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Operational decision making for medical clinics through the use of simulation and multi-attribute utility theory.

Bo Sun

OPERATIONAL DECISION MAKING FOR MEDICAL CLINICS THROUGH THE USE OF SIMULATION AND MULTI-ATTRIBUTE UTILITY THEORY

by

Bo Sun

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Bo Sun

A Dissertation Approved on

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by the Following Dissertation Committee:

Dr. Gerald Evans Dissertation Co-Director

Dr. Lihui Bai Dissertation Co-Director

Dr. Dar-jen Chang

Dr. Ki-Hwan Bae

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ABSTRACT

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Bo Sun

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Currently, health care is a large industry that concerns everyone. Outpatient health care is an important part of the American health care system and is one of the strongest growth areas in the health care system. Many people pay attention to how to keep basic health care available to as many people as possible. A large health care system is usually evaluated by many performance measures. For example, the managers of a medical clinic are concerned about increasing staff utilization; both managers and patients are concerned about patient waiting time.

In this dissertation, we study decision making for clinics in determining operational policies to achieve multiple goals (e.g. increasing staff utilization, reducing patient waiting time, reducing overtime). Multi-attribute utility function and discrete even simulation are used for the study. The proposed decision making framework using simulation is applied to two case studies, i.e., two clinics associated with University of Louisville in Louisville, Kentucky. In the first case, we constructed of a long period simulation model for a multi-resource medical clinic. We investigated changes to the interarrival times

for each type of patient, assigned patients to see different staff in different visits (e.g., visit #2, visit #5) and assigned medical resources accordingly. Two performance measures were considered: waiting time for patients, and utilization of clinic staff.

The second case involved the construction of a one-morning simulation model for an ambulatory internal medicine clinic. Although all the resident doctors perform the same task, their service times are different due to their varying levels of experience. We investigated the assignment of examination rooms based on residents' varying service times. For this model, we also investigated the effect of changing the interarrival times for patients. Four performance measures were considered: waiting time for patients, overtime for the clinic staff, utilization of examination rooms and utilization of clinic staff.

We developed a ranking and selection procedure to compare the various policies, each based on a multiple attribute performance. This procedure combines the use of multi-attribute utility functions with statistical ranking and selection in order to choose the best results from a set of possible outputs using an indifferent-zone approach. We applied this procedure to the outputs from "Healthy for Life" clinic and "AIM" clinic simulation models in selecting alternative operational policies. Lastly, we performed sensitivity analyses with respect to the weights of the attributes in the multi-attribute utility function. The results will help decision makers to understand the effects of various factors in the system. The clinic managers can choose a best scheduling method based on the highest expected utility value with different levels of weight on each attribute.

The contribution of this dissertation is two-fold. First, we developed a long term simulation model for a multi-resource clinic consisting of providers with diverse areas of expertise and thus vastly different no-show rate and service times. Particularly, we modeled the details on assigning patients to providers when they come to the clinic in their different visits. The other contribution was the development of a special ranking and selection procedure for comparing performances on multiple attributes for alternative policies in the outpatient healthcare modeling area. This procedure combined a multiple attribute utility function with statistical ranking and selection in determining the best result from a set of possible outputs using the indifferent-zone approach.

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I. INTRODUCTION

A. BACKGROUND

Nearly 15% of the gross domestic product of the United States is represented by the health care industry. The growing rate of the health care expenditures, which currently stands at 45%, is expected to double by 2050. Health care providers need to reduce costs and improve quality of service. Patients prefer to have a better health care service and shorter lengths of stay. Therefore, outpatient services are gradually becoming an important part in health care. These outpatient services include: 1) wellness and prevention, such as counseling and weight-loss programs, 2) diagnosis, such as lab tests and MRI scans, 3) treatment, such as some surgeries and chemotherapy and 4) rehabilitation, such as drug or alcohol rehab and physical therapy. (Outpatients Services website)

However, there are many problems for outpatient clinics. For example, Giachetti (2005) mentions three problems for the outpatient clinic: 1) high no show rate, 2) long waiting times, and 3) large appointment backlogs on the order of about 20 weeks.

When the patient misses an appointment without cancellation or with a late cancellation, we call it a no show. In some clinics, up to 42% of scheduled patients fail to show up for pre-booked appointments (Deyo and Inui, 1980). Moore (2001) pointed out that the no show wasted 25.4% of scheduled time in the clinic; in addition, these no shows cost clinics 14% of anticipated daily revenue. Also, when patients do not arrive for their appointments, negative influences include lower provider productivity, longer appointment lead times, and poor patient satisfaction.

Long waiting time is another problem in the outpatient clinic, especially for the patients who have made an appointment. The long waiting time is the major reason for patients' complaints about their experience in outpatient clinics. In order to improve patients' satisfaction, reducing waiting time plays a crucial role in the quality management. Bowman (1996) pointed out that a shorter waiting time results in better attendance rates. Huang (1994) did a survey on patients' attitude towards waiting in an outpatient clinic, and generally, the patients feel satisfied if they wait no more than 37 minutes when they arrive on time.

The third problem is the long appointment lead time. The lead time between an appointment request and the actual visit tends to be longer than before which is more than one month. The lead time is so long because the growth of outpatient capacity can not meet the increasing demand. The clinic manager considers many methods to reduce the lead time, such as additional slots arranged in each operating session to maintain a constant appointment lead time (Zhu, 2012).

B. PROBLEM STATEMENT

A well-designed appointment system has the potential to increase the utilization of medical resources as well as reduce waiting time for patients. In this dissertation, different appointment systems are applied in the simulation model. Many factors affect the performance of appointment systems, such as patients' no show rate, service time variability, patients' preferences and the experience level of the scheduling staff. The simulation model outputs patients' average waiting time, average utilization of staff and medical resources in the clinic, and the experienced overtime for the staff. The goal of this research is to find an effective scheduling system to match the patients' demand, so that we can improve utilization and patient waiting time.

We also study the tradeoffs between average waiting time and average utilization. For example, if we overbook the patients' appointment, the waiting time gets longer although the utilization for the staff is high. When we follow the service time to schedule the patients, the staff would be idle if the patients do not show up for their appointment. Therefore, if we want to achieve a high utilization of the staff and a low average waiting time, a bi-criteria appointment systems is needed.

