will demonstrate the opportunity for decision-making techniques to improve patient scheduling.

2.1 System Modeling in Healthcare

An overview of healthcare modeling is presented in Vissers (1998a). The applications within healthcare for modeling include, but are not limited to: disease prevention, capacity planning, estimating future resource needs, appointment systems and staff scheduling. Vissers reviews healthcare on the national, regional and local level as well as from different perspectives (e.g. process-oriented).

Two popular modeling techniques in healthcare are queuing and simulation. The following examples use simulation to model a healthcare system. First, Sepulveda et al. model a cancer treatment center using ARENA (1999). The purpose of the model is to analyze and improve patient flow in an existing outpatient system and then to convert the model to a new building. In Baesler and Sepulveda (2001), the cancer treatment center work presented in Sepulveda et al. (1999) is continued. Baesler and Sepulveda (2001) explains in more depth the development of a multi-objective optimization heuristic integrated with their simulation. The methodology is presented and integrates simulation, goal programming and genetic algorithms.

Simulation has also been used to model a family practice healthcare clinic found in Swisher et al. (2001). The authors build a simulation, which included a theoretical centralized information center and a single clinic. De Angelis, Felici and Impelluso (2003) applied simulation to model another healthcare system, a transfusion center. This thesis addresses management decision-making and provides an analysis of alternatives to produce best solutions. Further review of computer simulation modeling in the healthcare industry can be found in Fone et al. (2003). Our work is based in healthcare scheduling. A review of resource and patient scheduling follows.

2.2 Resource Scheduling

The healthcare scheduling literature encompasses several areas. Resource scheduling is one area that has been pursued over the years, nurse scheduling in particular. Several authors have studied operations research, work analysis and other mathematical tools to further nurse scheduling: (Soliman 1997, Millar and Kiragu 1999, Abernathy et al. 1973, Warner and Prawda 1972, Jaumard, Semet and Vovor 1998, Ferland 2001, Miller, Pierskalla and Rath 1976 and Warner 1976). Although nurse scheduling is a highly reviewed topic, the scheduling of other resources such as emergency room physicians is also studied (Carter and Lapierre, 2001). Resource scheduling in healthcare extends beyond staff scheduling. The scheduling of beds, staff and rooms is addressed in Vissers (1998b) and Harper (2002). Various bed-reservation schemes are evaluated in Kim et al. (2000), which look at beds in an intensive care unit. Another area of healthcare scheduling is patient scheduling. The scheduling decisions addressed this research are with respect to the patients, therefore we review some of the patient scheduling literature.

2.3 Patient Scheduling

Patient scheduling still contains a range of applications. Denton and Gupta (2003) and Everett (2002), for example, address the scheduling of elective surgeries. The scheduling of patient tests is also found in the literature. The scheduling of tests involves the coordination of resources, medical conditions and the patient (Kokkotos, Ioannidis and Spyropoulos 1997). Since our case study is a cancer center clinic, our work is concentrated in outpatient clinic appointments. Outpatient appointment scheduling literature follows.

Some common themes have been found in the outpatient scheduling literature. Simulation and queuing models are frequently used. The outpatient scheduling literature reviewed in this thesis use simulation, queuing models or both in their work. Similarly, cost, throughput, resource utilization and particularly wait time are common performance criteria. The balance of physician idle time and patient wait time is repeated throughout the literature and service time and arrival patterns are often considered as sources of variation.

Different approaches can be taken to an appointment-scheduling problem. A simulation was built to model a two-room clinic (Lehaney, Clarke and Paul 1999). The authors take a soft systems approach to reduce wait time and the number of no-show patients. A more quantitative approach is used in Robeinson and Chen (2003). Their objective is to minimize the weighted sum of patient waiting time and physician idle time. A heuristic is developed that performs within 2% of the optimal policy. Random service time is considered, however the authors assume the patient schedule is known.

Brahimi and Worthington (1991) and Worthington and Brahimi (1993) evaluated the appointment system of seven “plaster check” clinics. These clinics see patients who have previously attended the Emergency Room. Time study data is gathered and a queuing model approach is used. The objective is to balance patient wait time and physician idle time. This work takes no-show patients into account and improves patient wait time by varying the patient queue at the start of the day. An additional point is made in this work, the concept of physician behavior. Due to the nature of healthcare organizations, environmental factors such as no-show patients and the number of patients per session are often addressed in outpatient scheduling research.

Ho and Lau (1992) consider 27 combinations of three environmental factors; probability of a no-show, coefficient of variation of service time and number of customers per service session. Nine scheduling rules are evaluated under these conditions. The authors tackle the cost in scheduling outpatient appointments. Their model minimizes the weighted sum of staff and patient idle time. Efficient frontiers are used to help distinguish the best rule for a given environment. The authors continued this work in Ho and Lau (1999) where they evaluated the same environments. Service quality, facility utilization and variability of service times, in addition to cost are considered. Rohleder and Klassen (2002) also use cost of idle and wait times to evaluate an appointment system. This appointment system is done as a "rolling horizon" to capture the nature of scheduling, which is typically done over a period of time. Six different demand patterns, three static and three dynamic, are generated to simulate different loads of patient demand. These demand patterns are tested with six different overloading rules, which use double booking and overtime approaches. Variability in demand have caused double booking and overtime has become a reality in many healthcare organizations, which the authors address to help clinics make the best scheduling decisions under varying conditions.

Another environmental factor of outpatient scheduling is walk-in patients. Whether critical or not, walk-in patients arrive to a clinic with no previously scheduled appointment. Rising, Baron and Averill (1973) discusses the impact of walk-in patients on scheduling. Patients are classified as controlled if they have an appointment and uncontrolled for walk-in or emergency. The authors analyze the daily arrival patterns and create a schedule to smooth demand over the days of the week and the hours of each day. This system is conceptualized as a complex queuing system and computer simulation modeling was used. The idea of a priority system is also incorporated. Three levels of priority are assigned. The highest level is assigned to emergency patients and those returning from an ancillary service. The next level is previously scheduled patients and the lowest priority is assigned to walk-in patients. Increased patient throughput resulted. Su and Shih (2003) also deals with walk-in patients at outpatient clinics. Similarly, the scheduling system is designed to lower wait times and improve patient throughput. The authors address the case of a high level of walk-in patients, more than half. Scheduling policies are evaluated to improve already scheduled inter-arrival times with a mixed registration type appointment system. Further outpatient scheduling literature can be found in Cayirili and Veral's (2003) review.

While we have found environmental factors considered in the literature, we have not found outpatient-scheduling research that addresses factors that account for the environment, patient and the external system. We have also not found dynamic patient priority and appointment assignment models to help make same-day patient scheduling decisions. Clearly, there is a research opportunity for such models. These scheduling decisions can be represented as a multi-criteria decision making problem. An introduction to multi-criteria decision making is presented in the following section.

2.4 Multi-criteria Decision Making

The consideration of multiple factors to schedule late-arrival and walk-in patients creates a cognitive and time burden for clinic staff. Therefore, a method is needed to address these factors. The problem presented in this work can be formulated as a type of Multi-criteria decision making (MCDM) problem.

MCDM is a well-established branch of decision making that may be used to analyze the way people make decisions or the way people should make decisions. Two classifications of MCDM exists, Multi-objective decision making (MODM) and Multi-attribute decision making (MADM). MODM studies problems with a continuous decision space. An example of MODM is a mathematical programming problem with multiple objective functions. MADM addresses discrete decision spaces where decision alternatives are predetermined. MCDM methods may be further classified by data type (deterministic, stochastic or fuzzy) and number of decision makers (single or group) (Triantaphyllou 2000). MADM methods are explored further.

2.5 Multi-attribute Decision Making

Although diverse, MADM problems share the following characteristics (Yoon and Hwang 1995):

1. Alternatives – a finite number of alternatives are screened, prioritized and selected and/or ranked. This term is interchangeable with “option”, “policy”, “action”, “candidate” or others.
2. Multiple attributes – multiple relevant attributes for each problem. The number of attributes is problem dependant. This term may be interchanged with “goals”, “criteria” or “factors”
3. Incommensurable units – different units of measurement among the attributes.
4. Attribute weights – most MADM methods require information about the relative importance of each attribute, usually in the form of an ordinal or cardinal scale. Weights may be assigned by the decision maker (DM) or by other methods.
5. Decision matrix – MADM problems may be expressed in a matrix format, where columns indicate attributes and rows indicate alternatives.

Yoon and Hwang (1995) have also created a taxonomy of MADM methods shown in Figure 2.1. A comparison of these methods follow in the next section.

2.5.1 Comparison of MADM Methods

The taxonomy illustrates a number of methods that address MADM problems with cardinal attribute information. These methods may, however, yield different results when applied to the same problem. Inconsistencies may be attributed to the following: use of weights, approach to selecting the 'best' solution, scaling of objectives and introduction of additional parameters. The variety of methods creates the need to select the most appropriate, for which validity is stressed as the most important criterion. Validity implies that the values of the DM are accurately reflected in the choices. Due to the variation in how preference can be expressed, there is no absolute objective standard of validity (Zanakis et al.1998). These methods have been compared in the literature with respect to various criteria.

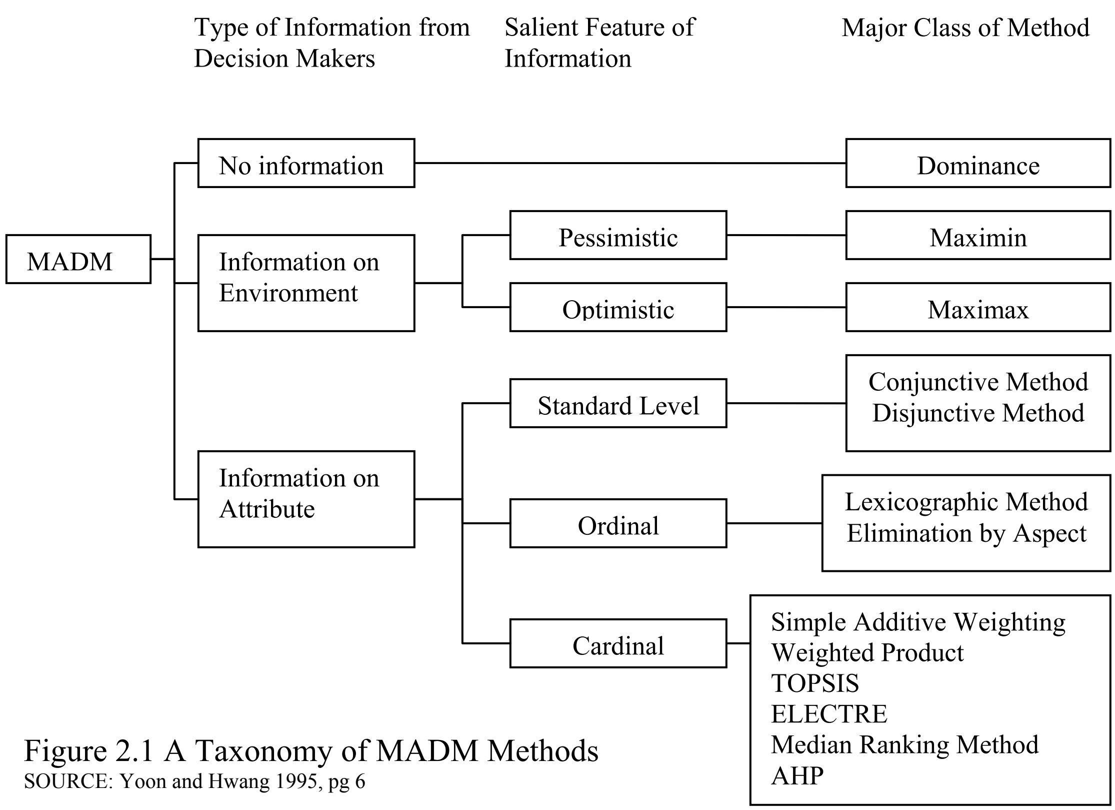

Figure 2.1 A Taxonomy of MADM Methods
SOURCE: Yoon and Hwang 1995, pg 6

Yeh (2002) reviews the Simple Additive Weighting (SAW), Weighted Product (WP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methods. These methods were chosen because they are applicable to large-scale decision problems where the rankings produced would likely be different. They are also simple in concept and computation. The decision problem considered is a single-level case, although the three methods are applicable to multi-level hierarchies. When an attribute hierarchy has more than three levels, the Analytic Hierarchy Process (AHP) should be applied. A procedure is used to determine the degree of sensitivity of each attribute to the ranking outcome of each method. TOPSIS was determined to be the most sensitive, matching the decision information from the decision matrix best. WP was found to be the least sensitive. The author also notes that no one best method can be assumed in general and a validation method is provided to identify an approach based on a specific data set.

A simulation comparison of methods is presented in Zanakis et al. (1998). The authors review; Elimination and Choice Translating Reality (ELECTRE), TOPSIS, Multiplicative Exponential Weighting (MEW), SAW and four versions of the AHP. The decision problem considered has N criteria weights and L alternatives. Simulation parameters included number of alternatives, criteria and criteria distributions. Two performance measures are used, comparison of final weights or ranks to the SAW method and rank reversal measures. The four AHP methods produced indistinguishable results and were always the closest method to SAW. In general as the number of alternatives increased, the methods produced overall weights closer to SAW, but large discrepancies in rank. On the contrary, as the number of criteria decreased, differences in final weights were greater. With respect to rank reversal, SAW and MEW did not produce any. TOPSIS performed the next best followed by AHP. It is noted that the SAW method should be used as a standard for comparisons, giving the most acceptable results for most single-dimensional problems.

Additional dimensions for method comparison are listed: simplicity, trustworthiness, robustness and quality. The authors also discuss the efficiency of a method as not only a result of the supporting theory or rigorousness of the math. Efficiency is also related to ease of use, user understanding and faith in results. These dimensions may also be applicable to review weighting methods. Most MADM methods require a relative weight for each criteria and therefore, a weighting method must also be selected.

2.5.2 Comparison of Weighting Methods

As in MADM methods, the weighting method used to assign attribute weights can also vary. Chang (2005) compares the AHP weighting method (Saaty's method) to utility theory and the Delphi technique (see Table 2.1). Hobbs (1980) compares weighting methods in power plant siting with respect to the weighting summation or linear model multi-attribute decision rule. This rule assumes the weights are proportional to the relative value of unit change in each attribute value function. This means is $W_1 = 2$ and $W_2 = 4$, the unit change in $V_1(X_1)$ must be half as valuable as a unit change in $V_2(X_2)$. This is a condition assumed by other decision rules, including the SAW method. Hobbs reviews many weighting methods: Ranking and Categorization, Rating, Ratio Questioning, Saaty's method and Metfessel Allocation, Indifference Trade-off method, the Churchman-Ackoff method, Decision Analysis Weight Selection and Observer-derived techniques. Only the Indifference Trade-off and Decision Analysis Weight Selection methods adhere to the proportionality assumption. However, these theoretically valid methods are difficult to use and therefore often give inconsistent results. The ability to test consistency of judgments is a strength of Saaty's method and is explored further in the following section.

2.5.3 Saaty's Method

The AHP is a MADM method developed by Thomas L. Saaty. It follows the descriptive theory and can accommodate either relative or absolute measurement. The AHP is used to develop ratio scales from pairwise comparisons in a multilevel hierarchy.

Comparisons among these elements may be from actual measurements or the fundamental scale. The eigenvector formulation is used to determine relative weights of the criteria (Saaty and Vargas 2001).

The literature has addressed the advantages and disadvantages of Saaty's method. One key advantage is that inconsistency in judgments is allowed and able to be measured (Kamenetzky 1982). If consistency does not hold, which it often does not, the eigenvector still produces a set of priorities that are all acceptable approximation, allowing 10% error (Forman and Gass 2001). Kamenetzky also mentions the easy elicitation of pairwise judgments as an advantage. Pairwise comparisons are straightforward, understandable and made efficiently. The relative judgments also tend to be more accurate than absolute judgments and individual comparisons.

Table 2.1 Comparisons within Several Weighting Methods

Methods	Descriptions	Strengths	Weaknesses
Utility theory	- Empirical modeling procedure - Also use experts' opinion for a qualitative problem structure	- Can present a preference function called utility function - An utility function can be used as an objective function in MODM environment	- When a problem size becomes big, this method gives more cognitive burden than AHP method - For that reason, right decision is more challenge than AHP method
Delphi technique	- Use experts opinion with several times of interviewing or surveying - Gives DM a chance to see what other DMs opinions are and how his/her opinion is different from them	- Relatively convenient than utility theory because an analyst dose not need any conditional types of question used in utility theory - Good quality of results	- Asking several times for the same problem by showing other DMs opinions can forces DMs to move into median or mean values which does not need to be best solution
AHP method	- Pairwise comparison is used - Eigenvector and eigenvalue approach are used	- By using pairwise comparison, this method has less cognitive burdens than other two methods - By using consistence index, any irrational response can be filtered to determine weights	- Still subjective as other two methods because this method is also dependents of experts opinion

SOURCE: Chang 2005, pg 62

They produce ratio-scale measures, which convey more information than interval or ordinal scales, and dimensionless ratio-scale priorities when no scale exists (Forman and Gass 2001). Additionally, the synthesized information contained in all possible pairwise comparisons (information redundancy) adds to the robustness of estimates (Kamenetzky 1982). The fundamental scale, also developed by Saaty, represents intensities of judgments and has also been discussed in the literature.

The fundamental scale has been theoretically justified for the comparison of homogeneous elements. The scale provides measurement for comparisons where one wants to know what fraction X is larger than Y, not how many more times is X larger than Y. These situations occur when elements are near equal (Saaty and Vargas 2001). This theory of near-equal elements came from Weber in 1846 who formulated a law regarding a stimulus of magnitude *s*. Weber's law states that "a change in sensation is noticed when the stimulus is increased by a constant percentage of the stimulus itself." Therefore, s can be increased by Δs to reach the point where human senses can just distinguish the difference between s and $s + \Delta s$. Then the ratio $r = \Delta s/s$ does not depend on s itself (Saaty 1980). The scale itself has been a subject of inquiry, as has the question asked to the decision maker.

The question "what fraction is X more important than Y?" has been considered ambiguous and in need of a reference point for the comparisons (Forman and Gass 2001, Dryer 1990). Harker and Vargas (1990) confirm that a reference point is required for pairwise comparisons. Similarly, vagueness of definition is a concern for Saaty's fundamental (verbal) scale (Donegan, Dood and McMaster 1992, Bard 1992). Donegan, Dodd and McMaster also question the rounding of values to Saaty's numbers and the assumption of least detectable differences in the numeric scale. Harker and Vargas (1990) explain the scale used only need to be bounded and compare criteria that are homogeneous with respect to it. They continue to justify the fundamental scale as robust, able to handle cases when errors are made. Bard (1992) notes that this method is better for individuals not familiar with decision making methods and when the majority of attributes are measured subjectively.

Our research uses the SAW and Saaty's method to build decision making models for outpatient clinic scheduling decisions. The model and approach follow in the next chapter.

Chapter Three

Problem Statement and Approach

Scheduling decisions must be made when a patient arrives to a clinic late or without an appointment. Clinic staff would like to consider all relevant patient information when making these decisions. An effective and efficient method is needed to integrate the information and support the decision maker.

At any point in time there are a given number of patients waiting to be seen in a clinic, where n is the total number of patients waiting. This state can change under two conditions requiring a scheduling decision to be made: (1) patient i ($i = 1,2,\ldots, n$) arrives without an appointment (walk-in) or arrives after his/her appointment time (late arrival) and wants to be added to the existing schedule and (2) of the n patients waiting, one must be selected to be seen when a practitioner becomes available. These decisions should be based on a set of factors ($j = 1,2,\ldots m$) that determine patient and appointment priority. Due to time and cognitive burden, it is not realistic for clinical staff to consider all factors when making these decisions. Therefore, a decision model is needed for better scheduling decisions.