In this dissertation, we develop a ranking and selection procedure for making comparisons of appointment systems. We apply multiple attribute utility theory to convert multiple performance measure to a scalar performance measure. This procedure combines multiple attribute utility theory with a two-stage ranking and selection method to select a best configuration (appointment system) from many possible alternatives using an indifference zone approach. This idea is based on (Butler et al.2001), and we believe that there are many advantages using this approach.

First, the decision maker would typically not be able to determine which appointment system is better based solely on the simulation results of average waiting time and average utilization. With multiple attribute utility theory, the decision maker can make the decision directly by comparing the expected utility of different appointment systems.

Second, this method does not require the complicated step of estimating a covariance matrix, as Gupta and Panchapakesan (1979) mentioned. Compared to estimating the covariance matrix, implementing the ranking and selection method is relatively easier and robust as well implement.

Third, as Andijani (1998) mentioned, it is difficult to determine if the number of replications is enough to identify the best performing configuration. With the two-stage ranking and selection method, we can estimate the number of replications required to select the best configuration.

Fourth, we use multiple attribute utility function with ranking and selection method to compare each configuration. For example, Gupta and Panchapakesan (1979) mentioned that when comparing two configurations, if the population mean of the first attribute in configuration A is larger than that in configuration B, while the population mean of the second attribute in configuration A is smaller than that in configuration B, these two configurations cannot be compared. In this dissertation, we will overcome this challenge by applying multiple attribute utility theory with a two-stage statistical ranking and selection method originally proposed by Butler et al. (2001).

Fifth, we perform sensitivity analyses with respect to the utility functions function used. Some papers perform a sensitivity analyses on the weight of each attribute to assess the robustness of the best configuration (Butler, et al., 2001). With different single attribute utility functions, we will choose different indifference zones for the ranking and selection. Consequently, we can find a best configuration which has the largest expected utility.

In this dissertation, we use two cases to illustrate the proposed the combined methodology of multi-attribute utility function and two-stage ranking and selection in simulation. The input data for the simulation models are collected from the clinics. The decision makers are the managers of the clinics. They will determine the weight for each attribute to make the decisions.

The first case study is for the “Healthy for Life” clinic in Louisville, Kentucky. The University of Louisville’s “Healthy for Life!” Clinic serves the state of Kentucky’s children. The department of Pediatrics at the University of Louisville has partnered with Passport Health Plan, the Kentucky Chapter of the American Academy of Pediatrics (AAP), YMCA, Kosair Children’s Hospital and other organizations to offer a solution. “Healthy for life” is a relatively new University of Louisville program which is attempting to stem the epidemic of childhood obesity. (Healthy for Life, website resource)

This program is a complete resource for overweight children, offering a broad range of services from experts who can evaluate each child’s individual needs and develop a customized treatment plan accordingly. There are six types of staff in the clinic, and the no show rate varies by staff type and time. We build a long term simulation model which runs nearly half a year. There are nine hours in one day and five days in a week.

The main issue faced by “Healthy for Life” is the rather high no show rate of approximately 50%. We develop simulation model to analyze various scheduling policies in order to increase staff utilization and decrease the patients’ waiting time. We first develop a one-day model to simulate the patients’’ activity flow during a visit, where one or two service providers may see a patient depending on the purpose of his/ her visit. We then extend this one- day model to a long term model, in order to examine the long term effects of alternative appointment scheduling systems under study. The long term model simulates each patient's multiple visits during a half year horizon. With regard to creating/ evaluating alternative appointment schedules, we vary the interarrival times for patients who see various staff according to the no show rate. In addition, we attempt to shorten the lead time between the actual appointment and the time when the reservation is made. The is motivated by the fact that the clinic currently makes appointments for patients one month in advance, which may contribute to the high no show rate. We design the simulation model such that the appointment lead time is changeable and we can then examine the effect (e.g., average waiting time and system utilization) of shortening the appointment lead time.

The second case study is for the "Ambulatory Internal Medicine" clinic ("AIM" clinic) in Louisville. This clinic is an outpatient clinic associated with the Medical School of University of Louisville. The AIM clinic is a teaching clinic, in which resident doctors are trained in this clinic for three years prior to graduation. The clinic normally will obtain a new group of first year residents in July. During the treatment, the attending physician will spend time on teaching residents. We help the "AIM" clinic to solve the problem of scheduling patients in order to increase resource (including different years of residents and examination rooms) utilization and decrease the patients' waiting time and over time experienced by staff. In particular, we take Tuesday morning as an example. In the case of the clinic, the clinic manager is not as concerned with the no show rate as in the case of the Healthy for Life Clinic, since most of the patients arrive on time. The clinic manager wants to limit waiting time of the patients and increase the number of patients seen. The resources in their clinic are fixed. Our approach is to make proper assignment (e.g., properly assigning examination rooms to residents with various levels of years of experience thus various service time) for each resource in order to achieve efficient use of the resources. Because these resources are shared in the system, making assignments for these resources interact with each other and is very interesting and challenging.

C. CONTRIBUTION

C.1 SIMULATION

C.1.1 “HEALTHY FOR LIFE” CLINIC

We build a long term model for this multi-resource clinic. In this clinic, there are six staff members and each has its own distinct expertise (e.g., general pediatrician, psychologist, nutritionist, exercise physiologist), patients no show rate and service time. The patients will be assigned to see different staff in their subsequent visits. We study how the patients should be assigned and scheduled to see different staff. While most work in appointment scheduling focuses on single-resource clinic and one-day model, we study a clinic with multi-resources in a longer range. Particularly, we model the details about the number of patients who come to the clinic in their different visit times and which staff the patient is assigned to different visit times. We examine different appointment methods to compare the average waiting time and average utilization.

C.1.2 “AIM” CLINIC

We take Tuesday morning as an example to build a one morning model.

This clinic is a teaching clinic. Therefore, residents with different years of experience offer different service time, i.e., time to see a patient. For the first year of residents, they use more time on patients and talking to their attending physicians. Also they will stay in the examination rooms longer than residents with more experience. How to schedule residents with various years of experience in seeing patients and how to assign the examination rooms to these residents are the goal of this dissertation. Our contribution to the literature is that we firstly assign the resources of the clinic (including residents and examination rooms), and then schedule the patients' interarrival time. We not only observe the average waiting time and average utilization for resources, but consider the overtime experienced by residents and staff as a key driver in the research.