3.1 Approach

Clinic decisions to handle late arrival and walk-in patients have been identified as a MADM problem. The approach taken follows problem identification, the three basic steps for utilization of a decision making technique and simulation. The three basic steps are as follows (Triantaphyllou 2000):

1. Determine the relevant criteria (attributes) and alternatives
2. Attach numerical measures to the relative importance of the criteria and to the impacts of the alternatives on these criteria
3. Process the numerical values to determine a ranking of each alternative

Several alternatives exist to accomplish each step. Criteria can be generated via various methods just as many weighting methods exist to attach measures of relative importance to each criteria. Similarly, the taxonomy of MADM methods from Chapter 2 list options to determine the ranking of alternatives. Our approach used interviews and observation of the clinic system to generate criteria. The eigenvector method was used to determine relative weights of importance and indexation and normalization were used to find relative performance values of each alternative with respect to each criteria. The SAW method was chosen to score and rank each alternative. A single-clinic computer simulation tests the impact of our models on the clinic system. Steps 1, 2 and 3 are explained further in the following sections.

3.2 Criteria Generation

Relevant criteria are established based on the problem definition. Criteria are generated via several methods. Literature survey, panel of experts and construction of goal hierarchy are all plausible. It is recommended that a desirable list of attributes should be complete and exhaustive, contain mutually exclusive items and be restricted to performance attributes of the highest degree of importance. Once the attributes have been established, the relative importance of each must be assigned (Yoon and Hwang 1995). Although this is a vital step, formulation of criteria does not have a standard procedure. More art then science may be involved (Triantaphyllou 2000). Our approach used observation to create an initial list of criteria followed by interviews of experts to confirm and amend the list.

3.3 Determination of Attribute Weights

Weights play an important role in the MADM process and provide valuable information. They quantitatively express with which items the DM is most concerned. Two types of attribute weighting are from ranks and ratio weighting. The simplest method is the use of ranks. Weighting from ranks requires that the attributes be listed in order of importance, most to least important. 1 is assigned to the most important and m (the total number of attributes) assigned to the least. The cardinal ranks can then be calculated from this rank. Although more direct, the rank method can place a cognitive burden on the DM. The preferred approach is the use of pairwise judgments, which provides a complete ranking. This method compares two attributes at a time and asks for the ration (importance) between them. The question asked, for example, may be "How much more important is attribute X than attribute Y?" (n-1) pairwise comparisons are needed to assign weights for m attributes (Yoon and Hwang 1995). The study presented in Zanakis et al. (1998) comments on dominating and dominated criteria (attributes). That is, once the weights have been determined, any criteria that dominates all others or is dominated by all others is removed. Weights are then reassessed.

3.3.1 The Fundamental Scale

One challenge of pairwise comparisons is how to quantify the qualitative answers provided by the DM. This can be accomplished by using a scale. A scale is simply a one-to-one mapping of a set of discrete qualitative answers for the DM to choose from and a discrete set of numerical values representing the importance of the choice. Two scales are based on numbers derived from psychological theories, linear and exponential. No scale can be determined as the best for all cases of decision making problems (Triantaphyllou 2000). The linear scale is preferred for cases with less then 10 entities. The fundamental scale, developed by Saaty, is a linear scale and used as part of our approach to determine relative weights of importance (see Table 3.1).

The eigenvector method uses these quantified judgments to calculate relative weights and is explained in the next section.

Table 3.1 The Fundamental Scale

Intensity of importance	Definition	Explanation
1	Equal Importance	Two activities contribute equally to the objective
2	Weak	
3	Moderate importance	Experience and judgment slightly favor one activity over another
4	Moderate plus	
5	Strong importance	Experience and judgment strongly favor one activity over another
6	Strong plus	
7	Very strong or demonstrated importance	An activity is favored very strongly over another; its dominance demonstrated in practice
8	Very, very strong	
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation

SOURCE: Saaty and Vargas 2000, pg 6

3.3.2 The Eigenvector Method

To calculate the vector of weights using the eigenvector method, a pairwise comparison matrix A must be determined. A is an $m \times m$ matrix, where m is the number of factors (attributes) being considered. Let $C_1, C_2, \ldots, C_n$ be the set of factors. A pairwise comparison of factors C_i and C_j will result in a quantified judgment a_{ij} (i, j = 1, 2, …, n), where a_{ii} for all i, and $a_{ij} = 1/a_{ji}$, for all $i > j$. That is, matrix A takes the following form.

$$A = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix}$$

This matrix represents the following rules that govern the pairwise judgments.

Rule 1. If $a_{ij} = \alpha$, then $a_{ji} = 1/\alpha$, $\alpha \neq 0$

Rule. If factor C_i is judged to be k times as important relative to factor C_j, then $a_{ij} = k$, and $a_{ji} = 1/k$ (i.e., factor C_j is judged to be $1/k$ times as important relative to factor C_i). In particular, $a_{ii} = 1$ for all i, since factor C_i has to be exactly as important as itself.

One judgment matrix will result from each DM. Multiple DMs may be surveyed and result in a synthesized judgment matrix (Saaty 1980).

Ideally, $a_{ij} = \dfrac{w_i}{w_j}$ (for i, j = 1, 2, …, n). This would only occur in the case that exact measurement with w_i representing the weight of i = 1, 2, …, n is available. Since quantified judgments are used, allowances must be integrated. Deviations in the ratio a_{ij} and the number n, now denoted by λ_{max}, lead to Equation 3.1.

$$w_i = \frac{1}{\lambda_{max}} \sum_{j=1}^{n} a_{ij} w_j, \qquad i = 1, 2, \ldots, n. \tag{3.1}$$

Deviations in a_{ij} can lead to large deviations in λ_{max} and w_i normally, but is not the case for the reciprocal matrix A satisfying the rule presented earlier. Associated with matrix A, there exists a stable solution. In matrix notation, the original problem is stated in Equation 3.2 as follows.

$$Aw = nw, \tag{3.2}$$

where matrix A is consistent. When considering the reciprocal matrix A', which is a variation of A created from the pairwise comparisons, the weight vector is a solution to Equation 3.3, where λ_{max} is the largest eigenvalue of A' (Saaty 1980).

$$A'w' = \lambda_{max}\, w' \tag{3.3}$$

Several approximation methods exist to compute the vector of weights. Only one gives a very good approximation according to Saaty (1980). We begin with the single *m*x*m* matrix created from the synthesized judgments. The values in each row are multiplied creating an *m*x1 column vector. Each value is now raised to the power 1/m.

Next, the column vector must be normalized; linear normalization is used. Therefore, the sum of the m values is calculated and then each value is divided by that sum. The resulting *m*x1 column vector is the vector of relative weights. A numerical example follows in the next section.

3.3.3 A Numerical Example

A', created from pairwise comparison judgments, is given as

$$A' = \begin{bmatrix} 1 & 5 & 6 & 7 \\ 1/5 & 1 & 4 & 6 \\ 1/6 & 1/4 & 1 & 4 \\ 1/7 & 1/6 & 1/4 & 1 \end{bmatrix}$$

The multiplication of each row results are (210, 24/5, 1/6, and 1/168) respectively. Each value is raised to the power 1/n. In this example n = 4. This results in the following.

$$\mathbf{m} = \begin{bmatrix} 210^{(1/4)} \\ 24/5^{(1/4)} \\ 1/6^{(1/4)} \\ 1/168^{(1/4)} \end{bmatrix} = \begin{bmatrix} 3.807 \\ 1.480 \\ 0.639 \\ 0.278 \end{bmatrix}$$

These values now need to be normalized. The sum of the four values of **m** is calculated, each value is then divided by that sum. In this example, the sum is found to be approximately 6.204. After normalization, the vector of weights is given by **w**.

$$\mathbf{w} = \begin{bmatrix} 3.807/6.204 \\ 1.480/6.204 \\ 0.639/6.204 \\ 0.278/6.204 \end{bmatrix} = \begin{bmatrix} 0.614 \\ 0.239 \\ 0.103 \\ 0.045 \end{bmatrix}$$

3.3.4 Consistency Index and Ratio

One strength of the eigenvector method is the ability to calculate the consistency of pairwise judgments. The consistency of each matrix should be tested and deemed acceptable prior to the use of attribute weights. In a consistent matrix, the ratio of values for each pair of attributes is the same. λ_{max}, the principle eigenvalue, is used to help estimate consistency. The closer λ_{max} is to n (the number of activities in the matrix), the more consistent is the result. The principle eigenvalue is found through a series of matrix multiplication. Matrix A' is multiplied on the right by the vector of weights, **w**. Let us call the resulting column vector **z**. Each value of **z** is divided by the corresponding value of **w**, creating a new vector **y**. Summing the values of **y** and taking the average gives λ_{max}, shown in Equation 3.4.

$$\mathbf{z} = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix} \begin{bmatrix} \mathrm{w_i} \\ \vdots \\ \vdots \\ \vdots \end{bmatrix} = \begin{bmatrix} \mathrm{z_i} \\ \vdots \\ \vdots \\ \vdots \end{bmatrix}$$

$$\mathbf{y} = \begin{bmatrix} \mathrm{z_i}/\mathrm{w_i} \\ \vdots \\ \vdots \\ \vdots \end{bmatrix} = \begin{bmatrix} \mathrm{y_i} \\ \vdots \\ \vdots \\ \vdots \end{bmatrix}$$

$$\lambda_{max} = \sum_{i=1}^{n} y_i \Big/ n \qquad (3.4)$$

Deviation from consistency is represented by the Consistency Index (CI) (see Equation 3.5). A Consistency Ratio (CR) of 0.10 or less is considered acceptable. The CR is the ratio of CI to the average (Random Index) RI, the consistency index of a randomly generated reciprocal matrix (Saaty 1980).

$$CI = \frac{\lambda_{max} - n}{n - 1} \qquad (3.5)$$

3.3.5 Synthesizing Judgment Matrices

The matrices of acceptable consistency need to be combined into one matrix before final weights can be calculated. For each pair of factors (C_i and C_j), the judgments will be combined using the geometric mean method. The consistency of a synthesized judgment matrix using geometric mean will be acceptable under the condition that each individual judgment matrix is acceptable (Xu 2000).

Geometric mean is computed by taking the n^{th} root of the product of n terms. The n terms represent the ratio judgments made about a specific pairwise comparison in each of the accepted matrices. For example, five experts were surveyed and each of their judgment matrices found to be consistent. When comparing the factors Pending information and Estimated treatment time the judgment ratios from the five experts were (5, 7, 5, 6, and 4). If all judgments are considered equal, the geometric mean is then calculated as follows.

$$(5*7*5*6*4)=4200$$
$$4200^{1/5}=5.305$$

Otherwise, the judgments are combined first by staff type, weighted and then combined to a single value. Once the geometric mean has been calculated for each pairwise judgment, a single matrix will result and will be used to determine the relative weight values as explained in section 3.3.2. (Saaty 1986, Aczel and Saaty 1983).

3.4 Relative Performance Values

Criteria are not uniform. They may be described by either quantitative or qualitative information and have different units of measurement. An example of these differences is the evaluation of a car based on miles/gallon and aesthetics. If the number of qualitative attributes is much larger than quantitative, methods can be applied to convert quantitative into qualitative. Otherwise, numerical values can be assigned to qualitative attributes. Scaling is the preferred approach for quantification. A Likert-type scale is often appropriate. Once all attributes are described by either data type, the values of each attribute must be normalized. This eliminates the comparison of attributes with different measurement units. To use the car example again, one would not be able to compare the cost of a car in dollars and the mileage in miles/gallon. Normalized values are dimensionless, allowing interattribute and intra-attribute comparisons (Yoon and Hwang 1995).

Attributes can be classified into three groups, for which each has a normalization technique. The three attribute classifications are (Yoon and Hwang 1995):

1. Benefit attributes – the greater the attribute value, the more its preference
2. Cost attributes – the greater the attribute value, the less its preference
3. Nonmonotonic attributes – the preferred value is located somewhere in the middle of the attribute range

Benefit attributes can be normalized by either linear or vector normalization. Linear normalization divides the rating of an attribute by its maximum value. The normalization of x_{ij} is given by

$$r_{ij} = \frac{x_{ij}}{x^*_j}, \quad i = 1, \ldots, n; \quad j = 1, \ldots, m \tag{3.6}$$

where x^*_j is the maximum value of the jth attribute and r_{ij} represents the normalized value. Vector normalization divides the rating of each attribute by its norm.

Cost attributes can be transformed to benefit attributes by taking the inverse of the rating (i.e., $1/ x_{ij}$). Then the transformed attribute (from cost to benefit) follows the same normalization process (see equation 3.7).

$$r_{ij} = \frac{x_j^-}{x_{ij}}, \quad i = 1, \ldots, n; \quad j = 1, \ldots, m \tag{3.7}$$

The relative value, r_{ij}, is the ratio of the minimum value of the jth attribute (x_j^-) and the attribute value (x_{ij}).

Nonmonotonic attributes are transformed to monotonic through the z score. A relative value is then obtained through one of the previously mentioned normalization processes (Yoon and Hwang 1995).

3.5 Score and Rank Alternatives

The Simple Additive Weighting (SAW) method is the most commonly used MADM. A SAW score is calculated by adding the contributions of each attribute. This is done through the multiplication of comparable ratings (relative values) and the weight of importance (weights) of each attribute, which is then summed over all attributes. The SAW method is generally expressed as

$$V_i = \sum_{j=1}^{m} w_j r_{ij}, \quad i = 1, \ldots, n \qquad (3.8)$$

where r_{ij} is the relative attribute value obtained from the normalization process. Each alternative then given a score, V_i, which is used to rank the alternatives.

The underlying assumption of the SAW method is the independence of attributes. This implies that the contribution of an individual attribute to the total score is independent of any other attribute values. The SAW method still produces very close results to the "true" value even when independence does not completely hold. This method also has a required characteristic for weights.

It is assumed that weights are proportional to the relative value of unit change: if the relationship of w_2 to w_1 is 2, then the DM must be indifferent to the difference between 2 units of v_2 and 1 unit of v_1 (Yoon and Hwang 1995).

Chapter Four

Criteria Generation and Weight Results

The clinics of H. Lee Moffitt Cancer Center were the source of information used to establish relevant criteria and weights of importance for scheduling late arrival and walk-in patients. H. Lee Moffitt Cancer Center is located on the campus of the University of South Florida in Tampa and has over a dozen disease-specific outpatient clinics. The Comprehensive Breast, Cutaneous, Genitourinary, Senior Adult, Sarcoma, Thoacic and Gastrointestinal clinics were studied. Although located in a hospital setting, Moffitt's outpatient clinics function similar to a typical doctor's office. Patients have specific practitioners (oncologists, surgeons or others) who provide treatment at the clinic visit. A clinic visit may be scheduled for a follow-up or to establish a new patient and can range in length from 15 minutes to an hour and a half.

Although patients may go to the clinic for various reasons, all patients follow the same general process within a clinic. Patients arrive to the clinic and check-in at the front desk. The majority of patients have a scheduled appointment to see their practitioner. Those individuals without an appointment inquire at the front desk about an appointment time. After check-in, patients will wait in the waiting room until a medical assistant calls their name. The medical assistant calls the patient from the waiting room, performs a screening of the patient (height, weight, blood pressure and temperature) and places the patient in an exam room. The nurse will see the patient next followed by the practitioner.

After the visit is complete, the patient exits the exam room, checks out at the front desk and leaves the clinic. This process is consistent for the clinics at Moffitt although individual clinics differ in specialty and size.

The clinic setting used in this research is modeled after the outpatient clinics of H. Lee Moffitt. Each practitioner at Moffitt has his/her own schedule of patients and personal scheduling style (e.g., new patient appointments may be 60 minutes for one practitioner and 90 minutes for another). A single practitioner is used in our simulation of a Moffitt clinic. Two types of patient schedules are tested, one representative of a surgeon schedule the other of an oncologist schedule. The majority of surgeon appointments are follow-ups and tend to be shorter in length than oncologist appointments. The number of exam rooms each practitioner has available can range from one to many depending on the number of practitioners in a clinic on a given day. We tested two exam rooms and three exam rooms in our simulation model. The other resources are a single medical assistant and a single nurse. No front desk resources were included due to negligible process times. The process data used to create our simulation of a Moffitt clinic was collected through patient shadowing, time studies and staff interviews at the Moffitt clinics mentioned above.

Further information was needed from Moffitt clinics to develop our patient priority and appointment assignment models. Clinic Operations Managers, practitioners, nurses, medical assistants and service representatives from the clinics also participated in the criteria generation and survey phases of our research. The criteria weights and values generated from the survey are used in the following general SAW model (see equation 4.1).

$$\pi_i(t) = \sum_{j=1}^{m} w_j * v_{ij}(t) \tag{4.1}$$

$\pi_i(t)$ represents the priority of patient i (the score of time slot i)

i = 1, 2,…, n, n is the number of patients waiting to be seen at

a given point in time (n is the number of time slots remaining in the day)

j = 1, 2, …, m, where m is the number of factors

w_j,, the weight of each factor

$v_{ij}(t)$, the value of each factor

The criteria, weights and values generated from the Moffitt survey for the patient priority and appointment assignment models in this research are explained in the remainder of this chapter.

4.1 Criteria Generation

Several methods were used to generate the criteria used by the clinic staff to schedule late arrival and walk-in patients, which includes:

1. Staff interviews
2. Patient and staff shadowing
3. Expert opinion
4. Decision flow diagrams

The decision flow diagram (see Figure 4.1) illustrates the decision process and identifies three decisions made by the clinic staff.

1. Take the patient today?
2. When can the patient be seen?
3. Call back patient?

The first question is a yes or no question. Either the patient can or cannot be seen that day in the clinic. If the patient is able to be seen, the second decision is to determine the best time to schedule to patient. The first 2 decisions only pertain to late arrival and walk-in patients. The third decision determines which patient waiting in the waiting room should be called back next to an exam room. This decision considers all patients in the waiting room.

Notes from interviews and staff shadowing (see Appendices A, B and C) are used to validate the decision process and list of criteria. A total of nine criteria were found for the three decisions.

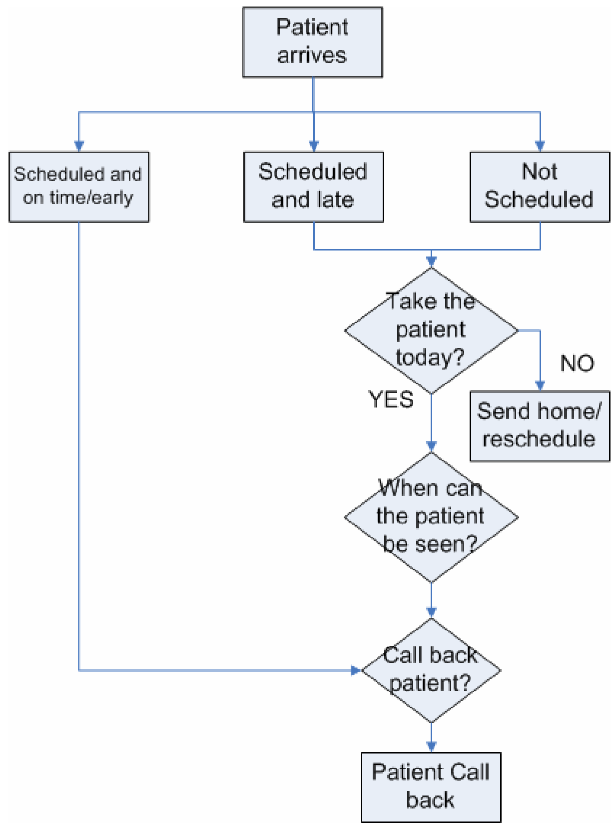

Figure 4.1 Decision Flow Diagram

1. Distance Traveled
2. Urgency
3. Schedule disruption
4. Other appointment
5. Time to appointment time
6. Cause of delay
7. Estimated treatment time
8. Demand per practitioner
9. Pending information

The definitions of each criterion are given in Table 4.1.