C.2 METHODOLOGY

In this dissertation, we build one long period simulation model for a multi-resource clinic and a one morning model for a single resource clinic. In the long period simulation model (Healthy for Life clinic), we measure performance on waiting time for patients and utilization of staff in the clinic. In the one morning model (AIM clinic), we measure performance on waiting time for patients, utilization for staff, utilization for examination rooms and over time. To compare multiple attributes' performance, we develop a ranking and selection procedure. This procedure combines a multiple attribute utility function with statistical ranking and selection to determine the best result from a set of possible outputs using the indifferent-zone approach. We apply this procedure to the outputs from these two simulation models. Also, we perform sensitivity analysis on the weight of each attribute to compare the results. The clinic managers can decide which level of weight is suitable for the attributes and choose a best scheduling method based on the highest expected utility value.

D. DISSERTATION ORGANIZATION

The remainder of the dissertation is organized as follows:

In Chapter 2, a comprehensive literature review is presented, including the literature related to problems in health care clinics, the literature related to reasons and effects of no show rate, and the literature related to methodology used this dissertation, i.e., simulation in health care, multiple attribute utility function and ranking and selection. Chapter 3 contains an overview of the MAU theory and the procedure of setting up the ranking and selection. Then details combining the ranking and selection and multiple attribute utility function are given. And finally, the application of the utility exchange by Butler et al., (2001) and the determination of parameter values for the indifference zone approach will be illustrated. Chapter 4 presents two cases studies including each clinic's background, problems statement, analysis of the original data and the developed simulation model. In Chapter 5, utility functions used in the ranking and selection method is applied to the results of the two simulation models. Further, sensitivity analysis on the weight of each attribute is examined, from which the best appointment alternative is recommended. Chapter 6 gives the conclusion and future research.

II. LITERATURE REVIEW

A. PROBLEMS IN CLINIC

Currently, health care is a large industry that concerns everyone. The government also discusses the health care system. Most recently, President Obama signed the Patient Protection and Affordable Care Act (Stolberg, 2010). Many people pay attention to how to keep basic health care available to as many people as possible. Many hospitals emphasize short queue length in the waiting room and shift care from inpatient to outpatient facilities. This in turn is forcing outpatient clinical facilities to reassess their operation and capacities (Muthurman and Lawley, 2008). Therefore, many industrial engineers do research on health care, such as how to increase the utilization of staff, how to structure the patient's flow and how to design a good scheduling method to solve medical clinic problems.

There are two main problems that need to be solved in this research. The first problem is the high no show rate of patients. Rust and Gallups (1995) claimed that the problem of patient no-shows (patients who do not arrive for scheduled appointments) was significant in many health care settings, where no show rates can vary from as little as 3% to as much as 80%. Verbov (1992) did a survey about the reason for the no show patients. The reasons can be categorized with the following factors: 1) other illness, such as flu, cold, throat infection. 2) related to work 3) feel better 4) forget to attend 5) car broken down 6) do not want to miss school 7) out of town on appointment day 8) mistaken date and time of appointment 9) appointment is too early in the day. For the "Healthy for Life" clinic, the no show rate is nearly 50% which is high enough to affect the operation of the clinic.

The most significant factor affecting no-show rates is the amount of time between scheduling the appointment and the appointment itself. According to the research, the longer time between the time of scheduling the appointment and the appointment itself, the more likely patients do not show up. A patient that was given an appointment that was less than a week away was more likely to show than a patient who booked six months in advance (Vozenilek, 2009). Hilxon et al., (1999) pointed out that younger patients were less likely to keep appointments. The no show rate was lower when the patients call to schedule their own follow up appointments. The reason why the no show rate of "Healthy for Life" clinic is high is that patients need to make appointments one month in advance for the next appointment. Specifically, the "Healthy for Life" clinic is focused on the overweight children. Children are special patients in that whether they show up or not is not only decided by themselves but also decided by their parents' schedule.

Patients' no show rates had many negative effects on the clinic, such as reducing provider productivity and clinic efficiency, increasing health care costs and limiting the ability of a clinic to serve its client population by reducing its effective capacity (LaGanga and Lawrence,2007). Hilxon et al. (1999) mentioned that when patients do not show up for their appointments, the time of staff in the clinic was wasted and residents missed the opportunity to see the progression of diseases or the outcome of treatments.

Chesanow, (1996), Murray and Berwick (2003) Murdock (2002) gave a conclusion that patients' no show rates will influence: 1) economics. With the national rate of no show at around 12%, the estimated total cost of missed appointment was $400 million per year, 2) underutilization of equipment and manpower, 3) patients health.

The second problem is patients' long waiting times. In the present climate, value for money and maximum use of resources are prime considerations. However, total waiting time is the most important factor affecting the patients' satisfaction. In UK, patients Charter was set up because the government agreed that the long waiting times for patients are unacceptable. This Charter offset a standard that the patients should not wait in the waiting room more than half an hour of their appointment time (Department of Health, 1991, 1995). An effective appointment system was a critical method to control patient waiting times (Harper, 2003).

For above two problems to the clinic, we need to find a way to improve the benefit of the medical clinic and make patients satisfied. The goal we want to achieve in this dissertation is a good scheduling method which can increase the utilization of resources and decrease the waiting time for patients.

B. MODELING METHEDOLOGY

B.1 SIMULATION APPLICATIONS IN OUTPATIENT CLINICS

Health care providers use the simulation method to analyze the current performance and compare alternatives. They are interested in using simulation to guide them in saving money and making clinics more efficient. Guo and West (2006) used the simulation method to help Cincinnati Children's hospital Medical Center, which diagnosed and treated all types of eye disorders for children, to improve their patients' appointment scheduling. The main contributing factors in this paper were randomness of patients demand, plenty of no show rates in patients' population, different types of follow-up patients and the variable staff schedule. They wanted to minimize the delays for patients to obtain an appointment and at the same time maximize the provider's' utilization. One benefit for the simulation was that they can easily track waiting time in the system and monitor the 95th percentile of the resulting waiting time distribution for the various appointment types.

LaGanga and Lawrence (2007) used the simulation method to animate the overbooking clinic. From the simulation results, they found that the overbooking method provides a good utility when the clinic serves large numbers of patients, no show rates were high and service variability was lower.