A survey was administered to the clinic staff at H. Lee Moffitt Cancer Center. The survey results and relative criteria weights are explained in the next section.

4.2 Determination of Relative Weights

Two versions of our survey were administered to the clinic staff at H. Lee Moffitt Cancer Center. The original version of the survey can be found in Appendix E. The surveys were individually tested for consistency. Of the original surveys, six had a CR ≤ 0.24 and all six surveys were completed by nurses. The final weight results from the original survey are shown in Table 4.2.

Table 4.1 Criteria Definitions

Criteria	Definition
Distance Traveled	the time traveled by the patient from home to Moffitt (1 hour, 2 hours, etc.)
Urgency	a medical state determined by clinical staff
Schedule Disruption	the number of patients scheduled in that same hour
Other Appointment	a scheduled appointment for the same day within Moffitt
Time to Appointment Time	the difference between the current time and the appointment time.
Cause of Delay	the reason the patient was late
Estimated Treatment Time	the appointment length predetermined by the type of visit and the physician being seen
Demand per Practitioner	the ratio of minutes scheduled for a given practitioner per hour
Pending Information	any information, such as lab results or X-rays, needed for treatment in the clinic that day

Table 4.2 Weight Results: Original Survey

Criteria	Weights
Distance traveled	0.05
Urgency	0.35
Schedule disruption	0.05
Other appointment	0.08
Time to appointment time	0.05
Cause of delay	0.07
Estimated treatment time	0.11
Demand per practitioner	0.14
Pending Information	0.10

Clearly, Urgency is a dominant factor and is therefore removed from the list or criteria. Additionally, using a CR of 0.24 was not acceptable by literature standards (Saaty 1980, Apostolou and Hassell 2002, Chu and Liu 2002) and the sample contained only nurses.

A second survey (see Appendix F) was restructured to reduce consistency errors and administered. Urgency was eliminated and weights were calculated for the criteria of each decision. A CR of 0.10, recommended by the literature, is used. The second survey increased the sample size and the variety of staff included. The results are as follows:

Table 4.3 Survey Sample Size and Distribution

	CR ≤ 0.10
Decision #1 Take the patient today?	n = 5 4 Pract., 1 Nurse
Decision #2 When can the patient be seen?	n = 12 4 Pract., 7 Nurses, 1 MA
Decision #3 Call back patient?	n = 4 4 Nurses

Table 4.4 Final Weights

	Decision #1 Take the patient today?	Decision #2 When can the patient be seen?	Decision #3 Call back patient?
Criteria	CR ≤ 0.10	CR ≤ 0.10	CR ≤ 0.10
Distance traveled	0.28	-	-
Schedule disruption	-	0.46	-
Other appointment	0.07	-	0.22
Time to appointment time	-	-	0.26
Cause of delay	0.06	-	0.19
Estimated treatment time	0.12	-	0.15
Demand per practitioner	0.17	0.54	-
Pending information	0.30	-	0.18

The weight results differ for decisions #1 and #3. This could be attributed to the different samples. As shown in Table 4.3, the weights for Decision #1 criteria are almost entirely based on the practitioner option. Where as the opposite is true for Decision #3 weights, based only the nurse opinion. Since consistency (CR) was tested for each question for each survey, the staff mix used for Decision 1, 2 and 3 weights are all different. All surveys were able to be used for Decision #2 weights. When only two criteria exist, there is no test for consistency. The amount of importance placed on the factors changes with respect to the surveyed population. A large difference is observed when weighting pending information, 0.30 for Decision #1 and 0.18 for Decision #3. Pending information was weighted much more heavily when practitioners were the majority. Differences are also observed for other appointment and cause of delay. The nurses placed a higher importance on both of these criteria. The opinions of each staff type were also weighted based on expert opinion. Physician opinion is weighted twice that of nurses and nurses twice that of Medical Assistants. No service representative data was included. The score calculations require both relative weights and relative values for each criterion. Relative value computation is explained in the next section.

4.3 Relative Value Calculations

Relative values must be calculated for each of the eight criteria (the original nine criteria listed in 4.1 minus Urgency). Scaling is used to convert qualitative criteria to quantitative, and then all eight criteria are normalized. Scaling is used for the following qualitative information:

Table 4.5 Scaled Values for Criteria

Criteria	Criteria Value	Scale Value
Other appointment	No	0
	Yes	1
Cause of delay	Not Moffitt	0
	Moffitt	1
Pending information	Yes	0
	No	1

A scale value of 1 indicates higher priority for that criteria value. For example, a patient who has another appointment that day, given all other criteria are the same, has a higher priority then the patient that does not. Patients who have been delayed by the hospital system (Moffitt) and who do not have any missing information (e.g. diagnostic reports), are given a higher priority. One other criteria is scaled, Distance traveled. Although not qualitative, a scale is used for ranges of distance traveled since that is how judgments are made currently at Moffitt. Table 4.5-B shows the Distance traveled scale.

Table 4.6 Scaled Values for Distance Traveled Criteria

Criteria	Criteria Value	Scale Value
Distance traveled	0 – 1 hour	1
	1 – 2 hours	2
	2+ hours	3

The patients who traveled the farthest are given the highest priority. Values of the remaining criteria are as follows:

- Schedule disruption = (0, 8) number of patient's with appointments beginning in a specified block of time. The maximum value of this criterion is determined by the minimum estimated treatment time and the ability to double or triple book. Here it is assumed that double booking is allowed. The minimum estimated treatment time is 15 minutes.
- Time to appointment time = (0, ∞) MAX (current time – appointment time, 0) (negative values represent patients who have arrived early).
- Estimated treatment time = 15, 30, 60 or 90 minutes
- Demand per practitioner = (0, 2) scheduled time / specified block of time. The maximum value of 2 represents a completely double booked block of time.

The eight criteria are now able to be normalized as described in section 3.3. Linear normalization is used.

The criteria represent both benefit and cost attributes. Benefit attributes are more preferred as the attribute value increases.

1. Distance traveled
2. Other appointment
3. Time to appointment time
4. Cause of delay

Cost attributes are less preferred as the attribute value increases.

1. Schedule disruption
2. Estimated treatment time
3. Demand per practitioner
4. Pending information

Relative value calculations are not needed for binary attribute values (Other appointment, Cause of delay and Pending information). The maximum attribute value is always 1, otherwise the value is zero. The next sections describe the specific relative value calculations for each decision.

4.3.1 Decision #1 Relative Values and Model

The relative attribute values for Decision #1 are calculated as follows:

- Relative Distance traveled = Distance traveled / 3
- Relative Demand per practitioner $= \dfrac{\text{MIN scheduled time / 30 minutes}}{\text{scheduled time / (5pm - current time)}}$

- Relative Estimated treatment time = 15 / Estimated treatment time
- Other appointment, Cause of delay and Pending information are all binary

The Decision #1 model compares a single late-arrival or walk-in patient to the system. Multiple patients are not compared. The values specific to that patient are used to calculate the relative values. Patient priority increases with the score. Decision #1 SAW model is shown in equation 4.2.

$$\begin{aligned} \text{Score} = {} & 0.28(\text{Relative Distance Traveled}) + 0.07(\text{Other appointment}) + \\ & 0.06(\text{Cause of Delay}) + 0.12(\text{Relative Estimated treatment time}) + \\ & 0.17(\text{Relative Demand per practitioner}) + 0.30(\text{Pending information}) \end{aligned} \tag{4.2}$$

4.3.2 Decision #2 Relative Values and Model

The relative attribute values for Decision #2 are calculated as follows:

- Relative Schedule disruption = Schedule disruption / MAX (Schedule disruption)
- Relative Demand per practitioner = Demand per practitioner / MAX (Demand per practitioner)

The relative values for Decision #2 correspond to a specific block of time in the schedule. The maximum value is the highest schedule disruption or demand per practitioner of the remaining time blocks in that day's schedule. Both of these criteria are cost attributes calculated as benefit attributes, therefore the lowest score will be selected. Decision #2 SAW model is shown in equation 4.3.

$$\text{Score} = 0.46(\text{Relative Schedule disruption}) + 0.54(\text{Relative Demand per practitioner}) \tag{4.3}$$

4.3.3 Decision #3 Relative Values and Model

The relative attribute values for Decision #3 are calculated as follows:

- Relative Time to appointment time = Time to appointment / MAX(Time to appointment)
- Relative Estimated treatment time = MIN (Estimated treatment time) / Estimated treatment time
- Other appointment, Cause of delay and Pending information are all binary

Decision #3 relative values compare patients in waiting room. The maximum and minimum values of Time to appointment time and Estimated treatment time respectively are the extreme values of the waiting room patients at a given point in time. Similar to Decision #1, the patient priority increases with the score. The SAW model for Decision #3 is as follows:

$$\text{Score} = 0.22(\text{Other appointment}) + 0.26(\text{Relative Time to appointment time}) + 0.19(\text{Cause of Delay}) + 0.15(\text{Relative Estimated treatment time}) + 0.18(\text{Pending information}) \tag{4.4}$$

Relative weights resulting from consistent surveys (CR $\leq$ 0.10) are used SAW model equations of sections 4.3.1 – 4.3.3.

The three SAW models are suggested as a better approach to current scheduling practices at Moffitt clinics. The decision process incorporating the three SAW models is tested using a discrete-event computer simulation. Both the current decision practices and the new approach are modeled. The simulation logic used is discussed in the next chapter.

Chapter Five

Simulation Logic

The simulation model represents a single outpatient clinic system. The system includes patient arrival, waiting room and treatment. It is a terminating system, each run representing one day. The day begins 8 am and ends when the last patient exits the system. A one-hour lunch break is assumed from noon to 1pm. All times are represented in minutes, starting at 8am. While hospital conditions such as other appointments are incorporated, none are specifically modeled. Each random distribution is individually seeded and thirty replications are run.

All patient entities entering the system represent patients seeking treatment in the clinic that same day. Patients can arrive to the clinic as either a scheduled or walk-in patient. Punctual scheduled patients, those who arrive within 30 minutes of their appointment time, are directed to the waiting room, represented by a queue, to be treated. The remaining patients, late scheduled patients or walk-ins, are sent through a set of decisions the clinic staff must make to incorporate them into the clinic that day. After which, the late and walk-in patients may join the waiting room queue. Patients are called back from the waiting room to begin the treatment process.

The treatment process includes a Medical Assistant (MA) screening process, nurse and practitioner processes. The treatment process begins with the MA when one exam room becomes available. Patients are delayed for a few minutes after the practitioner process, then exit the system. The next section describes all the entities modeled and their attributes.

5.1 Entities

There are four entity types (scheduled patients, late patients, walk-in patients and other tasks). All patient entities represent patients seeking treatment in the clinic that day. Patients enter the system as either a scheduled or walk-in patient. These two patient types are generated separately and with different arrival patterns. Scheduled patient entities are described further in the next section.

5.1.1 Scheduled Patient Entities

All scheduled patients set their appointments in advance. Therefore, scheduled patient entities are generated with one arrival and 32 entities per arrival at 0.00001 minutes. This is done to construct a patient schedule prior to the beginning of the clinic that day.

Scheduled patient entities take one of two paths in the simulation. They will either remain a scheduled patient entity or may become a late patient entity. Scheduled patients are redefined as "late" patients, based on the arrival and appointment time. Those who arrive more than 30 minutes after their appointment are considered "late". Redefining the entities is necessary because late patients have to be reassigned appointment times. Once a patient is classified as "late", they follow the same path as walk-in patients. Patient arrival distribution is based on real data, expert opinion or system observation at H. Lee Moffitt Cancer Center in Tampa, Florida.

Times studies, patient shadowing and staff interviews were conducted in multiple clinic of H. Lee Moffitt Cancer Center. Time study records of 83 patient visits were used to find the scheduled patient arrival distribution (see Figures 5.1 and 5.2). Figure 5.1 shows approximately 20% of the patients arrive after their appointment time. The data from Figure 5.1 was input into Arena's Input Analyzer to determine the most suitable distribution.

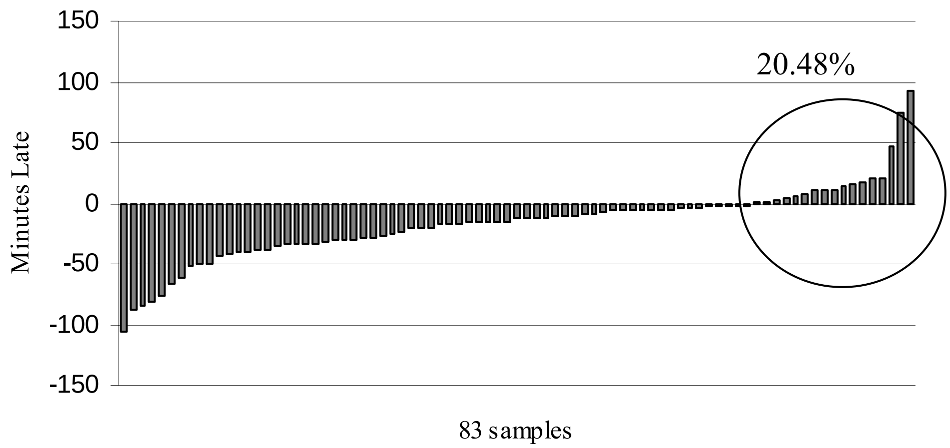

Figure 5.1 Patient Arrival Data

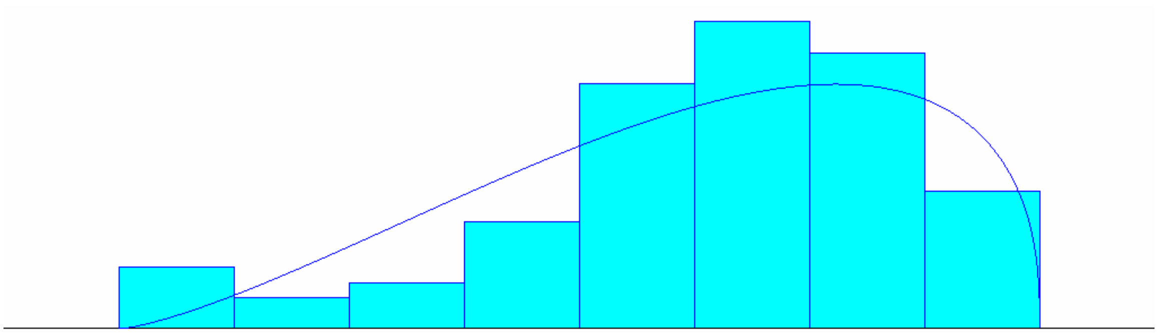

Figure 5.2 Arrival Data Distribution Summary

The Beta distribution

-87 + 108 * BETA(2.38, 1.39)

is used to represent scheduled patient arrival. Arrival time is one of many attributes assigned to each patient entity, which are used in the scheduling and operations of the clinic.

Every patient entity is assigned a set of attributes as it enters the system. The following attributes are assigned to the scheduled patients immediately after they are created.

1. Length - the length of the assigned appointment in minutes

   DISC(0.4, 15, 0.95, 30, 0.98, 60, 1, 90)

   The type of appointment and the practitioner determines the appointment length. For example, a follow-up appointment is typically 15 minutes long while a new patient appointment may be 60 minutes long. The above distribution is representative of a surgeon, who typically has more follow-up appointments. The distribution used to represent an oncologist appointment schedule is as follows

   DISC(0.05, 15, 0.3, 30, 0.8, 60, 1, 90)

2. Appointment end time = Appointment end time of the previous patient + length

   The Appointment end time is assigned as an attribute to create the schedule of patients. The end time of the previous patient is used as the appointment time of the next patient. The schedule creation is explained further in section 5.3.

3. Appointment time = Appointment end time-length

An appointment time is assigned to each patient. This attribute is used to make scheduling and operational decisions. It is also used to calculate waiting time. Waiting time of a patient is the difference between the appointment time and the time a patient enters an exam room.

4. Arrival time - represents the time the patient physically arrives at the clinic

The patient arrival time is used to assign the late patient entity type. It is also used to assign appointment times for a specific set of patients, urgent patients as well as those who arrive after 4 pm. Two distributions are used.

Appointment time + (-87 + 108 * BETA(2.38, 1.39))

includes all patient arrivals (on-time and late).

Appointment time - EXPO(26.3485)

only represents on-time patient arrivals.

5. Distance traveled - the time a patient travels from home to the clinic (1 = less than 1 hour, 2 = 1-2 hours and 3 = more than 2 hours)

DISC(0.65, 1, .76, 2, 1,3)

The distance a patient travels to the clinic is taken into consideration when making scheduling and operational decisions. This distribution is specific to H. Lee Moffitt Cancer Center and was collected from the Human Resources department at Moffitt.

6. Urgency - the medical state of the patient (0 = not urgent, 1 = urgent)

DISC(0.95, 0, 1.0, 1)

Only a clinical staff member can determine the medical urgency of a patient. Urgent patients are given the highest priority and sent to the front of the waiting room queue.

7. Another appointment – a appointment after the clinic appointment also at Moffitt (0 = no other appointment, 1 = another appointment)

   DISC(0.78, 0, 1.0, 1)

Patients at H. Lee Moffitt often have multiple appointments in a single day. These appointments could be at multiple clinics or a clinic and diagnostic testing, treatment or consultations. Only a single clinic is modeled in this simulation, but it is taken into consideration if the patient has another appointment later that same day at Moffitt.

8. Time to appointment time = TNOW – Appointment time

This attribute is used to track the patient relative to their appointment time. This attribute is time dependant and changes as the day progresses.

9. Cause of delay – the reason the patient arrived after the appointment time (0 = external cause, 1 = caused by Moffitt)

   DISC(0.25, 0, 1.0, 1)

The staff interviews and patient shadowing revealed that there are many reasons why a patient may arrive late to an appointment. Generally, the clinical staff only considers whether or not Moffitt delayed the patient. If a previous appointment or transaction that day at Moffitt caused the patient to be late to their clinic visit, that is included in scheduling and operational decisions. This distribution is based on the expert opinion of Clinic Operations Managers.

10. Pending information – Missing diagnostic information needed for clinic treatment (0 = pending information, 1 = no pending information)

    DISC(0.1, 0, 1.0, 1)

Often lab results or other diagnostic test results are needed for the practitioner to treat the patient. Pending information represents any information needed to treat the patient in the clinic that day. If any piece of information is missing, the patient has pending information. A 30 minute loop is used to change the pending information attribute status after the patient arrives to the clinic. This distribution is also based on expert opinion of Clinic Operations Managers. Walk-in patients are also assigned a similar set of attributes. Their attributes as well as their generation are explained in the next section.

5.1.2 Walk-in Patient Entities

Walk-in patient entities are generated separately from the scheduled patients. The first walk-in patient is generated with a distribution of

UNIF(1, 480) minutes

UNIF(1, 480) minutes between arrivals

and a maximum of 4 arrivals. 10% walk-in patients, about two patients, are typical of the clinic modeled. Therefore, four walk-in patients were used as an upper bound. See Appendix G for walk-in arrival data.

Walk-in patients are also assigned a set of attributes after they are created. Walk-in patient attributes are the same as for scheduled patients (Length, Appointment end time, Distance traveled, Urgency, Other appointment, Time to appointment time, Cause of delay and Pending information). The arrival time is assigned differently. Walk-in patient arrival time is set at the current clock time (TNOW) of the day.

5.1.3 Other Task Entities

The last entity type, other tasks, represents other work for which the practitioner is responsible. The other tasks may be phone calls, reviewing patient records, dictation or others. Time between arrivals is

UNIF(37,60)

with the first arrival at 5 minutes. Other tasks entities are assigned an attribute, Practitioner Process Time, equal to 15 minutes. The practitioner resource will only perform other tasks between patients. An other tasks entity will not interrupt a patient being processed and a maximum of 11 entities are generated.

5.2 Resources

Four resources are defined (MA, nurse, practitioner and exam room). There is one MA, nurse and practitioner and two or three exam rooms. Both the MA and nurse are assumed to be available to see a patient once an exam room is available and have no other tasks. Processing times for the MA and nurse are:

MA = UNIF (1,4)

Nurse = UNIF(5,10)

The practitioner processing time is based on the length of appointment assigned to each entity.

Practitioner = length*NORM(0.675,0.10833)

If a patient has a one-hour appointment, the practitioner spends between 56.667% and 78.333% of that time in the exam room with the patient. The remaining time represents other obligations for the practitioner such as phone calls, dictating notes and reviewing patient records, which will account for the remaining working time. These obligations are generated by the other tasks entities.

There is no processing time for the exam room. When an exam room is available, the next patient in the waiting room queue will seize it. After the practitioner process, the patient is delayed (uniformly distributed between 2 and 10 minutes) then the exam room resource is released. All resource processing times are based on patient shadowing and expert opinion.

5.3 Patient Entity Arrivals and Schedule Creation

There are two creation modules for patient entities, one generating scheduled and one generating walk-in patients. Scheduled patients are all created at one time. The max number of arrivals is one and there are 32 entities per arrival. 32 entities are generated to ensure that enough patients are in the system to fill the schedule. The bulk entity creation is needed to assign each patient the set of attributes listed in section 5.2 prior to the arrival to clinic.

One of these attributes is the appointment time. The appointment time is assigned using a system variable, End time. This variable keeps track of the last appointment end time assigned an entity (see equation 5.1).

$$\text{End Time} = \text{End Time} + \text{length of appointment} \tag{5.1}$$

The end time for the second entity will be the end time of the first entity plus the appointment length of the second. The attribute, Appointment end time, is then equal to the system variable, End time. Then the appointment time is assigned as the Appointment end time minus the appointment length (see equations 5.2 and 5.3)

$$\text{Appointment end time} = \text{End Time} \tag{5.2}$$

$$\text{Appointment time} = \text{Appointment end time} - \text{Appointment length} \tag{5.3}$$

After the entity is created and assigned a set of attributes, it goes through four decision models. The first decision checks the arrival time of the entity. The arrival distribution generates mostly early patients. If the arrival time is less than zero, the entity arriving before 8am, the arrival time is reassigned to zero. The second decision module checks the appointment time attribute. If the appointment time is less than or equal to 4pm (480 minutes), the patient continues to the third decision. Entities with appointments after 4pm are disposed, guarantying the last scheduled appointment each day is no later than 4pm. The third decision checks if the appointment time is between

11:30am and 1:00pm. If true, the entity is sent through an assign module to reassign the appointment time. The appointment time is reassigned to 1:00pm. This ensures that the last appointment before lunch is not later than 11:30am and no patients are scheduled during the lunch hour. To reassign the appointment time, the system variable End time is redefined as follows:

$$\text{End time} = 300 + \text{Appointment length} \tag{5.4}$$

where 300 represents 1:00pm. Once all appointments times are assigned, the entities are sent through the Scheduled Block Variables sub-model.

5.4 Schedule Block Variables sub-model

As the entity enters the sub-model, it first goes through an N-way by condition decision module. The attributes position the entity based on the current system time (see Figure 5.3). The entity will begin at the earliest time block and go through the remaining blocks for that day. These sub-models are used to update three systems variables: scheduled time, number of appointments and demand. Scheduled time is the total time in minutes during the hour block for which a patient is scheduled. This value could be less than, equal to or greater than 60 minutes. Appointments variable record the number of appointment that begin during the one-hour block. Demand variable is the scheduled time divided by 60 minutes. The system variables are recorded in a Schedule Block Variables sub-model using decide and assign modules.

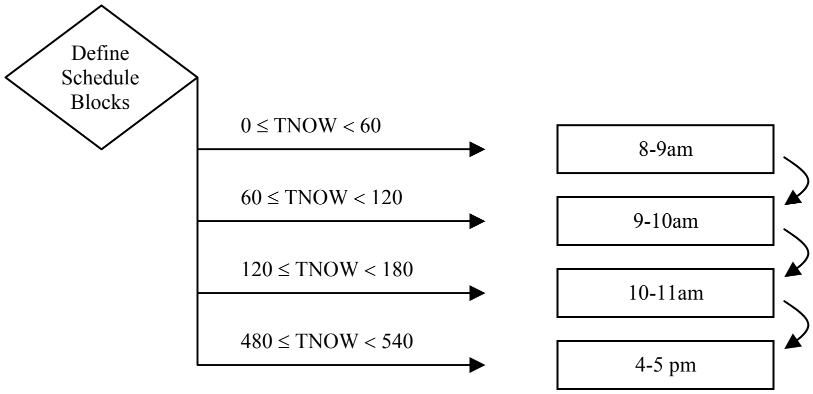

Figure 5.3 Schedule Block Variables Sub-model: Block Definition

The entity enters a second sub-model where it goes through another decision module (see Figure 5.4).

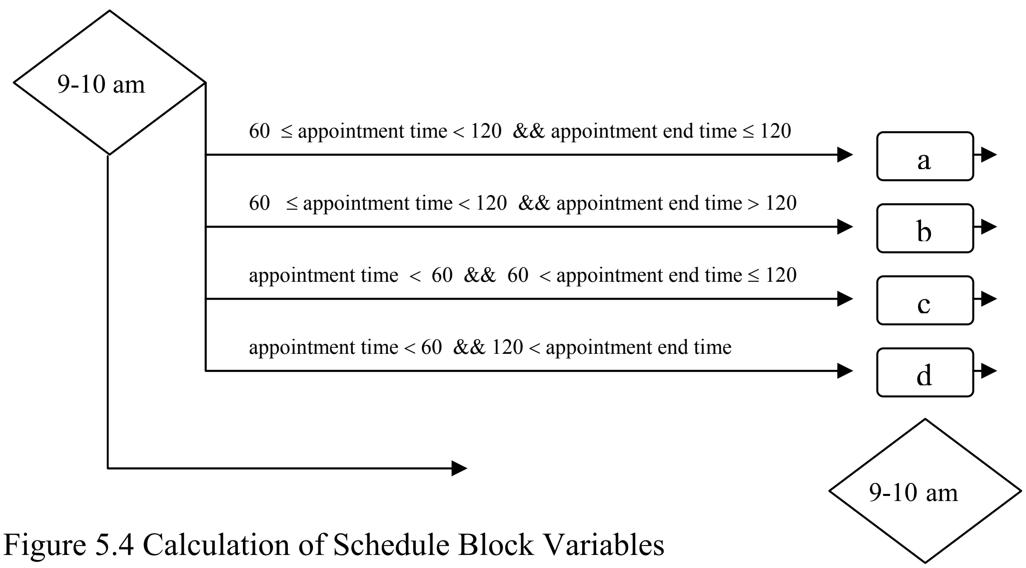

Figure 5.4 Calculation of Schedule Block Variables

Depending on the appointment time and end time, an assign module (a, b, c, or d) will add the correct number of minutes and number of appointments to the scheduled time and appointments variables respectively.

The demand variable will also be updated. Continuing with the 9-10 am block example from Figure 5.5, the four assign modules are as follows where 9-10 SchedTime is the scheduled time system variable, 9-10 Appts is the appointments system variable and 9-10 Demand is the demand variable for the 9-10 am time block.

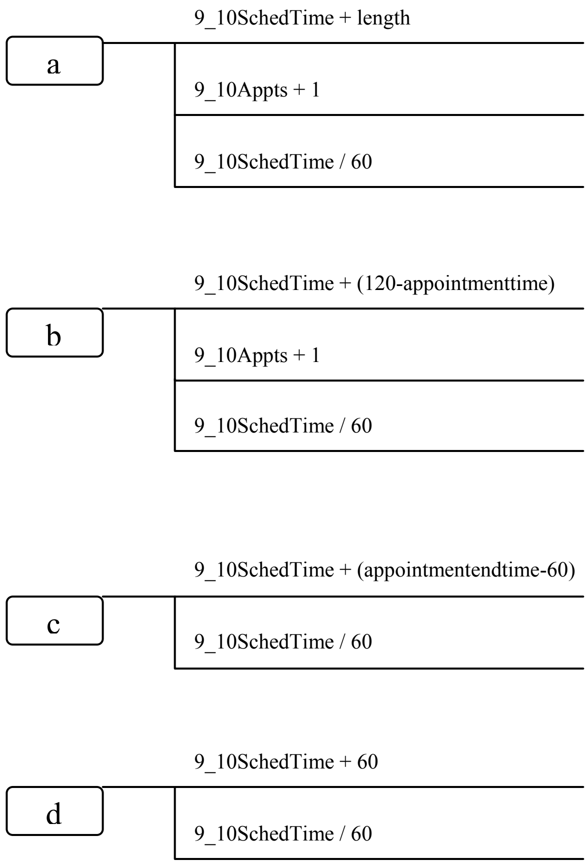

Figure 5.5 Schedule Block Variables Assignment

One Schedule Block Variables sub-model is used, located just before the hold block representing the arrival of scheduled patient entities into the clinic system.

5.5 Scheduled Patient Arrival to Clinic System

The 32 scheduled patient entities are sent to a hold block. The hold block queue represents the clinic arrival for scheduled patients. Patients are released from this queue when the arrival time attribute equals the current simulation time (TNOW). In physical terms, this models the patient walking into the clinic and checking in at the front desk. The actual check-in process is not modeled due to the minimal processing time. As patients are released from the queue for scheduled patient arrivals, they are sent through the fourth decision module. If the scheduled patient entity is punctual, it is sent to the waiting room queue. If the scheduled patient entity is late, it is reassigned the entity type "late" and joins walk-in patient entities to go through a new appointment time decision process.

5.6 Appointment Assignment and Urgent Patients

Once the late and walk-in entities have been assigned the set of attributes a few decisions are made prior to new appointment assignment.

1. If the entity is urgent and it is before 5pm (540 minutes), it is assigned an appointment time of TNOW and sent straight to the waiting room queue. Urgent patients are assigned TNOW as an appointment time to ensure the practitioner sees them as soon as possible.
2. The non-urgent entities go through another decide module that checks the current system time. If TNOW is less than 480 minutes, the entities are sent to a sub-module to be assigned a new appointment time. If TNOW is between 480 and 540 minutes, the entity is assign an appointment time of TNOW and sent to the

waiting room queue. Patients who arrive before 4pm are assigned an appointment time. Patients who arrive after 4pm, but before 5pm use their arrival time as an appointment time since the clinic only schedules through 5pm.

3. If the entity arrives after 540 minutes, it is disposed. This represents a patient arriving after 5pm. Late and walk-in patients are only taken the same day if they arrive before 5pm.

Entities are assigned new appointment times in a sub-model. Entities are first separated by time as shown in Figure 5.3. After which, they are sent through an assign module assigning an attribute of the demand of each hour block remaining in that day's schedule. After the attribute assignment, the entities go through another decision module. If the demand of an hour block is less than 1, the entity is assign a new appointment time at the beginning of that hour. If multiple blocks have a demand less than 1, the earliest hour is selected. The following blocks are checked in this decision module:

- 9-10am
- 10-11am
- 11am-12pm
- 1-2pm
- 2-3pm
- 3-4pm

If all of these blocks have a demand greater than or equal to 1, the entity is sent through another set of decisions.

The next hour block checked is the lunch hour, 12-1pm. If the demand of that hour is less than 1, the entity is assigned to 12pm. If the lunch hour demand is greater than or equal to 1, the last hour of the clinic is checked, 4-5pm. If that hour has a demand less than 1, the entity is assigned 4pm as an appointment time. Otherwise, the entity will be double booked. An entity is double booked by beginning assigned to the earliest available time that is already booked with one 15-minute appointment. Only 15 minute appointments are double booked.

Once the late or walk-in entity has a new appointment time, it is sent to a hold block before the waiting room queue. This is to prevent an entity entering the waiting room queue significantly before the new appointment time. The following distribution is used to delay the entity.

UNIF(appointmenttime-TNOW-10,appointmenttime-TNOW-1)

It is assumed that all late and walk-in patients with new appointment times will be punctual. After the patient is released from the hold module, it enters the waiting room queue, which is ordered by appointment time. The earliest appointment time is released first. Finally, the entity seizes an exam room and is processed.

5.7 Processing

After an entity is called back, it will seize one room resource. This represents the patient occupying the exam room. Following the seize module, the entity is sent through a decide block that checks the pending information status of the entity.

If the entity still has pending information when it is seizes a room, it will be sent to a delay block and be held for the following number of minutes:

$$30\text{-(tnow-arrivaltime)} \tag{5.5}$$

The delay represents the time required for the nurse to obtain the pending information needed to treat the patient. Patient information is typically received 30 minutes after the patient arrives. Once all information is available, the patient begins to be processed. The MA sees the patient first.

The entity is processed by the MA first and then sent to a hold block. The release condition for the hold is the practitioner resource is not busy. Once the entity is released from the hold, it is processed by the nurse followed by the practitioner. After the entity releases the practitioner resource it is sent through one more module. The patient is delayed for a few minutes after the practitioner is done to represent the time needed to wrap up the visit. Finally, the patient entity exits the clinic.

Our model modifies the late and walk-in entity decision process, new appointment assignment and waiting room queue. The logic of our suggested system is explained in the remainder of this chapter.

5.8 Priority 1 Assignment and Urgent Patients

Late and walk-in patient entities merge into the same path. This occurs at the assign module, Assign Priority 1 (see Figure 5.6). The purpose of this module is to assign a priority 1 score to each late and walk-in entity. Priority 1 is the product sum of a relative weight and relative value of six predetermined factors discussed in Chapters 3 and 4:

1. Distance traveled
2. Estimated treatment time
3. Another appointment
4. Practitioner demand
5. Cause of delay
6. Pending information

This module assigns a total of four attributes:

1. Relative distance traveled
2. Relative estimated time
3. Relative demand
4. Priority 1

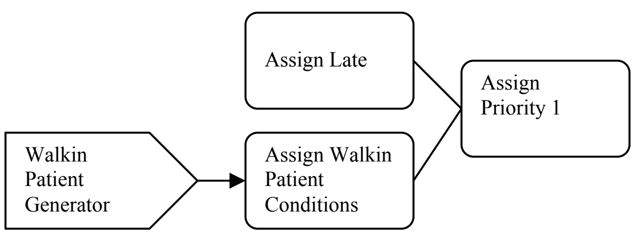

Figure 5.6 Priority 1 Assignment

After entities (late and walk-in) have been assigned a priority 1 attribute, they go to a decision module. The question, "Is the patient urgent?" is asked. If the entity is urgent, urgency attribute is one, the entity is sent to another assign module. Urgent entities are reassigned an appointment time equal to the current time (TNOW) and a corresponding appointment end time (Appointment time + length). These reassignments are done to send urgent entities to the front of the waiting room queue, which is explained further in section 5.10.

If the entity is not urgent, it is sent to another decide module asking "Will the patient be seen today?". This decision model determines if the late or walk-in patient will be seen in the clinic that day. The decision is two-way by condition. If the priority 1 attribute is greater than the specified value, the patient will be accepted and assigned an appointment time. If not, the patient is disposed and assumed to return another day. Before the accepted entities are assigned an appointment time, they go through one more decision module that checks the arrival time attribute. This decision module is three-way by condition:

1. If the arrival time is between 4pm (480 minutes) and 5pm (540 minutes), the entity is assigned an appointment time equal to TNOW and sent to the waiting room queue. Physically, this represents a patient coming very close to the clinic closing time. In which case, the patient is added directly to the waiting room to be seen as soon as possible.
2. If the arrival time is before 4pm, the entity is sent to a sub-model for an appointment assignment.
3. Any entities that arrive after 5pm are disposed. The clinic does not accept patients after 5pm.

5.9 Appointment Assignment for Late and Walk-in Patients

The accepted late and walk-in entities arriving prior to 4pm (condition 2 listed above) must have an appointment time attribute assigned to them. For late entities, the appointment time attribute will be reassigned. Appointment time assignment is based on half-hour blocks of time. Half-hour blocks are defined beginning with 8-8:30am (0-30 minutes) and ending with 4:30-5pm (510-540 minutes). The block for which the appointment time will be assigned is selected based on two criteria:

1. Practitioner demand
2. Schedule disruption

The Appointment Selection score is an attribute and is calculated by adding the product of the relative weights and values for each criteria. The block with the lowest score is selected.

To find the relatives values of each block, the current block value must be known. This is captured using system variables because the values are dynamic. Three system variables are used for each time block: scheduled time, appointments and demand and are updated in the Schedule Block Variables sub-model, section 5.5.

As the entities enter this sub-model, they will first go through a decision model like Figure 5.3. They are positioned according to the current system time, but instead of going to a second sub-model, the entities are sent to an assign module (see Figure 5.7). Three types of attributes are assigned: relative demand, relative number of appointments and a score.

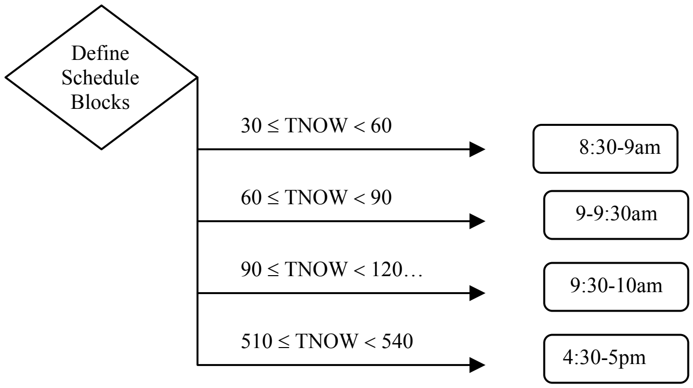

Figure 5.7 Assign New Appointment Sub-model: Block Definition

These three attributes will be assigned for all time blocks remaining that day. In other words, if the current time is 3:15pm, the entity will be assigned attributes for 3-30pm, 3:30-4pm, 4-4:30pm and 4:30-5pm. It is assumed that no late or walk-in entity will be added to the block in which it arrives. This means, if an entity arrives at 9:15am, the 9:30-10am block will be the first considered and the 8-8:30am block will never have a late or walk-in patient added. To guarantee this, the score of all other blocks (earlier and current) are assigned a high score since the time block with the lowest Appointment Selection score will be selected.

Following the assign modules, all entities are sent through a second decision module. This decide module determines which time block has the lowest score (see Figure 5.8).