Giachetti (2005) used the discrete event simulation to do the simulation. The author analyzed patients' appointment time and percent of daily appointment and gave clinics some suggestions as follows. First, arrival rates need to match the service rates, consequently the patients do not need to wait. Second, service providers should work when the first patients came to the clinic. For the clinic under study in the paper, the appointment time was earlier than the working time. Third, the service order in which the patients were called. Giachetti (2008) used the simulation method to reduce the appointment lead time and patient no show rate. The author mentioned three methods. First is to reduce the number of appointment types by letting. All the appointments have the same weight. Second, instead of using overall overbooking, they used individual overbooking, such as patients who missed two or more appointments. Third, they found that using a single queue for multiple resources had shorter waiting time.

Cote (1999) built a simulation model to examine the relationship between examining room and patients flow across four clinic performance measures. After using ANOVA for the experimental design, the author concluded that the number of examining rooms did not significantly affect examining room queue lengths or patients flow time.

Kopach et al., (2007) used discrete event simulation, experimental design to study the effects of variables such as: making long term appointments, overbooking and the fraction of patients being served on open access on clinic throughput and patient continuity of care. The result was that if correctly configured, open access can improve the throughput of the clinic.

Harper and Gamlin (2003) also developed a simulation model to an outpatient clinic. They changed different appointment schedules to examine whether appointment systems influenced patients waiting time in the clinic. The results showed that alternative appointment schedules could drastically reduce patient waiting times and the clinic did not need to hire more resources.

B.2 MULTIPLE ATTRIBUTE UTILITY FUNCTION

Multiple attribute utility (MAU) function had been used in a variety of settings to solve real project problems. Ozernoy et al., (1981) helped to select a commercial GIS (Geographic Information System). They needed to consider three attributes to choose a best one which are software capabilities, hardware capabilities, and vendor performance. Stafford et al,. (1979) analyzed some basic attributes which influenced the effectiveness of outpatient clinics, such as different facilities, the patient routs though the clinic, number of observers in each facility, etc. They used these attributes to evaluate the operating procedures and policies. Dyer and Lorber (1982) used multiple attribute utility function to evaluate three competing vendors for the commercial generation of electricity by nuclear fusion. There were eleven attributes needed to be considered and eight decision makers did the evaluation. The reason that these papers used multiple attribute utility theory was that it provided a logical way to solve the conflicting objectives problem (Keeney and Raiffa, 1976).

Although simulation is a useful tool in the modeling and analysis of a wide variety of complex real systems, we still need to combine other methods (such as MAU theory) to do the optimization and choose the best alternatives from all the configurations. Sometimes, we also need to consider the trade-offs between multiple conflicting configurations for the system. Anderson et al.,(2006) used the simulation model to employ multi-objective decision analysis and then performed optimization. The paper uses the variance reduction techniques of common random numbers and antithetic variants. Tekin et al., (2004) conducted a comprehensive survey on the techniques for simulation optimization which apply multi-objective decision analysis. They categorized the existing techniques to many problems, such as objective function (single or multi objectives), parameter spaces (discrete or continuous parameters). This paper introduced the advantages and disadvantages on existing methods. Lee (2008) used the simulation optimization method with multi-objective evolutionary algorithm. It is applied on a multi-objective aircraft spare parts allocation problem to find a set of non-dominated solutions. Butler et al. (2001) used the simulation model in multi-objective decision analysis.

Their method is unique in that they used multiple attribute utility theory (MAU) to convert multiple performance measures to a single scalar performance measure. They used this method on a real project to evaluate configurations for a land seismic survey in geophysical exploration for oil and gas.

B.3 RANKING AND SELECTION

Ranking and Selection (R&S) procedures are statistical methods specifically developed to select the best system or a subset that contains the best system design from a set of *k* competing alternatives (Goldsman and Nelson, 1994). Boesel (2000) and Boesel et al. (2003) find the best system from the large numbers of systems. These two paper developed statistical procedures that find the best system by using subset selection and indifference-zone. Some generally used measures of selection quality are the probability of correct selection *P (CS)*. There were many papers on the R&S area in the last decades, and several papers are available in R&S field. (Kim and Nelson, 2003, 2007; Swisher et al., 2003).

Many approaches to the ranking and selection problem have been proposed. The differences between these methods are how to allocate replications to certain designs.

One popular R&S method is the two-stage indifference zone method which was proposed by Rinott (1978). He chose an initial sample of simulation replications and then determines the number of additional replications needed in the second-stage. Since Rinott's seminar work, many have made improvements based on "Rinott's two-stage" procedure. Nelson et al. (2001) proposed to find the best expected performance from the simulated system and they also used the ranking and selection method. However, they find that the procedure needs more computation. They eliminated the uncompetitive alternatives at the first stage, and then avoid the larger sample at the second stage. Kim and Nelson (2006) also want to select the best simulated system. The procedures were suitable when the procedure repeatedly obtained small and incremental samples from the simulated system. The goal of their paper was to eliminate the sequential procedure. Alrefaei and Alawneh (2004) also selected the best expected performance measure from the stochastic system. They faced a problem that the number of alternative system was large. They used two-stage procedure which used the standard clock simulation method. In the first stage, they screened out the uncompetitive alternatives and kept the better alternatives which had a pre-specified large probability. Then they used R&S method finding the best alternative from which had been chosen at the first stage.

Another different and popular way to select the best systems is due to Dudewicz and Dalal (1975). Their method guarantees that the performance measure value of the selected λ_i differs from the optimal solution value by at most a small amount δ, with a probability of at least P^*. The difference from Rinott (1978) was that D&D procedure uses the weighted sample means from the systems. This procedure required fewer replications than the Rinott (1989) procedure, for the “h” value was smaller. Their contribution was that they eliminated variance constraints for R&S Indifference zone.

Most of the ranking and selection method were applied on the single attribute problem. However, in the real life, most of the projects and systems were multiple attribute problems. In this setting, the problem of selecting non-dominated designs from a few alternatives through simulation became the problem of multiple attribute R&S. This problem was also the topic of this research. Swisher and Jacobson (2003) gave a survey of the literature about using R&S method and multiple comparison procedures to select the best configurations from a finite set of alternatives. Swisher and Jacobson (2002) used the simulation model to determine appropriate staffing and physical resources in a clinic. They used simulation-based statistical techniques, which included R&S and multiple attributes comparison. Nelson and Matejcik (1995) chose the best among k simulated systems by using indifference-zone and multiple-comparison. They used the variance reduction technique of common random numbers to reduce the sample size. Butler et al. (2001) exchanged traditional single-attribute ranking and selection procedures to multiple attributes by using MAU theory. After exchange was performed, they just needed to consider single attribute instead of multiple attribute. When they did the ranking and selection, they chose the best result from the expected value of the utility function. We will use this approach in the current dissertation.