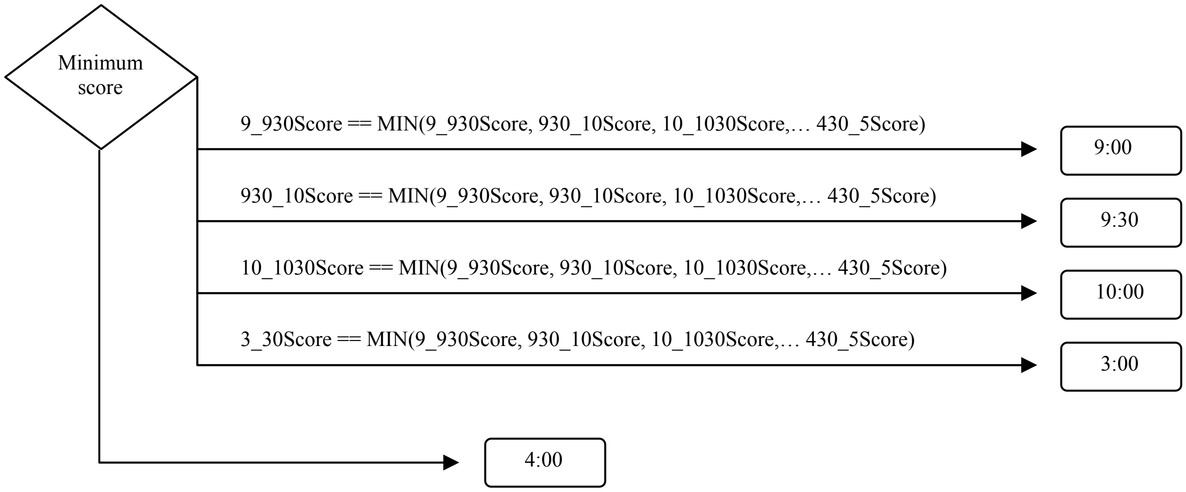

Figure 5.8 New Appointment Assignment

Depending on which condition is found to be true, the entity will go to an assign module and an appointment time will be asigned. 4pm is the last appointment time that will be assigned for this appointment assignment process.

After a new appointment time has been assigned, the entities are sent through the Schedule Block Variables sub-model to update the system variables. Since an entity could be assigned an appointment time several hours later, a hold module is used after the schedule block variables sub-model. Only non-urgent late or walk-in entities before 4pm are sent to the hold module. The release condition form the hold is the current time equal to 1 minute before the appointment time. Once an entity is released from the hold module, it will merge with the scheduled entitiy path to join the waiting room queue. The waiting queue and resrouce process logic follows in the next section.

5.10 Waiting Room Queue and Priority 2 Assignment

Selection of the next entity from the waiting room queue is based on a second priority score. Priority 2 score, like the first, is the product sum of a relative weight and relative value of five predetermined factors.

1. Relative Time to appointment time
2. Relative Estimated treatment time
3. Relative Other appointment
4. Relative Pending information
5. Relative Cause of delay
6. Priority

An entity is to be released from the waiting room queue when a room resource is available. It then goes through decide modules, which check the urgent and pending information conditions of each entity. If the entity is urgent, a priority 2 score of 2 is assigned. This ensures that urgent patients will be released to the exam rooms first. If a patient has been in the system for at least 30 minutes, the pending information condition is changed to no pending information. The priority 2 score is assigned after the decide modules. The entities enter a hold block after the assign module where they are ordered by priority 2 score. The entity to be released is the one with the highest Priority 2 score. A last decide module is used to send the first entity in the Ordered queue to an exam room and redirect all other back to the waiting room queue (see Figure 5.9). To guarantee the highest Priority 2 score is selected, the scores of each entity in the queue are recalculated each time a room is available. A series of hold and signal blocks are used to release the queues.

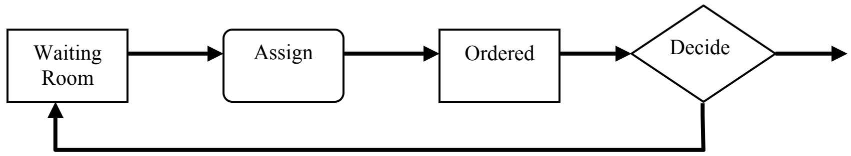

Figure 5.9 Priority 2 Score Recalculation

5.11 Verification and Validation

The simulations were verified using several techniques. Many variable displays were used to ensure correct appointment assignment, variable calculation, resource utilization, and time. The time the last entity left the system was continuously used to ensure no unexpected delays existed. The current system time was also used extensively to verify the timing of simulation events. Entities were sent through the system at a significantly decreased speed to verify the simulation decisions at each step. The number of patients generated and percentage of late patients for each run were also used for verification. Validation was done by using information from the real clinic system and its staff. Clinic closing time, practitioner utilization, number of patients seen, and waiting time were used to validate the simulation model.

The two computer simulations described in this chapter are used to determine the effect the patient priority and appointment assignment models have on the clinic system. Results from the simulations are given in the next chapter.

Chapter Six

Simulation Results

The purpose of our clinic simulation is two-fold, to replicate the current system and decision making process at H. Lee Moffitt and test the effect of our decision models in the Moffitt clinic. Two computer simulations were built to be identical except for the decision making processes. A number of variables can be tested using these simulations. Preliminary analysis was done to determine which variables would be tested for this research. Eight settings and four variations of our clinic simulation were defined. A total of 40 different model and setting combinations were run (four variations of our model and the current system model each run under eight settings). Analysis was based on six outputs:

1. Number of patients
2. Practitioner utilization
3. Clinic close time
4. Waiting room wait time
5. Total wait time
6. Room utilization

The average output of 30 runs was used. Output definitions are given in the following section. The remainder of this chapter discusses preliminary analysis, selection and definition of the eight settings and results of the simulation models.

6.1 Analysis of Simulation Variables

A number of variables (setting conditions and inputs) can be modified in the clinic simulations. An initial list of setting conditions and inputs is found in Appendix H. The outputs used in this research to test all variables are consistent throughout the document and are defined as follows:

1. Number of patients – the total number of patients (scheduled, late and walk-in) seen by the MA, nurse and practitioner. Patients turned away and expected to return to the clinic another day are not included.
2. Practitioner utilization – the ratio of the total value-added time of the practitioner (seeing patients and doing other tasks) to the clinic close time.
3. Clinic close time – the time the last patient exits the system.
4. Waiting room wait time – time spent by a patient in the waiting room after their appointment time.
5. Total waiting time – time spent by a patient in the waiting room after their appointment time plus the idle time (patient not being seen by an MA, nurse or practitioner) in the exam room.
6. Room utilization – the ratio of the total time spent by patients in an exam room (the time the patient entered the exam room to the time he/she exits the exam room) to the clinic close time and number of rooms.

Four variables were selected and an analysis of variance (ANOVA) was performed for each of the six outputs. Preliminary analysis and the selection of settings are explained in section 6.2.

6.2 Analysis of Variance and Setting Selection

To maintain a manageable number of combinations, four variables were selected to test for statistical significance. Two of the variables were specific to our decision model:

1. Block length – the amount of time for which the clinic schedule is divided into and evaluated. In other words, when looking to assign an appointment time to a patient, how much of the schedule is evaluated at a time. The block length was tested at 30 minutes and 60 minutes.
2. Priority criteria – the patient priority criteria value set for Question #1 (Take the patient today?). If a patient's priority score is less than this criterion, the patient will be sent home. The priority criterion was tested at 0.00, 0.25, 0.50 and 0.75.

The other variables tested were setting variables:

3. Number of rooms – the number of exam rooms was tested at two and three rooms.
4. Percentage of late patients – the patient arrival distribution calculates the patient arrival time to the clinic with respect to their appointment time. Two arrival distributions were tested, one calculated from all the Moffitt patient arrival data and the other calculated from only the patient arrival data where the patient arrived prior to the appointment time.

An analysis of variance was performed to test the impact of the four variables on system outputs. The ANOVA results are shown in Table 6.1.

Table 6.1 ANOVA Results

Source	Number of Patients p-value Prob > F	Practitioner Utilization p-value Prob > F	Clinic Close Time p-value Prob > F	Waiting Room Wait Time p-value Prob > F	Total Wait Time p-value Prob > F	Room Utilization p-value Prob > F
Model	< 0.0001	< 0.0001	< 0.0001	0.0003	0.3440	< 0.0001
A-Block	0.9363	0.3608	0.7278	0.9835	0.3210	0.6435
B-Rooms	0 9928	0.0218	0.2017	0.0005	0.3488	< 0.0001
C-Late Percent	0.0396	< 0.0001	0.9863	0.7599	0.2905	< 0.0001
D-Priority	< 0.0001	< 0.0001	< 0.0001	0.0001	0.2122	< 0.0001

None of the four variables had a significant effect on all six outputs. The number of rooms, percentage of late patients and priority criteria did impact some of the outputs. The block length did not have any statistically significant affect and none of the variables affected the total waiting time. Total waiting time is much larger in magnitude than the waiting room wait time. A statistically significant variation in time only appears in the waiting room wait time output. Variable interactions were excluded from analysis. From these results two settings were defined to run a second ANOVA.

The settings were defined by three variables:

1. Number of rooms – two and three exam rooms were tested (R2, R3)
2. Percentage of late patients – two distributions were tested, all patient arrivals with approximately 20% late patients (L20) and only on-time patient arrivals (L0)

An additional variable was added to the previous four, patient appointments. As mentioned in Chapter 4, the type of scheduled appointments can vary with respect to the practitioner.

3. Appointments - two appointment schemes are tested, one representative of a surgeon schedule (A15) and the other representative of an oncologist schedule (A90).

Surgeon schedules are typically shorter appointments. The results are shown in Tables 6.2 and 6.3.

Table 6.2 Setting R2 L20 A90 ANOVA Results

	Number of Patients	Practitioner Utilization	Clinic Close	WR Wait Time	Room Utilization
	p-value	p-value	p-value	p-value	p-value
Source	Prob > F	Prob > F	Prob > F	Prob > F	Prob > F
Model	< 0.0001	0.0022	0.0006	0.0047	< 0.0001
A-Block	0.9992	0.7578	0.7476	0.7141	0.7899
B-Priority	< 0.0001	0.0006	0.0001	0.0010	< 0.0001
C-Late definition	0.1161	0.0129	0.8338	0.8941	0.0163

The first setting (R2 L20 A90) shown in Table 6.2 is a clinic with two exam rooms, approximately 20% late patient arrivals and an oncologist appointment scheme. Total wait time was removed from this analysis since none of the previous variables had a significant affect on total wait time. All other outputs remain the same.

Three variables were tested in the R2 L20 A90 setting. All four variables shown in Table 6.1 were incorporated. The number of rooms and percentage of late patients became part of the setting definition. The remaining two variables; block length and priority criteria are tested again. A third variable, late patient definition, is added.

Late patient definition – the amount of time a patient arrives after his/her appointment time used as a criteria to classify the patient as a late patient. Two definitions are tested. Any patient arriving more than 15 minutes after his/her appointment and any patient arriving more than 30 minutes after his/her appointment.

Table 6.2 shows block length to again have no statistically significant affect on the outputs in the R2 L20 A90 setting. Priority criteria were found to impact all of the outputs while the late patient definition only affected practitioner and room utilization. The same outputs and variables were used in a third ANOVA for the setting R3 L20 A15. The setting R3 L20 A15 has three exam rooms, approximately 20% late patient arrivals and a surgeon appointment scheme. The ANOVA results for setting R3 L20 A15 are shown in Table 6.3.

Setting R3 L20 A15 results are similar to setting R2 L20 A90. Block length has no affect on the system outputs. Priority criteria again have a statistically significant affect on all five outputs while late patient definition impacts waiting room wait time in setting R3 L20 A15.

Table 6.3 Setting R3 L20 A15 ANOVA Results

Source	Number of Patients p-value Prob > F	Practitioner Utilization p-value Prob > F	Clinic Close p-value Prob > F	WR Wait Time p-value Prob > F	Room Utilization p-value Prob > F
Model	0.0030	0.0064	0.0090	0.0142	0.0012
A-Block	0.9997	0.7605	0.9302	0.5679	0.8874
C-Priority	0.0006	0.0015	0.0020	0.0052	0.0003
D-Late definition	0.2965	0.1431	0.3729	0.0326	0.0528

In addition to the ANOVAs shown in Tables 6.2 and 6.3, the simulation output results from settings R2 L20 A90 and R3 L20 A15 are also analyzed. The average output range for each of the three variables (block length, priority criteria and late patient definition) is shown in Tables 6.4 and 6.5. Tables 6.4 and 6.5 show the physical impact each variable had on the five outputs when all other variables are held constant. The following units are used to report the outputs

1. Number of patients = number of patients
2. Practitioner utilization = percent utilization
3. Clinic close time = number of minutes

4. Waiting room wait time = number of minutes
5. Room utilization = percent utilization

Table 6.4 Setting R2 L20 A90 Average Output Range

	Number of Patients	Practitioner Utilization	Clinic Close	WR Wait Time	Room Utilization
Block	0.01	0.08%	1.61	0.31	0.17%
Priority	0.92	0.76%	19.90	1.88	4.79%
Late definition	0.08	0.54%	4.57	0.69	1.20%

Table 6.5 Setting R3 L20 A15 Average Output Range

	Number of Patients	Practitioner Utilization	Clinic Close	WR Wait Time	Room Utilization
Block	0.00	0.13%	0.77	0.28	0.26%
Priority	1.01	1.10%	17.78	0.88	3.17%
Late definition	0.27	0.36%	10.51	0.87	1.16%

As expected, the actual impact block length had on each of the output measures was negligible. Minimal effects were observed in five of the Clinic close time was the only output with notable changes in value. Although late definition was statistically significant in waiting room wait time, practitioner and room utilization, the physical impacts on those three outputs were minor. Since priority criteria had the largest range values, it will be tested in the final simulations. The other two variables were held constant at the following levels:

1. Block length = 30 minutes
2. Late patient definition = 30 minutes

The block length of 30 minutes was selected because it can schedule in smaller increments than hour blocks. Moffitt clinics did not have a standard late patient definition. The staff used a variety of times to determine if a patient was late. 30 minutes was selected as the late patient definition and used in both our clinic simulation model as well and the current system simulation model. As a result of the preliminary analysis, eight final settings were defined and one variable used. An explanation of output analysis for the eight settings follows in the next section.

6.3 Clinic Simulation Output Analysis

Following the preliminary analysis discussed in section 6.2, eight clinic settings were defined to run simulations of our clinic model and the current system model. The eight settings are combinations of three variables, two levels of each. Number of rooms, percentage of late patients and appointments are the three setting variables defined in section 6.2. The eight settings are defined as follows

1. R2 L0 A15 – two exam rooms, no late patient arrivals and surgeon appointments
2. R2 L0 A90 - two exam rooms, no late patient arrivals and oncologist appointments
3. R2 L20 A15 - two exam rooms, all patient arrivals and surgeon appointments
4. R2 L20 A90 - two exam rooms, all patient arrivals and oncologist appointments
5. R3 L0 A15 – three exam rooms, no late patient arrivals and surgeon appointments
6. R3 L0 A90 - three exam rooms, no late patient arrivals and oncologist appointments
7. R3 L20 A15 - three exam rooms, all patient arrivals and surgeon appointments
8. R3 L20 A90 - three exam rooms, all patient arrivals and oncologist appointments

Each model was run under all eight settings and information on six outputs was collected (number of patients, practitioner utilization, clinic close time, waiting room wait time, total wait time and room utilization).

Total wait time was collected to provide a complete analysis of the clinic simulations. An analysis of our clinic model outputs is discussed in 6.3.1.

6.3.1 Clinic Simulation Model Analysis

The Patient Priority Model and Appointment Assignment Models developed in this research were tested through a simulation of a Moffitt clinic. Four versions of our model were run in each of the eight settings. Changing the priority criteria variable generated the four versions. Priority criterion was tested at 0.00, 0.25, 0.50 and 0.75. Altering the priority criteria changed the strictness of the system by allowing more or less walk-in and late patients to be added to that day's schedule. The higher the criteria, the fewer patients permitted into the schedule. Table 6.6 shows the simulation results for our model. Each setting was replicated 30 times and the average output is reported.

The outputs in Table 6.6 show the priority criteria variable has minimal to no impact when changed from 0.00 to 0.25. A small change in output values is observed when the priority criterion is set at 0.50. The greatest change in values is observed when the priority criterion is 0.75. At this level, all of the output values are decreased. Therefore, an improvement is seen for clinic close, waiting room wait time and total wait time outputs. A decrease in the number of patients, practitioner and room utilizations are not considered an improvement. The cause of the lowered output values is the decrease in the number of patients. Patients wait less, the clinic closes earlier and the practitioner and rooms are used less when fewer patients are seen.

Table 6.6 Clinic Model Average Outputs: All settings

	Number of Patients	Practitioner Utilization	Clinic Close Time	Waiting Room Wait Time	Total Wait Time	Room Utilization
R2 L0 A15						
Priority = 0.00	19.3	84.76%	598.06	24.312	55.034	93.87%
Priority = 0.25	19.3	84.79%	596.2	24.062	54.765	93.91%
Priority = 0.50	19.1	84.79%	591.23	23.742	54.497	93.82%
Priority = 0.75	17.7	84.33%	557.87	16.01	46.599	91.36%
R2 L0 A90						
Priority = 0.00	10.7	89.12%	589.03	11.366	56.396	80.50%
Priority = 0.25	10.7	89.12%	589.03	11.366	56.396	80.50%
Priority = 0.50	10.5	89.14%	583.86	9.4605	54.298	79.60%
Priority = 0.75	9.1	88.27%	550.5	3.7861	46.422	73.24%
R2 L20 A15						
Priority = 0.00	18.8	83.82%	596.22	27.987	59.466	93.04%
Priority = 0.25	18.8	83.82%	596.22	27.987	59.466	93.04%
Priority = 0.50	18.5	83.81%	590.8	26.81	58.455	92.86%
Priority = 0.75	17.1	83.74%	556.91	18.831	50.086	90.32%
R2 L20 A90						
Priority = 0.00	10.7	88.09%	597.61	13.078	56.211	77.97%
Priority = 0.25	10.7	88.09%	597.61	13.078	56.211	77.97%
Priority = 0.50	10.4	88.25%	590.54	10.11	53.164	77.03%
Priority = 0.75	9.1	87.45%	557.59	5.6628	45.215	69.93%
R3 L0 A15						
Priority = 0.00	18.7	86.88%	573.67	5.8344	52.838	81.43%
Priority = 0.25	18.7	86.88%	573.67	5.8344	52.838	81.43%
Priority = 0.50	18.4	86.82%	567.26	5.0728	51.933	80.89%
Priority = 0.75	17.2	86.22%	536.71	2.8316	47.324	76.96%
R3 L0 A90						
Priority = 0.00	10.7	89.79%	583.46	2.5838	57.294	60.22%
Priority = 0.25	10.7	89.79%	583.46	2.5838	57.294	60.22%
Priority = 0.50	10.5	89.79%	578.87	1.9084	55.227	58.73%
Priority = 0.75	9.1	88.82%	546.47	0.35074	48.017	51.99%
R3 L20 A15						
Priority = 0.00	18.7	86.14%	579.16	8.1425	53.801	79.02%
Priority = 0.25	18.7	86.14%	579.16	8.1425	53.801	79.02%
Priority = 0.50	18.5	86.20%	573.99	7.4896	53.008	78.62%
Priority = 0.75	17.2	85.53%	543.51	5.5822	48.443	74.19%
R3 L20 A90						
Priority = 0.00	10.7	88.68%	593.58	4.4041	56.671	57.99%
Priority = 0.25	10.7	88.68%	593.58	4.4041	56.671	57.99%
Priority = 0.50	10.4	88.56%	588.45	3.4147	54.3	56.30%
Priority = 0.75	9.1	87.48%	556.79	2.8671	46.784	49.19%

To better understand the behavior of the outputs with respect to the priority criteria variable, outputs for three settings (R2 L0 A15, R2 L20 A15 and R2 L20 A90)

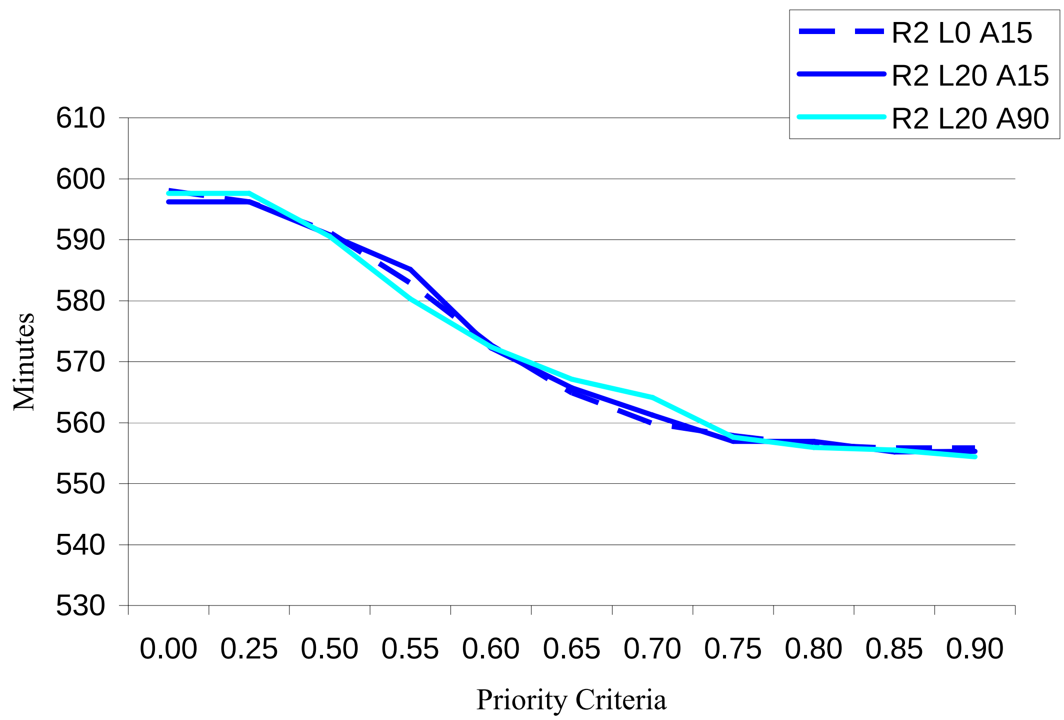

Figure 6.1. Priority Criteria vs. Clinic Close Time

were plotted. Minimal variation was observed for practitioner and room utilization. Similar behavior was observed for clinic close time, waiting room wait time and total wait time outputs. Clinic close time behavior with respect to priority criteria is shown in Figure 6.1. Priority criterion of 0.75 appears to be the lowest criteria value to achieve the lowest clinic close time.

When the priority criterion is set at 0.00, all patients (walk-in or late) who arrive before the clinic closes will be added to the days' schedule. No patients will be sent home. This is the current practice at Moffitt. Using the 0.00 version of our model will directly compare the decision model developed in this research to the current decision processes at Moffitt. Therefore, the remaining analysis will compare the current system model to only two versions of our clinic model, priority criteria of 0.00 and 0.75. Output analysis of our clinic model and the current system model are discussed in the next section.

6.3.2 Clinic and Current System Model Comparison

All eight settings are used to compare the impact of our decision models on a Moffitt clinic. Table 6.7 shows the average outputs for each setting for both the clinic model with a priority criterion of 0.00 and the current system model. A third line is included in the table to show any improvement. A negative improvement, the current system performed superior to our clinic model, is shown in parentheses. No clear difference is observed and for that reason, our decision model appears to perform similar to the current practice. One possible reason our model performed so closely to the current system model is because of the number of scheduled patients in the system.

The number of scheduled patients generated in the settings is a direct result of the appointment schemes, the distributions of appointment lengths. These distributions are based on surgeon and oncologist appointments at Moffitt. Surgeon appointment scheme generated between 18 and 20 scheduled patients each day. Oncologist appointment scheme generated 10 or fewer scheduled patients per day. The small number of scheduled patients minimized the number of opportunities for our model to be utilized. The fewer scheduled patients entering the system, the fewer late patients and smaller waiting room queue. Under the surgeon appointment scheme, waiting room queues were observed, but generally in the later part of the day. Multiple patients in the waiting room under the oncologist appointments was infrequent. To test the system response under different conditions, the R2 L20 A15 setting was used to overload the system with scheduled patients. Reducing the appointment lengths to 10-minute and 15-minute visits generated over 30 patients per day. The late patient definition was also adjusted to allow for more late patients in the system. A 21.61 minute improvement was observed in clinic close time. 13.23-minute and 14.67-minute improvements were also observed for waiting room wait time and total waiting time respectively. Practically no difference was found in practitioner or room utilization. Therefore, given more opportunities to be utilized, our model may improve clinic close time and waiting times.

To illustrate the scheduling and operational differences of the clinic and current system models under Moffitt clinic conditions, two gantt charts (setting R2 L0 A15 and R2 L0 A90) can be found in Appendix I. Table 6.8 shows the output variance for each setting.

Table 6.7 Clinic and Current System Model Average Output Comparison

	Number of Patients	Practitioner Utilization	Clinic Close Time	Waiting Room Wait Time	Total Wait Time	Room Utilization
R2 L0 A15						
Clinic Model, priority = 0.00	19.3	84.76%	598.06	24.31	55.03	93.87%
Current System	19.3	83.70%	605.82	23.78	55.35	94.03%
Improvement		*1.06%*	*7.76*	*(0.54)*	*0.31*	*0.16%*
R2 L0 A90						
Clinic Model, priority = 0.00	10.7	89.12%	589.03	11.37	56.40	80.50%
Current System	10.7	89.04%	591.31	9.81	55.14	80.68%
Improvement		*0.08%*	*2.28*	*(1.55)*	*(1.25)*	*0.18%*
R2 L20 A15						
Clinic Model, priority = 0.00	18.8	83.82%	596.22	27.99	59.47	93.04%
Current System	18.8	83.23%	601.38	25.14	57.02	92.88%
Improvement		*0.59%*	*5.16*	*(2.84)*	*(2.45)*	*-0.16%*
R2 L20 A90						
Clinic Model, priority = 0.00	10.7	88.09%	597.61	13.08	56.21	77.97%
Current System	10.7	88.06%	597.32	12.92	56.61	78.53%
Improvement		*0.04%*	*(0.29)*	*(0.15)*	*0.40*	*0.57%*
R3 L0 A15						
Clinic Model, priority = 0.00	18.7	86.88%	573.67	5.83	52.84	81.43%
Current System	18.8	86.55%	577.65	5.45	52.75	81.26%
Improvement		*0.33%*	*3.98*	*(0.39)*	*(0.09)*	*-0.18%*
R3 L0 A90						
Clinic Model, priority = 0.00	10.7	89.79%	583.46	2.58	57.29	60.22%
Current System	10.7	89.84%	584.80	2.39	57.56	60.54%
Improvement		*-0.05%*	*1.34*	*(0.19)*	*0.26*	*0.32%*
R3 L20 A15						
Clinic Model, priority = 0.00	18.7	86.14%	579.16	8.14	53.80	79.02%
Current System	18.8	85.95%	581.68	8.08	53.84	78.89%
Improvement		*0.19%*	*2.52*	*(0.06)*	*0.04*	*-0.13%*
R3 L20 A90						
Clinic Model, priority = 0.00	10.7	88.68%	593.58	4.40	56.67	57.99%
Current System	10.7	88.69%	592.99	3.95	57.08	58.57%
Improvement		*-0.01%*	*(0.59)*	*(0.46)*	*0.41*	*0.59%*

Table 6.8 Clinic and Current System Model Variance Comparison

	Number of Patients	Practitioner Utilization	Clinic Close Time	Waiting Room Wait Time	Total Wait Time	Room Utilization
R2 L0 A15						
Clinic Model, priority = 0.00	19.3	0.03%	1313.49	205.35	221.73	0.16%
Current System	19.3	0.04%	1576.87	206.69	249.14	0.18%
R2 L0 A90						
Clinic Model, priority = 0.00	10.7	0.10%	1420.02	199.22	381.61	0.78%
Current System	10.7	0.11%	1245.71	179.35	354.98	0.82%
R2 L20 A15						
Clinic Model, priority = 0.00	18.8	0.06%	1573.26	243.95	274.76	0.19%
Current System	18.8	0.07%	1951.21	230.24	266.74	0.18%
R2 L20 A90						
Clinic Model, priority = 0.00	10.7	0.10%	1192.70	140.73	338.51	0.98%
Current System	10.7	0.10%	1268.93	137.69	323.94	0.98%
R3 L0 A15						
Clinic Model, priority = 0.00	18.7	0.07%	1193.82	35.58	124.39	0.80%
Current System	18.8	0.07%	1015.62	41.26	122.92	0.66%
R3 L0 A90						
Clinic Model, priority = 0.00	10.7	0.09%	1312.48	18.07	343.54	1.23%
Current System	10.7	0.10%	1086.03	33.27	377.98	1.28%
R3 L20 A15						
Clinic Model, priority = 0.00	18.7	0.07%	1183.24	30.90	128.74	0.72%
Current System	18.8	0.07%	1028.07	31.82	140.23	0.77%
R3 L20 A90						
Clinic Model, priority = 0.00	10.7	0.11%	1038.48	14.87	294.79	1.23%
Current System	10.7	0.11%	1117.17	15.75	296.84	1.29%

Table 6.9 Clinic and Current System Model Comparison with Reduced Patients: Average Output

	Number of Patients	Practitioner Utilization	Clinic Close Time	Waiting Room Wait Time	Total Wait Time	Room Utilization
R2 L0 A15						
Clinic Model, priority = 0.75	17.7	84.33%	557.87	16.01	46.60	91.36%
Current System	19.333	83.70%	605.82	23.78	55.35	94.03%
Improvement / Patient Loss	*1.63*	*0.63%*	*47.95*	*7.77*	*8.75*	*-2.68%*
% gain	*8.45%*	*0.75%*	*7.91%*	*32.66%*	*15.81%*	*-2.85%*
R2 L0 A90						
Clinic Model, priority = 0.75	9.0666	88.27%	550.50	3.79	46.42	73.24%
Current System	10.733	89.04%	591.31	9.81	55.14	80.68%
Improvement / Patient Loss	*1.67*	*-0.77%*	*40.81*	*6.03*	*8.72*	*-7.44%*
% gain	*15.53%*	*-0.87%*	*6.90%*	*61.41%*	*15.81%*	*-9.22%*
R2 L20 A15						
Clinic Model, priority = 0.75	17.1	83.74%	556.91	18.83	50.09	90.32%
Current System	18.766	83.23%	601.38	25.14	57.02	92.88%
Improvement / Patient Loss	*1.67*	*0.51%*	*44.47*	*6.31*	*6.93*	*-2.55%*
% gain	*8.88%*	*0.61%*	*7.39%*	*25.10%*	*12.15%*	*-2.75%*
R2 L20 A90						
Clinic Model, priority = 0.75	9.0666	87.45%	557.59	5.66	45.22	69.93%
Current System	10.733	88.06%	597.32	12.92	56.61	78.53%
Improvement / Patient Loss	*1.67*	*-0.61%*	*39.73*	*7.26*	*11.40*	*-8.61%*
% gain	*15.53%*	*-0.69%*	*6.65%*	*56.18%*	*20.13%*	*-10.96%*

Table 6.9 (Continued)

	Number of Patients	Practitioner Utilization	Clinic Close Time	Waiting Room Wait Time	Total Wait Time	Room Utilization
R3 L0 A15						
Clinic Model, priority = 0.75	17.166	86.22%	536.71	2.83	47.32	76.96%
Current System	18.766	86.55%	577.65	5.45	52.75	81.26%
Improvement / Patient Loss	*1.60*	*-0.33%*	*40.94*	*2.62*	*5.43*	*-4.29%*
% gain	*8.53%*	*-0.38%*	*7.09%*	*48.03%*	*10.28%*	*-5.28%*
R3 L0 A90						
Clinic Model, priority = 0.75	9.0666	88.82%	546.47	0.35	48.02	51.99%
Current System	10.733	89.84%	584.80	2.39	57.56	60.54%
Improvement / Patient Loss	*1.67*	*-1.02%*	*38.33*	*2.04*	*9.54*	*-8.55%*
% gain	*15.53%*	*-1.14%*	*6.55%*	*85.34%*	*16.58%*	*-14.12%*
R3 L20 A15						
Clinic Model, priority = 0.75	17.166	85.53%	543.51	5.58	48.44	74.19%
Current System	18.766	85.95%	581.68	8.08	53.84	78.89%
Improvement / Patient Loss	*1.60*	*-0.43%*	*38.17*	*2.50*	*5.40*	*-4.70%*
% gain	*8.53%*	*-0.50%*	*6.56%*	*30.93%*	*10.02%*	*-5.96%*
R3 L20 A90						
Clinic Model, priority = 0.75	9.0666	87.48%	556.79	2.87	46.78	49.19%
Current System	10.733	88.69%	592.99	3.95	57.08	58.57%
Improvement / Patient Loss	*1.67*	*-1.21%*	*36.20*	*1.08*	*10.30*	*-9.38%*
% gain	*15.53%*	*-1.36%*	*6.10%*	*27.35%*	*18.04%*	*-16.02%*

Similarly, all eight settings are used to evaluate the output improvements that result from our clinic model with priority criteria 0.75. As previously mentioned, clinic close time, waiting room wait time and total wait time show an improvement as compared to the current system. However, poorer performance in practitioner and room utilization also occurs. The output changes can be attributed to the change in number of patients. By using the stricter acceptance priority criteria, fewer late and walk-in patients are added to the day's schedule. The actual improvement / patient loss is shown in Table 6.9. The percent gain, the ratio of the actual output improvement to the current system value, is also shown in Table 6.9. The percentage of patients lost can be compared to the percent gain for each output to evaluate total system impact. Unfortunately, information outside the scope of this work (e.g., cost, patient satisfaction and hospital reputation) would be needed to determine if a loss in number of patients is justified by an improvement in clinic close time and waiting times.

An analysis of results from the clinic and current system simulation models was presented in this chapter. The decision models developed in this research were tested as a case study of an H. Lee Moffitt outpatient clinic. Conclusions from this case study, additional applications of the decision models and future research extensions are discussed in the Chapter 7.

Chapter Seven

Conclusions and Future Work

We were motivated to provide a decision making model for outpatient clinics to improve patient waiting time. The obvious disconnect between a scheduled appointment time and the actual time a patient sees his/her practitioner initiated our research. Eventually, our work focused on the daily scheduling decisions clinics make to handle variable patient demand. The purpose of our models is to handle the scheduling and rescheduling of walk-in and late patients respectively as well as determine in what order the practitioner should see patients.

Due to the complicated nature of healthcare and patient conditions, scheduling and operational decisions in an outpatient clinic are complex. Many factors can influence these decisions, many of which are dynamic. Clinics may not have the resources (time or staff) to thoroughly evaluate all relevant factors and make a well-informed decision every time. This work attempts to improve system performance (including patient waiting time) by developing decision models that incorporate all relevant factors and generate information to make the decision. The inclusion of all relevant factors was expected to improve scheduling and operational decisions. A computer simulation modeled after a Moffitt clinic tested our models. Conclusions from this case study are discussed in the next section.

7.1 H. Lee Moffitt Case Study Conclusions

The proposed decision models (PPM and AAM) successfully made walk-in and late patient scheduling decisions as well as modified the sequence in which patients were called back. When there was no reduction in number of patients, our models performed the same as the current system. Differences were within one percentage for practitioner and room utilization and within three minutes for waiting time. The greatest improvement in any of the eight settings was an average clinic close time improvement of 7.76 minutes. Although our decisions models did not generate a clear improvement to the system outputs measures, the models did incorporate all the relevant criteria defined by Moffitt without any adverse effect.

The contributions of this research include identifying, defining and weighting of relevant decision making criteria at H. Lee Moffitt. The criteria and weights were successfully modeled in our Patient Priority and Appointment Assignment Models and tested using a single-clinic computer simulation. Our decision models guaranteed all of the defined criteria are included every time a walk-in or late patient decision must be made. Therefore, making more informed decisions that are centered on the patient and clinic conditions. Based on these findings, implementation of the PPM and AAM with no reduction in number of patients would improve scheduling and operational decisions while not affecting clinic output measures. Considering a reduction in number of patients through the use of our PPM should also be discussed.

One aspect of our PPM is the priority criteria. This criterion determines if a late or walk-in patient will be added to the day’s schedule. This is not current practice at Moffitt. Using our PPM to create a score for each walk-in and late patient and setting the criteria at 0.75 reduced the average number of patients seen and showed some system improvement. On average the clinic closed between 36.20 minutes and 47.95 minutes earlier. Waiting time was also lowered, although not as significantly as clinic close time. Average total waiting time was reduced between 5.43 minutes and 11.40 minutes. While reducing patients made improvements in clinic close time and waiting time, practitioner and room utilization suffered. Generally, the current system (with all patients) reported better practitioner and room utilizations. The tradeoff among number of patients seen, resource utilization, waiting time and clinic close time cannot be fully assessed solely on the information gathered in this research. Additional information such as costs, patient satisfaction and clinic/hospital reputation would also need to be considered. These recommendations are based only on the decision model performance in the Moffitt clinic setting. Using H. Lee Moffitt as a case study imposed certain assumptions and conditions on this research. The implications of using Moffitt clinics as a case study are discussed in the following section.

7.2 H. Lee Moffitt Case Study Assumptions and Conditions

H. Lee Moffitt is a hospital providing comprehensive treatment to a specific segment of the population, cancer patients. Moffitt patients are either in need of diagnosis, receiving treatment or monitoring previous conditions. Patients are generally assigned to a practitioner and have scheduled appointments. As a result of the highly specialized nature of Moffitt and its reputation, people travel distances and wait months to become a Moffitt patient. Clearly, this patient population is different than the population of a community hospital, for example.

The patient attributes (factors defined in Chapter 4) used to in the clinic simulation models were all based on Moffitt patients. The list of attributes and distributions of each attribute were generated by Moffitt clinic staff. Urgency, distance traveled and a second same-day appointment are a few examples of patient attributes where the distribution would most likely change in an alternate hospital setting. In addition to the list of patient attributes and corresponding distributions, Moffitt staff was also used to generate the relative weights and values used in our decision models. The Moffitt clinic staff was surveyed and responses were used to calculate the relative weights and values reported in Chapter 4. The results reported in this work are specific to Moffitt. However, the decision models are transferable to other outpatient facilities.

7.3 Other Applications

The decision model concept described in this work can be transferred to other outpatient settings. Although the specific factors, weights and values defined in Chapter 4 may not be applicable, they can be replaced. Any outpatient facility is able to generate a list of factors that influence scheduling and operational decisions. Relative weights and values are able to be produced in a fashion similar to that described in Chapters 3 and 4. To create a global set of factors, weights and values that are able to effectively be used in any outpatient setting would involve the collaboration of a multi-discipline healthcare team. However, creating a set of factors, weights and values specific to a facility is plausible.

The outpatient clinics at Moffitt are just that, outpatient clinics within a hospital setting. Our decision models are just as appropriate for independent outpatient facilities, such as a primary care doctor's office, dentist or eye doctor. Any facility that is subject to patient demand that includes walk-in and/or late patients could apply our decision models. The decision models could also be applied to a strictly walk-in patient facility or a system that does not assign a patient to a practitioner. Some modification might be needed. For example, late patients would not exist if there were no scheduled appointments. Although the original motivation for the decision models stemmed from the adherence to a scheduled appointment time, a schedule is not necessary to apply our decision models. The PPM and AAM do address same-day decisions, therefore are less likely to apply in an inpatient setting.