III. METHODOLOGY

A. MULTIPLE ATTRIBUTE UTILITY FUNCTIONS

Engineers always need to make decisions, such as choosing the location of a new factory or choosing the method to produce the product. Poor decisions can result in losing money, resources and time. Therefore, making good and reasonable decisions is important. The decision process is quite complicated, especially when decision makers (DM) need to trade off between various criteria. For example, Keeney and Raffia (1993) illustrated a case about air pollution control, they need to tradeoff among instructional programs, fire department operations, structuring of corporate preferences, evaluating computer systems, and siting and licensing of nuclear power facilities.

The utility theory in decision making can help decision maker to decide and choose a best alternative from many alternatives with a mathematical model.

A.1 SINGLE ATTRIBUTE UTILITY FUNCTIONS

Single attribute functions are obtained by a set of lottery questions based on certain equivalence. Let Y be a lottery yielding consequences X1 and X2 each with probability 0.5. This situation is a 50-50- chance lottery. The certain equivalent of 50-50- chance lottery is an amount of Z which is certain when the decision maker is indifferent to Y and Z.

The procedures to identify the types of single attribute utility function as follows:

Step 1: Design the best level $u(x^*)$ and the worst level $u(x^0)$. Normally, the best outcome is set at 1, and the worst is at 0.

Step 2: Estimate the certainty equivalent value at the level $x^{0.5}$ for which the utility value equals to 0.5. If the certain equivalent $x^{0.5} = (x^*+x^0)/2$, the utility function is a risk neutral type. If $x^{0.5} < (x^*+x^0)/2$, then the utility function is a risk averse type. If $x^{0.5} > (x^*+x^0)/2$, then the utility function is a risk prone type.

Step 3: The risk prone type or risk averse type utility functions are needed to estimate the unknown parameters, a, b, and c. Kainuma (1986) mentioned that applying Newton-Raphson method on the three pointes which are x^*,x^0 and $x^{0.5}$ to estimate the unknown parameters. There are two types of single utility function, one is risk aversion type and risk prone type functions Eq. (1), and the other is risk neutral utility function Eq. (2). Figure 1 illustrated three types of single utility function. (Kainuma et al. 2006)

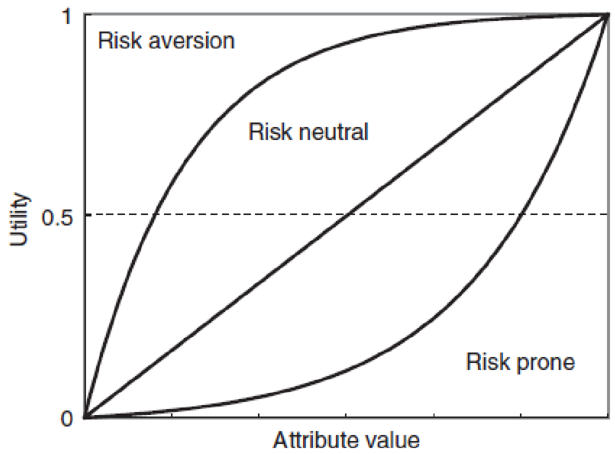

Figure 1. Three types of single- attribute utility function

$$u_i(x_i) = a - bexp(-cx_i) \tag{1}$$

$$u_i(x_i) = a + bx_i \tag{2}$$

There is another form of single utility function mentioned by Butler et al. (2001), $u_i(x_i) = A_i - B_i e^{x_i RT_i}$, where RT_i is the DM's assessed risk tolerance and A_i and B_i are scaling constants.

A.2 MULTIPLE ATTRIBUTE UTILITY FUNCTIONS

Multi- attribute utility theory (Keeney and Raiffa, 1976) was one of the major tools in the field of decision analysis. Using MAU analysis evaluates the alternatives and help to identify which alternative performing well on majority measures. In MAU analysis the first step is to form a matrix. In this matrix, each row represents an alternative and each column corresponds to a performance measure. The cells of this matrix represent the performance of each alternative on each performance measure. Then, the single attribute utility function will be needed which the scales performance from 0 to 1. When certain independence conditions are met, all the single attribute utility function can have a mathematical combination with scaling constants into a multiple attribute utility function. A multiple attribute utility function is a mapping from an attribute space with 2 or more attributes into the space of real numbers (Decision Making Slides, 2013). The utility function scales performance is also from 0 to 1.

The form of the MAU function depends on the independence conditions by the different SAU functions.

- THE MULTILINEAR UTILITY FUNCTION

Multilinear utility function is the most general form, as shown in (3a).

$$
\begin{aligned}
\mathrm{u(x)} = & \sum_{i=1}^{n} w_i u_i(X_i) \\
& + \sum_{i=1}^{n} \sum_{j>1} w_{ij} u_i(X_i) u_j(X_j) \\
& + \sum_{i=1}^{n} \sum_{j>i} \sum\nolimits_{m>j>i} w_{ijm} u_i(X_i) u_j(X_j) u_m(X_m) + \cdots \\
& + w_{123\ldots n} u_1(X_1) u_2(X_2) \ldots u_n(X_n)
\end{aligned} \tag{3a}
$$

where u_i is a single attribute utility function over x_i scaled from 0 to 1, and w_i (0 < w_i< 1) is the scaling constant for attribute i and w_{ijm} are scaling constants which measure the impact of the interaction between attributes i, j, and m on preferences (Decision Making Slides, 2013). To determine whether a decision maker's preference satisfy the correct conditions, we can use (3a), and we need to define the utility independence (Decision Making Slides, 2013). A set of attributes X is utility independent (UI) of its complementary set X' if the conditional preference structure over lotteries on X given X' does not depend on the value of X'. For example, there are two attributes. The first attribute is the shortage and the second attribute is the outdating. The attribute $x_1's$ range is from 0 to 10% and attribute $x_2's$ range is from 0 to 15%. When $x_2 = 1\%$, the CE for $x_1 =< 1\%, 9\% >$. When $x_2 = 9\%$, the CE for x_1 does not change, we can say that x_1 is UI of x_2.

Given $\mathrm{X} = (X_1, X_2, \ldots .X_n), n \geq 2,$ the mulilinear utility function will be appropriated if X_i is utility independent of X_j for all $i \neq j$.