Extension outside the healthcare industry is also possible. The decision models are applicable where there exists a server, appointment system and variable demand. If everyone always arrived on time and with an appointment, there would be minimal need for these decision models. Plans for further work are discussed in the last section.

7.4 Future Work

The first step in this research was to test our decision models against the current system at Moffitt. The decision models were expected to improve clinic system performance. However, our findings do not support that suspicion. Therefore, future work is needed to understand why the performance was the same despite the changes made to scheduling and operational decisions. Future work is also needed to determine what changes will affect clinic system performance or if there was in impact at the hospital level of performance. Alterations to patient distributions, factors or weights could potentially change system outputs. This can be accomplished my modifying the information gathered from Moffitt or by studying a different outpatient clinic setting.

References

Abernathy, W. J., Baloff, N., Hershey, J. C., Wandel, S., 1973, “A three-stage manpower planning and scheduling model – a service sector example,” Operations Research, 21 (3), 693-711.

Aczel, J. and Saaty, T. L.,1983, “Procedures for Synthesizing Ratio Judgment,” Journal of Mathematical Psychology, 27, 93-102.

Baesler, F.F., Sepulveda, J.A., 2001, “Multi-objective simulation optimization for a cancer treatment center,” Proceedings of the Winter Simulation Conference, 1405-1411.

Bard, J. F., 1992, “A comparison of the analytic hierarchy process with multiattribute utility theory: a case study,” IIE Transactions, 24 (5), 111-121.

Brahimi, M., Worthington, D.J., 1991, “Queueing models for out-patient appointment systems-A case study,” The Journal of the Operational Research Society, 42(9), 733-746.

Carter, M. W., and Lapierre, S. D., 2001, “Scheduling emergency room physicians,” Health Care Management Science, 4 (4), 347-360.

Cayiril, T., and Veral, E., 2003, “Outpatient scheduling in health care: a review of literature,” Production and Operations Management, 12 (4), 519-549.

Chang, J., 2005, “A generalized decision model for naval weapon procurement: Multi-attribute decision making,” Unpublished dissertation, University of South Florida.

De Angellis, V., Felici, G., and Impelluso, P., 2003, “Integrating simulation and optimization in health care centre management,” Eruopean Journal of Operational Research, 150, 101-114.

Denton, B., and Gupta, D., 2003, “A sequential bounding approach for optimal appointment scheduling,” IIE Transactions, 35 (11), 1003-1016.

Donegan, H. A., Dodd, F. J. and McMaster, T. B. M., 1992, “A new approach to AHP decision-making,” The Statistician, 41 (3), 295-302.

Dryer, J. S., 1990, "Remarks on the analytic hierarchy process," Management Science, 36 (3), 249-258.

Everett, J. E., 2002, "A decision support simulation model for the management of an elective surgery waiting system," Health Care Management Science, 5 (2), 89-95.

Fábregas, A. et al., 2004, *Simulación de sistemas productivos con Arena,* EdicionesUninorte. Barranquilla.

Ferland, J. A., 2001, "Generalized assignment type goal programming problem: application to nurse scheduling," Journal of Heuristics, 7, 391-413.

Fone, D., Hollinghurst, S., Temple, M., Round, A., Lester, N., Weightman, A., Roberts, K., Coyle, E., Bevan, G., and Palmer, S., 2003, "Systematic review of the use and value of computer simulation modelling in population health and health care delivery," Journal of Public Health Medicine, 25(4), 325-335.

Forman, E. H. and Gass, S. I., 2001, "The analytic hierarchy process" An exposition," Operations Research, 49 (4), 469-486.

Harker, P. T. and Vargas, L. G., 1990, "Reply to "Remarks on the analytic hierarchy process" by J. S. Dryer*," Management Science, 36 (3), 269-273.

Harper, P. R., 2002, "A framework for operational modeling of hospital resources," Health Care Management Science, 5 (3), 165-173.

Hing, E., and Middleton, K. (2004). *National hospital ambulatory medical care survey: 2002 outpatient department summary* (345). Advance Data from Vital and Health Statistics, US Department of Health and Human Services.

Ho, C., Lau, H., 1992, "Minimizing total cost in scheduling outpatient appointments," Management Science, 38(12), 1750-1764.

Ho, C., Lau, H., 1999, "Evaluating the impact of operating conditions on the performance of appointment scheduling rules in service systems," European Journal of Operational Research, 112, 542-553.

Hobbs, B. H., 1980, "A comparison of weighting methods in power plant siting," Decision Sciences, 11, 725-737.

Jaumard, B., Semet, F., and Vovor, T., 1998, "A generalized linear programming model for nurse scheduling," European Journal of Operational Research, 107, 1-18.

Kamenetzky, R. D., 1982, "The relationship between the analytic hierarchy process and the additive value function," Decision Sciences, 13, 702-713.

Kim, S., Horowitz, I., Young, K. K., Buckley, T. A., 2000, "Flexible bed allocation and performance in the intensive care unit," Journal of Operational Research, 18, 427-443.

Klassen, K. J., and Rohleder, T. R., 2004, "Outpatient appointment scheduling with urgent clients in a dynamic, multi-period environment," International Journal of Service Industry Management, 15 (2), 167-186.

Kokkotos, S., Ioannidis, E. V., and Spyropoulos, C. D., 1997, "A system for efficient scheduling of patient tests in hospitals," Medical Informatics, 22 (2), 179-190.

Lehaney, B., Clarke, S. A., and Paul, R. J., 1999, "A case of an intervention in an outpatients department," Journal of Operational Research Society, 50, 877-891.

Miller, H. E., Pierskalla, W. P., and Rath, G. J., 1976, "Nurse scheduling using mathematical programming," Operations Research, 24 (5), 857-870.

Millar, H. H., Kiragu, M., 1998, "Cyclic and non-cyclic scheduling of 12 h shift nurses by network programming," European Journal of Operational Research, 104, 582-592.

National Center for Health Statistics, Centers for Disease Control and Prevention. (2004). *Heath, United States, 2004 with Chartbook on Trends in the Health of Americans* (28).Hyattsville, Maryland: US Department of Health and Human Services.

Rising, E., Baron, R. and Averill, B., 1973, "A systems analysis of a university health service outpatient clinic," Operations Research, 21(5), 1030-1047.

Robinson, L. W., Chen, R. R., 2003, "Scheduling doctor's appointments: optimal and empirically-based heuristic policies," IIE Transactions, 35(3), 295-307.

Rohleder, T. R., Klassen, K. J., 2002, "Rolling horizon appointment scheduling: A simulation study," Health Care Management Science, *5*(3), 201-209.

Saaty, T. L. (1980). *The Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation*. McGraw-Hill. New York.

Saaty, T. L.,1986, "Axiomatic Foundation of the Analytic Hierarchy Process," Management Science, 32 (7), 841-855.

Saaty, T. L. and Vargas, L. G. (2001). *Models, Methods, Concepts and Applications of the Analytic Hierarchy Process*. Kluwer Academic Publishers. Boston.

Sepulveda, J.A., Thompson, W.J., Baesler, F.F., Alvarez, M.I. and Cahoon, L.E., 1999, "The use of simulation for process improvement in a cancer treatment center," Proceedings of the Winter Simulation Conference, 1541-1548.

Sofaer, S., and Firminger, K., 2005, "Patient perceptions of the quality of Health services," Annual Review of Public Health, 26, 513-559.

Soliman, E., 1997, "Improving resource utilization through patient dependency systems," Journal of Medical Systems, 21 (5), 291-302.

Swisher, J.R., Jacobson, S.H., Jun, J.B., and Balci, O., 2001, "Modeling and analyzing a physician clinic environment using discrete-event (visual) simulation," Computers and Operations Research, 28, 105-125.

Su, Syi, Shih, Chung-Liang, 2003, "Managing a mixed-registration-type appointment system in outpatient clinics," International Journal of Medical Informatics, 70(1), 31-40.

Triantaphyllou, Evangelos (2000). *Multi-criteria Decision Making Methods: A Comparative Study*. Kluwer Academic Publishers. Boston.

Vaidya, O. S., and Kumar, S., 2006, "Analytic hierarchy process: an overview of applications" European Journal of Operational Research, 169, 1-29.

Vissers, J.M.H., 1998a, "Health care management modeling: a process perspective," Health Care Management Science, 1, 77-85.

Vissers, J. M. H., 1998b, "Patient flow-based allocation of inpatient resources: a case study," European Journal of Operational Resources, 105 (2), 356-370.

Warner, D. M., 1976, "Scheduling nursing personnel according to nursing preference: a mathematical programming approach," Operations Research, 24 (5), 842-856.

Warner, D. M., Prawda, J., 1972, "A mathematical programming model for scheduling nursing personnel in a hospital," Management Science, 19 (4), 411-422.

Worthington, D., Brahimi, M., 1993, "Improving out-patient appointment systems," International Journal of Health Quality Assurance, 6(1), 18-23.

Xu, Z., 2000, "On consistency of the weighted geometric mean complex judgment matrix in AHP," European Journal of Operational Research, 126, 683-687.

Yeh, C., 2002, "A problem-based selection of multi-attribute decision making methods," International Transactions in Operational Research, 9, 169-181.

Yoon, P. K. and Hwang, C., (1995). *Multiple Attribute Decision Making: An Introduction*. Sage Publications. California.

Zanakis et al., 1998, "Multi-attribute decision making: A simulation comparison of select methods," European Journal of Operational Research, 107, 507-529.

Appendices

Appendix A: Moffitt Clinic Observations

PSRs
GU Tuesday, December 20 2005

- If patient arrives within 15 minutes of appointment time
  - checked in as usual

- If patient arrives more than 15 minutes late
  - Patient asked why they are late
  - PSR does not change anything in the system when a patient arrives late
  - PSR consults with Nurse before the patient can be checked in
  - According to PSR, Nurse typically asks PSR why the patient arrived late
  - PSR may use their own discretion if Nurse is unavailable
  - Nurse may also consult with the Physician

- If a patient needs to be added on
  - PSRs (Check-in and Scheduler) consult with Nurse before a patient without an appointment can be added into the schedule
  - Needs to be a clinical reason for the patient to be an add-on
  - If the patient is physically in the clinic, a NOW appointment (for that current time) is made – otherwise, the Nurse determines what time to add the patient
  - Some patients who arrive without an appointment may only need to speak to the Nurse, an appointment is not made

- Physician preference or common practice is used as a guideline for decision making
- Type of visit (ex. New Patient) is taken into consideration when a patient arrives late

GI Tuesday, December 27 2005

- If the patient arrives late
  - PSR consults with Nurse and asks how it should be handled
  - Nurse either tells the PSR to register the patient or consults with the Physician and then instructs the PSR

- If the patient needs to be added on
  - PSR consults with Nurse (avg of 12 add-ons / day)
  - Nurse either tells the PSR to register the patient or consults with the Physician and then instructs the PSR – some Physicians are always consulted
  - When Nurse instructs PSR to add the patient, the PSR “pre-registers” the

  - patient – the patient is then sent to another PSR (scheduler) to be added into the schedule.
  - Scheduler consults with the Nurse again about what time to add in the patient
  - If a Nurse specifies a time, the scheduler adds the patient in at that time regardless of availability. The Nurse may also leave the appointment time up to the scheduler's discretion (next time slot – regardless of availability)

Cutaneous Tuesday, January 3 2006

- If a patient arrives late
  - PSR handles differently depending on Physician, some Physicians always have to be consulted
  - Patients always fit into the schedule – Physicians are only in clinic certain days each week.
  - Patient appointments adjusted at Physician's request
  - PSR will check with the MA and Nurse – they make the decision about when to call back the patient – Patient appointment not changed in the schedule

- If a patient needs to be added on
  - Nurse is consulted
  - Patients always fit into the schedule
  - Happens frequently

Breast Thursday, January 5 2006

- If the patient arrives late
  - The check-in PSR contacts the registration PSR that the patient is late and asks if / when the patient will be seen
  - Registration PSR decides if the patient will be registered – they usually take into account the condition of the patient
  - Visit type is considered (ex. Procedures) may be rescheduled due to the length of the visit

- If the patient needs to be added on
  - PSR contacts the scheduler or sends the patient directly to the scheduler
  - 3 add-ons / day is high for this clinic

- PSRs have very little contact with the Nurses

Appendix A: (Continued**)**

MA
GU Thursday, December 22 2005

- Call back
  - Generally, in appointment order MA

- If patients arrive early MA
  - Patients may be taken early, Physician dependant
  - MA asks and Physician decides if the patient is brought back to a room early
  - May depend on type of visit (New vs. Established patients)
  - May depend also on Physician "speed" and preference

- If the patient arrives late (more than 15 minutes) MA
  - Moffitt will always see the patient, becomes a matter of priority
  - Patient may be put at the end of clinic for that day (after the last scheduled patient) if a low priority
  - May consider past behavior (is the patient always late?)
  - May also consider the cause of delay (patient coming from IC)
  - The MA screen shows who is checked in

Cutaneous Tuesday, January 3 2006

- Call back MA
  - Normally, by appointment
  - If no show – go to next appointment
  - If double booked – call back whomever arrived first

- If the patient is early
  - May take early if the Physician is available

- If the patient is late
  - MA will consult Nurse
  - Emergencies are a priority
  - Will consider if the patient had another Moffitt appointment (ex. IC)

Breast Thursday, January 5 2006

- Call back MA1
  - As Arrive, not necessarily by appointment (as long as it is close to the appointment time)

  - Wont call back 2 or 3 hours early
  - If the patient is ill, they will bring them back to rest in a bed until their appointment time (may call back to a room if one is available)
  - Call back when you don't have anyone who is scheduled

- If the patient is early MA1
  - Will only take a patient a few minutes early (10 minutes)

- If the patient arrives late MA1
  - (30 min – 1 hour) MA will call back at their discretion
  - Patient wont have to wait all day, just until there is a space
  - If (5-10 min) late MA will still call back as usual as long as no other patient was called back or if the patient's name was not called yet

- If the patient needs to be added on MA1
  - MA will consult Nurse

- Call back MA2
  - Ill patients are a priority
  - Physicians preference is considered – want situations handled differently
  - If the patients are waiting for labs or reports – will delay call back – MA will call next patient instead

- If the patient is early MA2
  - Check if patient had labs done
  - Wont call a patient back just because they are early

- If the patient is late MA2
  - Consult Nurse

- If the patient needs to be added on MA2
  - Decision made by Physician and Nurse

Appendix A: (Continued)

Nurses

GU Thursday, December 22 2005

- If the patient is late (more than 15 minutes) Nurse
  - Nurse decides how to schedule the patient
  - If the patient is really late, they may be turned away (more than 2 hours) if:
    - Physician is already backed up
    - It is a follow-up appointment
    - Habitual lateness
  - Nurse does not want to back up other patients
  - Nurse may consider:
    - Appointment type
    - Illness
    - Distance (Patient's who travel)
    - Overbooked anyway
    - Physician is backed up and their ability to see the patient

- If the patient needs to be added on Nurse
  - Use the same criteria if at the clinic or on phone (medical need)
  - Nurse may decide or may consult the physician
  - Nurse cannot consider all factors
  - Use experience and judgment

Senior Adult Thursday, December 22 2005

- If the patient is late Nurse
  - Will see even if late
  - Find a time in the schedule

- If the patient needs to be added on Nurse
  - Finds a place in the schedule
  - Try not to make on-time patients wait

Cutaneous Tuesday, January 3 2006

- Call back Nurse
  - Generally, in appointment order
  - Nurse makes most calls, may even tell MA when to call back the next patient

Appendix A: (Continued)

- If the patient is late Nurse
    - If the patient is "very late" (not specifically defined) treated the same as an add-on
    - If the patient is not "very late" (15-30minutes) they are treated as usual – the clinic is usually running late – late patients end up being "on time"

- If the patient needs to be added on Nurse
    - Added in as able
    - Patients brought in at the end of clinic if needed
    - Already scheduled patients have priority

- General priority to patients who Nurse
    - Very sick
    - VIP
    - Causing an issue in the waiting room

Breast Thursday, January 5 2006

- If the patient is late Nurse
    - Try to see – have other resources (Fellows, residents… anyone on the same Physician team) can see the patient
    - Generally consider the symptoms

- If the patient needs to be added on Nurse
    - If it is an emergency – patient will be seen in the first available space
    - If the patient just walked in, they will wait – the registered patients have priority
    - Some patients will be turned away – very rarely

- Call back Nurse2 (plastic surgery)
    - Critical patients have priority
    - Physicians want rooms filled
    - Will call back patients who are in the waiting room – even if early – wont take a patient in front of another (as far as appointment time)
    -
- If the patient is late Nurse2 (plastic surgery)
    - Less than 20 – 30 min – treated as usual
    - More than 20 – 30 min – treated like an add on

Appendix A: (Continued)

- If a patient needs to be added in Nurse2 (plastic surgery)
  - Will overbook and double book
  - Typically added on at the end of the day

- Patients can be sent to Triage

Summary
What patient to call back next:

1. Appointment time (in order) *
2. Arrival time *
   a. If double booked
   b. As long as close to appointment time
   c. Wont take back 2-3 hours early, only take a few minutes early *
3. Physician preference *
4. Physician ability to see patients (speed)
5. Medical condition / urgency *
6. Pending labs / reports (will delay patient call back)
7. VIP patients

When to schedule / see a late or add-on patient:

1. How late is the patient *
   a. 15 min criteria
   b. 30min – 1hr criteria
   c. 15-30 min criteria
   d. More than 2 hours – may be turned away
2. Current Physician schedule
   a. If already backed up
   b. Don't want to cause delay for scheduled patients *
   c. Scheduled patients have priority
3. Cause of delay *
   a. Coming from another Moffitt appointment
4. Medical condition / urgency *
5. Physician Preference *
6. Type of visit / expected length of visit *
7. Past behavior (habitually late) *
8. Physician ability to see patients (speed)

Standard – next appointment
End of clinic
* - mentioned more than once

Appendix B: Interviews with 3rd floor Clinic Nurses

May 19, 2006

Decision: to see a walk-in patient the same day

- Based on medical condition (urgency)
- If the patient is unable to be treated in the clinic (very urgent) they will be sent to the Direct Referral Center (DRC)
- Patient may be sent home if condition does not warrant being seen the same day – although one nurse said they will always see them

Decision: choose an approximate time to see the walk-in

1. an open space (possibly from a no-show or cancellation)
2. use some of the lunch hour
3. end of the day
4. If nothing is available at the end of the day… may double book
    - 1 nurse does NOT ever double book
    - No triple booking
    - Will only double book so many patients in a day (2 or 3)
    - Double book shorter appointment lengths (follow-ups 10 or 15 mins)
    - Do NOT double book new patient appts (longer appointment lengths)
    - *If 2 patients are double booked – take in arrival order or shortest appt length first.*

- *The best place to put a patient is where there is the least delay for patients*
- *They do consider medical state – an urgent patient will be seen ASAP. Less urgent walk-ins will wait for the next opening after the scheduled patients have been seen. If the walk-in is urgent, they may be seen before a scheduled patient. One nurse said the scheduled patient is ALWAYS the priority over the walk-in. They would have the walk-in wait as long as needed.*

Decision: to see a late patient

- Will only NOT see if very late (hours) or the clinic is already closed (5pm)
- Will see late patients since they had a scheduled appointment

Decision: choose an approximate time to see the **late** patient

5. if less than ~ 30 min late – will see as usual (will take the next patient on the schedule first and then the late patient right after) – appointment order
6. if more than ~ 30 min late - next open space
7. lunch hour
8. end of day
9. If nothing is available at the end of the day… may double book
    - 1 nurse does NOT ever double book
    - No triple booking
    - Will only double book so many patients in a day (2 or 3)

Appendix B: (Continued**)**

- Double book shorter appointment lengths (follow-ups 10 or 15 mins)
- Do NOT double book new patient appts (longer appointment lengths)
- *If 2 patients are double booked – take in arrival order or shortest appt length first*.