- MULTIPLICATIVE MAU MODEL

A set of attributes X is mutually utility independent (MUI) if every subset X'∈ X is utility independent (UI) of its complement. For example, X_1, X_2, X_3 is mutually utility independent, if and only if X_1 is UI of X_2, X_3; X_2 is UI of X_1, X_3; X_3 is UI of X_1, X_2; X_1, X_2 is UI of X_3; X_1, X_3 is UI of X_2; X_2, X_3 is UI of X_1. If $X = (X1, X2 \dots Xn)$, a set of attributes, is MUI, then its utility function can be written as $1 + \mathrm{wu(X)} = \prod_{i=1}^{n}(1 + \mathrm{w}w_i u_i(X_i))$. If we expand this form of the multiplicative model, we can obtain (3b),

$$\mathrm{u(X)} = \sum_{i=1}^{n} w_i u_i(X_i)$$

$$+ \sum_{i=1}^{n}\sum_{j>1} w w_i w_j u_i(X_i) u_j(X_j)$$

$$+ \sum_{i=1}^{n}\sum_{j>i}\sum\nolimits_{m>j>i} w^2 w_i w_j w_m u_i(X_i) u_j(X_j) u_m(X_m)$$

$$+ w^{n-1} \prod_{1}^{n} w_i \, u_i(X_1)$$

(3b)

where $0 \leq w_i \leq 1$, $-1 < w < \infty$, w is a constant such that $1 + w = \prod(1 + ww_i)$, and the product is formed over $i = 1 \; to \; n$. The multiplicative form is a special case of the mutilinear model.

- ADDITIVE MAU MODEL

"Additivity Independence (AI) occurs if preferences over lotteries on {X} depend only on the marginal probability distributions of the x_i and not on the overall joint probability distribution over the {X}" (Decision Making Slides, 2013),

$$\mathrm{u}\,(\mathrm{X}) = \sum_{i=1}^{n} w_i\, u_i(X_i) \tag{3c}$$

where $0 \le w_i \le 1$ and $\sum_{i=1}^{n} w_i = 1$.

Additive MAU model is a very restrictive condition, and therefore rarely holds.

- STEPS TO ASSESS OF A MAU FUNCTION:

The assessment process of MAU Function needs an analyst and a decision maker. There are three basic steps.

The first step is assessing the single attribute utility functions and scaling constants. Also need to establish a set of independence conditions and choose a particular function form.

The second step is to give points on the individual attribute utility function curves. For example, to decide the certainty equivalent, check these points whether fit for linear function or others.

The third step is for the decision maker to make a decision to express these two alternatives are indifference. This decision will lead to a set of equations involving the scaling constants for these two alternatives' expected utilities are equal.

B. RANKING AND SELECTION METHODS

The goal to use ranking and selection is to select one of the k systems as the best alternative, and in probabilistic sense, it is also to control the probability that the selected system is the best one. Assume there are more than two project configurations. Let X_{ij} be the random variable of interest from the jth replications of the ith project configurations, and let $\mu_i =$

$E(X_{ij})$. Let μ_{iZ} be the Zth smallest of the μ_i, so that $\mu_{i1} \leq \mu_{i2} \leq \mu_{i3} \leq \cdots \leq \mu_{ik}$ denote the order of expected value. Our goal is to choose the smallest expected value μ_{i1}. (If we want to choose the largest expected value μ_{ik}, the signs of the X_{ij} and μ_i can be reserved.) If the R&S procedure identified the configuration correctly, we will say that a correct selection (CS) is made.

We can never know for certain whether we make the correct selection, but we can to specify the probability of CS. If μ_{i1} and μ_{i2} are very close, we may not care about if we choose the configuration of i_2 by mistake. Therefore, we need a method to avoid making large number of replications to resolve unimportant difference. We ask decision maker to specify indifference zone parameter δ^*. If $\mu_{i2} - \mu_{i1} \geq \delta^*$, we can say that μ_{i2} is significantly better than μ_{i1}.

In general, the ranking and selection procedure (Law, 2007) is designed to satisfy the following requirement:

$$P\{CS\} \geq P^* \text{ whenever } \mu_{i2} - \mu_{i1} \geq \delta^* \tag{4}$$

where $(1 / K) < P^* < 1$ and$0 < \delta^* < 1$. If $\mu_{i2} - \mu_{i1} \leq \delta^*$, the procedure will select a best configuration within $\delta^*$with probability at least P^*.

In this research, we use two- stage indifferent zone procedure for R&S. The following formulations is quoted from the book Law (2007).

In the first stage, we make a fixed number of replications $(n_0 \geq 2)$ for each of the k configurations. We calculate the sample mean and variance.

$$\overline{X_{\iota(n_0)}}=\frac{\sum_{j=1}^{n_0} X_{ij}}{n_0} \tag{5}$$

$$S_i^{\,2}(n_0) = \frac{\sum_{j=1}^{n_0}[X_{ij}-\overline{X_{\iota(n_0)}}]^2}{n_0-1} \tag{6}$$

For $i = 1,2, \ldots . k$, then we need to compute the total sample size N_i

needed for configuration i.

$$N_i = \max\{n_0 + 1, \left\lceil \left(\frac{h}{\delta^*}\right)^2 S_{i(n_0)}{}^2 \right\rceil\} \tag{7}$$

where h depends on k, P^* and n_0 which is a constant that can be obtained from the table in Bechhoter et al. (1995, pp61-63) or in Law (2007, pp573).

In the second stage, we make $N_i - n_0$ more replications of system i $(i = 1,2 \ldots k)$ and then calculate the second-stage sample means.

$$\overline{X_{\iota(N_\iota - n_0)}} = \frac{\sum_{j=n_0+1}^{N_i} X_{ij}}{N_i - n_0} \tag{8}$$

Then we need to define the weights

$$w_{i1} = \frac{n_0}{N_i}[1 + \sqrt{1 - \frac{N_i}{n_0}(1 - \frac{(N_i - n_0)(d^*)^2}{h^2 S_i{}^2(n_0)}}\ ] \tag{9}$$

where $w_{i2} = 1 - w_{i1}$, for $i = 1, 2 \ldots \ldots k$.