General clinic information:

- Last patient usually scheduled around 3:30 / 4pm.
- Number of patients able to be added to the end of the schedule
    - 1-2 (said by 2 nurses)
    - Up to 5 (said by 1 nurse)
- Clinic closes at 5pm – means that the PSRs leave – nurses and practitioners may still be there. They don't bring anyone back after 5pm. The nurses / practitioners stay until the last patient is seen.
- Of working time in the clinic – practitioners spend between 60% and 75% of their time in the exam rooms with patients
- Maximum number of patients seen in a day 13-17
- Assigned appointment lengths are pretty accurate for the total amount of time a patient spends in the exam room (time after called back)
- After the practitioner leaves the patient spends ~ 5 min extra in the exam room – may be more if there is education/teaching involved – they will try to move the patient to a consult room in this case.

Appendix C: Responses from Clinic Operations Managers Meeting

May 25, 2006
Clinic hours

- Normal clinic hours are 8am-5pm
- The first patient typically scheduled at 8am
- It is possible to see patients before 8am since staff arrives early

Lunch

- Some practitioner take a lunch break, some schedule patients straight through(particularly if they are not working a full day)
- Those who schedule a lunch break, schedule it from noon-1pm
- If there is a lunch from 12-1, the last patient is scheduled at 11:30am

Taking late/ walk-in patients

- May continue to take late or walk-in patients even after 5pm if there are other patients still in exam rooms and the practitioner is still there
- If there is an available slot, staff does NOT consider the length of the slot. The patient will be given that time to be seen
- If the patient is URGENT, they will be seen at the next available time – even if they need to double book
- If the patient is NOT URGENT, the staff will schedule them in the following order:
    - Open slot
    - Lunch
    - End of schedule
    - Double book

Clinic performance measures

- A patient satisfaction score is used for a number of measures – each clinic is surveyed twice a year
- The performance of the schedule is discussed with individual practitioners when needed
- COMs typically consider patients being seen close to appointment time as evaluation criteria for schedule or practitioner performance

Scheduled Appointments

- 5%-10% new patients
- Established patient(EP), Post Operation(PO), Pre-Chemo(PC) visits are either 15 or 30 minutes
- New patient (NP) or New established patient(NEP) visits are either 30, 60 or 90 minutes
- Surgeons see more patients/day than Medical Oncologists because of the types of visits typically scheduled for each.

Patient demographics(from Jenny Mikos)

- 65% from surrounding 7 counties
- 11% from Hernando, Manatee and Sarasota
- 21% from other areas in Florida
- 3% from outside of Florida

Appendix C: (Continued)

Distribution estimates

- 5% urgent patients (or less)
- 75% (or more) of patient delays caused by Moffitt
- 10% of patients have pending information when they arrive to the clinic that is needed for their visit
- Pending information causes delays from 30-60minutes
- Walk-in arrival patterns are random (majority before noon, but can continue throughout the rest of the day)
- Practitioners spend 50% of their time in the rooms with patients
- Practitioners work for ~ 15mins (at a time) when doing other work(calls, reviewing patient information, etc.)
- Average number of rooms per practitioner: 2-3 rooms, 4 is high. May have up to 6 if no other practitioner is working that day.

Appendix D: Appointment Assignment Rules for Late and Walk-in Patients

Moffitt clinic rules (based on nurse and staff interviews)

Walk-in patients
Decision to accept patients:
- Assume all patients will be seen unless expected beginning appointment time is after 5pm
- Assume all walk-in patients that arrive will be seen in the clinic (not sent to Direct Referral Center)

Decision to assign an approximate appointment time:
1. Consider patient medical state (urgency) - urgent patients moves to the front of the queue to be seen by the practitioner
2. an open space (possibly from a no-show, cancellation or a patient visit that ended early)
3. lunch hour
4. end of day (up to 5pm for the start of the appointment)
5. double book
   - Time that disturbs the least number of patients (schedule disruption)
   - Will only double book so many patients in a day (2 or 3)
   - Double book shorter appointment lengths (follow-ups 10 or 15 mins)
   - Do NOT double book new patient appointments (longer appointment lengths)

Late patients
Decision to accept patients:
- Assume all patients will be seen unless expected beginning appointment time is after 5pm
- Assume all late patients that arrive will be seen in the clinic (not sent to Direct Referral Center)

Decision to assign approximate appointment time:
1. if less than 30 min late – add to queue and take in appointment order
2. if more than 30 min late - next open space
3. lunch hour
4. end of day
5. double book
   - Will only double book so many patients in a day (2 or 3)
   - Double book shorter appointment lengths (follow-ups 10 or 15 mins)
   - If multiple follow-up slots – choose first
   - Do NOT double book new patient appointments (longer appointment lengths)

Appendix E: Original Survey

Pair-wise Comparison Survey for Patient Priority Factors

This survey form is designed to determine the amount of importance placed on different factors that affect decisions made with respect to the priority of a patient. We hope to capture how decisions are made by clinic staff by asking you to rate the importance you place on each factor when making decisions such as:
1. Can you add a late or walk-in patient to the existing schedule today?
2. Among all the waiting patients, which one should be called back next?

Your sincere answers are very important to develop a successful decision model, which is expected to help clinical staff make the best scheduling decisions with respect to multiple influencing factors. Please read each question carefully and give your answers.

General Questions
1. What is your current job title?
   a. Clerical   b. Medical Assistant   c. Nurse   d. Practitioner   e. Management
2. How many years have you worked at Moffitt?
   a. Less than 1   b. 1-5   c. 5-10   d. more than 10
3. How many years have you been in the healthcare field? __________ years
4. What role do you play in the daily decisions made about patient scheduling?
   a. Supervisor   b. Decision maker   c. Carry out the decision   d. None

Factor Comparisons

The criteria below show how to compare two factors at a time. If you think Factor A (Urgency) is very strongly more important than Factor B (Schedule Disruption), you should mark on the number 7 placed on the A-side as follows.

Table E.1Criteria Table for Factor Comparisons: Original Survey

Intensity of Importance	*Definition*	*Explanation*
1	Equal Importance	Two activities contribute equally to the objective
3	Moderate Importance	Experience and judgment slightly favor one activity over another
5	Strong Importance	Experience and judgment strongly favor one activity over another
7	Very Strong Importance	An activity is very strongly favored over another; its dominance demonstrated in practice
9	Extreme Importance	The evidence favoring one activity over another is of the highest possible order of affirmation

Intermediate values such as 2, 4, 6 and 8 are possible to use by selecting the dash (-) between values.

Appendix E: (Continued)

Factor (A)	Relative Importance	Factor (B)
Urgency	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Schedule Disruption

← A is more important   B is more important →

Nine factors have been identified and defined for you. Please read them carefully. Answer the factor comparisons as you would when determining the priority of a patient with respect to scheduling walk-in or late arrival patients or which patient to call back next.

Table E.2 Factor Definitions: Original Survey

Factor	Definition
Distance Traveled	the time traveled by the patient from home to Moffitt
Urgency	a medical state determined by clinical staff
Schedule Disruption	the number of patient with previous appointment times
Other Appointment	a scheduled appointment for the same day within Moffitt that will be delayed if the patient is not seen at the current time
Time to Appointment Time	the difference between the current time and the appointment time. (Current time – Appointment time)
Cause of Delay	the reason the patient was late
Estimated Treatment Time	the appointment length predetermined by the type of visit and the physician being seen
Demand per Practitioner	the daily ratio of patient hours scheduled for a given practitioner compared to the patient hours available in the schedule
Pending Information	any information, such as lab results or X-rays, needed for treatment in the clinic that day

Appendix E: (Continued)

Factor (A)	Relative Importance	Factor (B)
Distance Traveled	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Urgency
Distance Traveled	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Schedule Disruption
Distance Traveled	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Other Appointment
Distance Traveled	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Time to Appointment
Distance Traveled	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Cause of Delay
Distance Traveled	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Estimated Treatment Time
Distance Traveled	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Demand per Resource
Distance Traveled	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Pending Information

← A is more important B is more important →

Urgency	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Schedule Disruption
Urgency	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Other Appointment
Urgency	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Time to Appointment
Urgency	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Cause of Delay
Urgency	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Estimated Treatment Time
Urgency	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Demand per Resource
Urgency	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Pending Information

← A is more important B is more important →

Appendix E: (Continued)

Schedule Disruption	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Other Appointment
Schedule Disruption	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Time to Appointment
Schedule Disruption	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Cause of Delay
Schedule Disruption	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Estimated Treatment Time
Schedule Disruption	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Demand per Resource
Schedule Disruption	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Pending Information

A is more important B is more important

Other Appointment	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Time to Appointment
Other Appointment	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Cause of Delay
Other Appointment	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Estimated Treatment Time
Other Appointment	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Demand per Resource
Other Appointment	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Pending Information

A is more important B is more important

Time to Appointment	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Cause of Delay
Time to Appointment	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Estimated Treatment Time
Time to Appointment	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Demand per Resource
Time to Appointment	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Pending Information

A is more important B is more important

Appendix E: (Continued)

Cause of Delay	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Estimated Treatment Time
Cause of Delay	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Demand per Resource
Cause of Delay	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Pending Information

← A is more important B is more important →

Estimated Treatment Time	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Demand per Resource
Estimated Treatment Time	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Pending Information

← A is more important B is more important →

Demand per Resource	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Pending Information

← A is more important B is more important →

Open-ended Questions

1. If you think there is room for improvement in the current patient scheduling practices of the clinics, what area do you think could use the greatest improvement?

2. Are there any other factors affecting the priority of a patient, with respect to scheduling, that you think should be included in this survey?

Appendix F: Final Survey

Pair-wise Comparison Survey for Patient Priority Factors

This survey form is designed to determine the amount of importance placed on different factors that affect decisions made with respect to the priority of a patient. We hope to capture how decisions are made by clinic staff by asking you to rate the importance you place on each factor when making decisions such as:

Question #1. Can you add in a late or walk-in patient to the schedule today?
Question #2. Which patient should be called back next?

Your sincere answers are very important to develop a successful decision model, which is expected to help clinical staff make the best scheduling decisions with respect to multiple influencing factors. Please read each question carefully and give your answers.

General Questions

1. What is your current job title?
   a. Clerical   b. Medical Assistant   c. Nurse   d. Practitioner   e. Management
2. How many years have you worked at Moffitt?
   a. Less than 1   b. 1-5   c. 5-10   d. more than 10
3. How many years have you been in the healthcare field? __________ years
4. What role do you play in the daily decisions made about patient scheduling?
   a. Supervisor   b. Decision maker   c. Carry out the decision   d. None

Factor Comparisons

The criteria below show how to compare two factors at a time. If you think Factor A (Other Appointment) is very strongly more important than Factor B (Pending Information) with respect to the given question, you should mark on the number 7 placed on the A-side as follows.

Table F.1 Criteria Table for Factor Comparisons: Final Survey

Intensity of Importance	*Definition*	*Explanation*
1	Equal Importance	Two activities contribute equally to the objective
3	Moderate Importance	Experience and judgment slightly favor one activity over another
5	Strong Importance	Experience and judgment strongly favor one activity over another
7	Very Strong Importance	An activity is very strongly favored over another; its dominance demonstrated in practice
9	Extreme Importance	The evidence favoring one activity over another is of the highest possible order of affirmation

Intermediate values such as 2, 4, 6 and 8 are possible to use by selecting the dash (-) between values.

Appendix F: (Continued)

Factor (A)	Relative Importance	Factor (B)
Other Appointment	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Pending Information

A is more important ← → B is more important

PART A

Factors related to Question #1 have been identified and defined for you. Please read them carefully. Answer the factor comparisons as you would when determining the priority of a walk-in or late arrival patient with respect to:

Question #1: Can you add in a late or walk-in patient to the schedule today?

Table F.2 Factor Definitions: Final Survey

Factor	Definition
Distance Traveled	the time traveled by the patient from home to Moffitt (1 hour, 2 hours, etc.)
Other Appointment	a scheduled appointment for the same day within Moffitt
Cause of Delay	the reason the patient was late
Estimated Treatment Time	the appointment length predetermined by the type of visit and the physician being seen
Demand per Practitioner	the daily ratio of patient hours scheduled for a given practitioner compared to the patient hours available in the schedule (e.g., double booked)
Pending Information	any information, such as lab results or X-rays, needed for treatment in the clinic that day

Factor (A)	Relative Importance	Factor (B)
Distance Traveled	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Other Appointment
Distance Traveled	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Cause of Delay
Distance Traveled	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Estimated Treatment Time
Distance Traveled	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Demand per Resource
Distance Traveled	9 - 7 - 5 - 3 - 1 - 3 - 5 - 7 - 9	Pending Information

A is more important ← → B is more important

Other Appointment	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Cause of Delay
Other Appointment	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Estimated Treatment Time
Other Appointment	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Demand per Resource
Other Appointment	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Pending Information

A is more important B is more important

Cause of Delay	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Estimated Treatment Time
Cause of Delay	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Demand per Resource
Cause of Delay	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Pending Information

A is more important B is more important

Estimated Treatment Time	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Demand per Resource
Estimated Treatment Time	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Pending Information

A is more important B is more important

Demand per Resource	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Pending Information

A is more important B is more important

Appendix F: (Continued)

PART B

Factors related to Question #2 have been identified and defined for you. Please read them carefully. Answer the factor comparisons as you would when determining the priority of a patient with respect to:

Question #2: Which patient should be called back next?

Factor	Definition
Other Appointment	a scheduled appointment for the same day within Moffitt
Time to Appointment Time	the difference between the current time and the appointment time. (Current time – Appointment time)
Cause of Delay	the reason the patient was late
Estimated Treatment Time	the appointment length predetermined by the type of visit and the physician being seen
Pending Information	any information, such as lab results or X-rays, needed for treatment in the clinic that day

Time to Appointment	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Cause of Delay
Time to Appointment	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Estimated Treatment Time
Time to Appointment	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Other Appointment
Time to Appointment	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Pending Information

← →

A is more important   B is more important

Cause of Delay	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Estimated Treatment Time
Cause of Delay	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Other Appointment
Cause of Delay	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Pending Information

← →

A is more important   B is more important

Appendix F: (Continued)

Estimated Treatment Time	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Other Appointment
Estimated Treatment Time	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Pending Information

← A is more important B is more important →

Other Appointment	9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9	Pending Information

← A is more important B is more important →

Open-ended Questions

1. If you think there is room for improvement in the current patient scheduling practices of the clinics, what area do you think could use the greatest improvement?

2. Are there any other factors affecting the priority of a patient, with respect to scheduling, that you think should be included in this survey?

Appendix G: Simulation Data

Table G.1 Add on patients, October 2005

Clinic	# visits	# add-ons	%
Direct Referral Center	136	130	95.6
Amb Internal Medicine Clinic	72	1	1.4
Integrative Medicine Clinic	27	3	11.1
GI Clinic	892	20	2.2
Neuro Clinic	489	51	10.4
Infusion Center	3847	863	22.4
GU clinic	770	35	4.5
Breast Clinic	488	19	3.9
Senior Adult Clinic	288	11	3.8
Heme Clinic	729	51	7.0
BMT clinic	430	35	8.1
BMT Infusion Area	1325	400	30.2
Women's Clinic	401	20	5.0
Sarcoma Clinic	294	23	7.8
Head & Neck Clinic	514	29	5.6
Thoracic Clinic	699	27	3.9
Breast Clinic	720	38	5.3
Cutaneous Clinic	833	40	4.8
Anesthesia Pain Clinic	46	2	4.3

Appendix H: Simulation Variables

System Settings
1. # rooms
2. # practitioners
3. # nurses
4. # MAs
5. Clinic hours
6. Lunch hour
7. Last appointment
8. Last appointment before lunch
9. Time last add-in patients accepted
10. Double booking
11. Patient assignment to Practitioner

Input Data
1. Arrival distribution (% late patients)
2. Walk-in arrival distribution
3. Max # of walk-in patients
4. Appointment distribution
5. Practitioner extra task distribution
6. Max # of Practitioner extra tasks
7. Nurse extra task distribution
8. Max # of Nurse extra tasks
9. MA extra task distribution
10. Max # of MA extra tasks
11. Practitioner process distribution
12. Nurse Process distribution
13. MA process distribution

Outputs
1. Number of patients
2. Practitioner Utilization
3. Clinic close time
4. Waiting room wait time
5. Room utilization

Appendix I: Gantt Charts

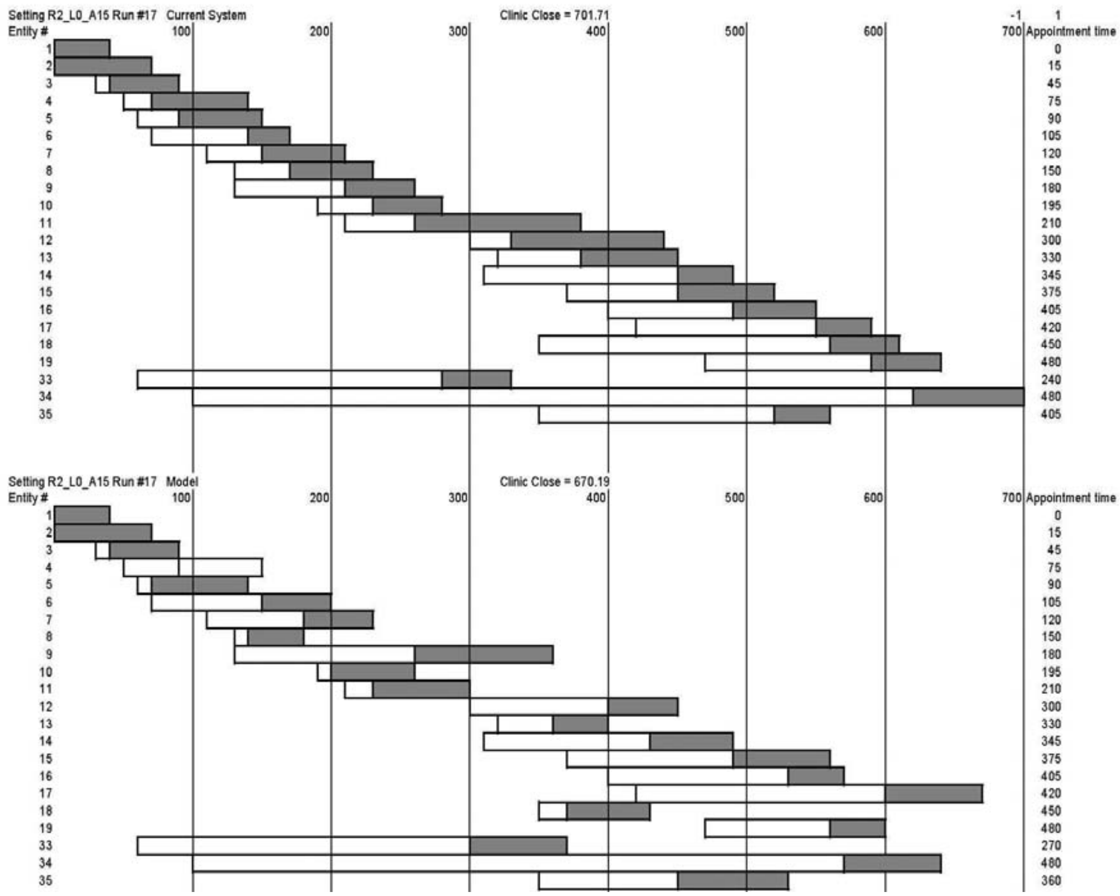

Figure I.1 Setting R2 L0 A15 Gantt Chart

Appendix I: (Continued)