Finally, we can calculate the weighted sample means.

$$\widetilde{X_\iota(N_\iota)} = w_{i1}\overline{X}_\iota(n_0) + w_{i2}\overline{X}_\iota(N_i - n_0) \tag{10}$$

We need to choose the configuration with the smallest$\widetilde{X_\iota(N_\iota)}$. This result is the best one we using two-stage R&S method.

C. UTILITY FUNCTION USED IN RANKING AND SELECTION

C.1 UTILITY EXCHANGE

In MAU function, we need to consider more than two attributes in the utility function and compare the results. In this dissertation, we consider to select one attribute as the standard measurement and exchange utility on the other attribute in the standard measure.

For example, a clinic manger considers to develop an optimal schedule for patients, where average patients' waiting time and utilization of staff are two important performance measures. The manager tries many different schedules and obtains average waiting time and utilization from each schedule. Table 1 illustrates four alternatives by measures matrix for schedule selection.

Table 1 Alternative by Measures Matrix for Schedule Selection

Alternative	Waiting time(minutes)	Utilization
Schedule 1	30	0.4
Schedule 2	60	0.5
Schedule 3	90	0.6
Schedule 4	120	0.7

From the above table, it is difficult to decide which schedule is the best choice. If we want to make this problem simpler, we can let the utilization be at the same level. Suppose we artificially set the utilization of each schedule to a common level, such as 0.5 and ask the decision maker (the clinic manager) to adjust the waiting time of each schedule. Finally, the "new" schedule should be equally preferred to the original configuration.

For example, the schedule 1's waiting time is 30 minutes with utilization 0.4. If we increase the utilization from 0.4 to 0.5, the patients will wait longer. Suppose the decision maker agrees that waiting time is 50 minutes with utilization 0.5. Repeat the same procedure with other schedules. Then the decision maker will face with a choice with the new schedules in Table 2.

Table 2 New Choices of the Schedules

Alternative	Waiting time(minutes)	Utilization
Schedule 1	50	0.5
Schedule 2	60	0.5
Schedule 3	70	0.5
Schedule 4	80	0.5

The above procedure converts the original alternatives into the hypothetical schedules without using MAU function, and the decision maker has his own internal utility function to provide the numbers required.

We also can use access weight and utility function to formalize the procedure of the utility exchange. Butler et al. (2001) proposed a "utility exchange" where one selected a medium for exchange or standard measure. In the last example, waiting time is the standard measure. Then select the other criteria as the common level of utility c_i $(2 \leq i \leq n)$. Again, in the last example, utilization is the common level which all the utilization are 0.5. We also can illustrate in a formula: $u_i(x'_{ki}) = c_i,\ i = 2,\ 1 \leq k \leq K$. The final step is to calculate the utility exchange. Base on the value of c_i, change the utility $u(x_{k1})$ to $u(x'_{k1})$.

Butler et al. (2001) gave three propositions, which allowed one to convert an indifference zone for an attribute to an indifference zone for expected utility.

The first proposition states that the procedure for calculating the utility exchange. The equation of u (x'_{k1}) is used for the multilinear, multiplicative and additive MAU function. The equation is like this

$$x'_{k1} = u_1^{-1}\left(\frac{u(X_k)-Q_1}{Q_2}\right) \tag{11}$$

Q_1 and Q_2 are constants which depend on the MAU form and assessed utility function and weights.

In this dissertation, we use additive MAU function and consider two attributes. After we do the utility exchange. We can get the equation like this:

$$w_1 u_1\left(x_{k_1}\right) + w_2 u_2\left(x_{k_2}\right) = w_1 u_1\left(x_{k_1}{}'\right) + w_2 c_2$$

$$u_1(x'_{k1}) = u_1(x_{k1}) + \frac{w_2}{w_1}(u_2(x_{k2}) - c_2) \tag{12}$$

The utility exchange approach relies on the separability on preferences to convert multiple performance measures into a single measure of performances. After the utility change, the indifference zone approach for the single indifference zone procedure. So it changed to be

$$\mathrm{E}\big[\mathrm{u}\big(x'_{[1]1}\big)\big] \le \mathrm{E}\big[\mathrm{u}\big(x'_{[2]1}\big)\big] \le \mathrm{E}\big[\mathrm{u}\big(x'_{[3]1}\big)\big] \le \mathrm{E}\big[\mathrm{u}\big(x'_{[4]1}\big)\big] \ldots\ldots \le \mathrm{E}\big[\mathrm{u}\big(x'_{[K]1}\big)\big] \qquad (13)$$

$\mathrm{u}(x_{k1})$ is the utility of first attribute in the configuration k.

$\mathrm{u}\big(x'_{[k]1}\big)$ is after the utility exchange of first attribute in the configuration k.

The goal is to select the project configuration of the k competing systems that contains the one with the largest expected performance.

The second proposition is obtaining the variance after utility exchange. Because we use the ranking and selection method, we need to use variance to calculate the number of replications needed more. Calculating the rescaled variance for the first attribute, we obtain:

$$\mathrm{var}\big(u_1(x'_{k1})\big) = \frac{\mathrm{var}\big(u(X_k)\big)}{{Q_2}^2} \qquad (14)$$

In the two attributes additive MAU function, we can change the equation as following:

$$\mathrm{var}\big(u_1(x'_{k1})\big) = \frac{Var(w_1 u(x_{k1}) + w_2 u(x_{k2}))}{{w_1}^2} = \frac{{w_1}^2 Var(u(x_{k1})) + {w_2}^2 Var(u(x_{k2}))}{{w_1}^2} \qquad (15)$$

Finally, from the third proposition, we can change the procedure from accessing the δ^*on the MAU function to accessing the ${\delta_1}^*$ on the single attribute utility function corresponding to the standard performance measure.

$${\delta_1}^* = \frac{\delta^*}{w_1} \qquad (16)$$

C.2 ESTABLISHING THE INDIFFERENCE ZONE

In the single attribute utility function, the certainty equivalent is equal to the inverse of the utility function evaluated at the expected utility (Clemen 1991, p372). i.e.

$$\mathrm{E}\big[\mathrm{u}_1\big(\mathrm{X}_{\{K\}1}\big)\big] = \mathrm{u}_1(\mathrm{CE}_{[K]1}) \qquad (17)$$

Then we can take (17) into (4)

$$u_1(CE_{[K]1}) - u_1(CE_{[K-1]1}) = \delta_1{}^* \tag{18}$$

where RT_i is the DM's assessed risk tolerance and A_i and B_i are scaling constants. They are the parameters of the single attribute utility function. From the Butler et al. (2001), we know that when $\delta_1{}^*$ increases, the indifference zone gets larger, so the number of replications gets smaller.

C.3 DETERMINE THE INDIFFERENCE ZONE

The decision maker first needs to determine $\delta_1{}^*$. We can ask the decision maker to consider the following questions to determine $\delta_1{}^*$. For example, configuration A and configuration B are measured on expected waiting time. If the expected waiting time of configuration A is 30 minutes, what is the minimum waiting time of configuration B at which you will think configuration B is better than configuration A? Suppose that the decision maker answers that the minimum waiting time is 20 minutes. From (18), we obtain u (20) –u (30) =$\delta_1{}^*$. Hence, the decision maker determines that $\delta_1{}^*$ = 0.22 (i.e. there is no difference of waiting time between 20 minutes and 30 minutes).

In Table 3, there are two groups of indifference zone numbers correspond to the indifference of waiting time which are decided by the decision maker. When the gap for waiting time gets larger, the indifference zone gets larger.

Table 3 Two Groups of Indifference Zone

DM is indifference to a change in these two waiting times (minutes)		Indifference Zone for Expected Utility
20	30	0.22
20	25	0.1

IV. CASE STUDIES

A. CASE STUDY ONE: HEALTHY FOR LIFE

A.1 INTRODUCTION

The University of Louisville's "Healthy for Life!" Clinic serves the state of Kentucky's overweight children. "Healthy for Life!" offers a broad range of services from experts who can evaluate each child's individual needs and develop a customized treatment plan accordingly. The clinic always uses the Body Mass Index (BMI) value to determine whether children are overweight or not. BMI is a number calculated from a person's weight and height and is computed as $BMI = \frac{weight\ in\ pounds * 703}{height\ in\ inches^2}$ (What Health, internet resource) BMI provides a reliable indicator of body fatness for most people and is used to screen for weight categories that may lead to health problems (Center for disease control and prevention, internet resource). Children with a BMI in the 85th percentile or above are referred to the "Healthy for Life!" program.

In addition, clinic services are free to children covered by the Passport Health Plan, Indiana Medicaid Insurance and Kentucky Medicaid Insurance. Services are also available to private-pay and privately-insured patients on a fee-for-service basis.

The "Healthy for Life!" clinic opened in June, 2009 in a newly renovated space donated by Kosair Children's Hospital. It features examination rooms, a counseling center, a group therapy space and a play center with treadmills, and exercise bikes. Activities at the clinic include demonstrations, healthy-meal planning lessons and taste tests for parents and their children. The clinic also includes a teaching kitchen where staff members offer cooking lessons. (Healthy for Life, internet resource)

Figure 2 shows a layout of the clinic.

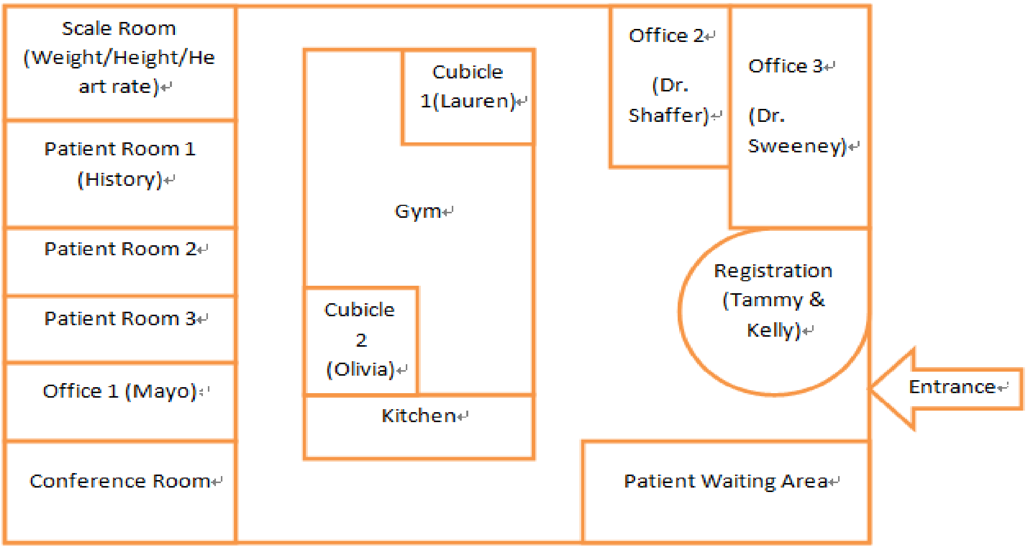

Figure 2. Layout of "Healthy for Life" clinic

A.2 PROBLEM STATEMENT

The basic problem addressed by this dissertation involves the scheduling of the patients in order to improve the utilization of staff and decrease the waiting time for the patients. The manager of the clinic found that patients who make appointments often do not show up, which means that staff in the clinic has to wait for them and cannot see other patients. The manager wants to solve this problem and keep all the staff in this clinic busy. She also wants to decrease the waiting time for patients and keep the "show up rate" high for very sick patients.

We built a long term simulation model and investigated different scheduling methods to estimate the utilization of the staff, the waiting time for patients in the clinic, the patients flow times and patients types in terms of staff resource requirements order these different methods. In the research, we considered average waiting time and average utilization as two important performance measures.

A.3 SIMULATION MODEL

A.3.1 DATA INPUT IN THE MODEL

A.3.1.1 STAFF AT “HEALTHY FOR LIFE” CLINIC

There are eight staff members in the clinic: one receptionist, one nurse, one nurse practitioner, two physicians, one exercise physiologist, one psychologist and one nutritionist.

The receptionist is responsible for the check in and check out of patients, as well as some paper work. Additionally, one day before the appointment day, receptionist makes reminder phone calls to patients. At that time, the patient either confirms with the appointment, or reschedules a new appointment, or leaves a message.

The nurse is responsible for escorting patients into the clinic and recording the basic physical data, which takes nearly twenty minutes. Both new and follow up patients see the nurse before they see the physician, the nurse practitioner, or the nutritionist.

The responsibility of the exercise physiologist is in offering children a range of physical activities and suggesting exercise options to them.

The nutritionist helps patients with a healthy dietary habit. For new patients, nutritionist will spend half an hour in the teaching kitchen offering cooking demonstrations and healthy meal planning lessons for parents and their children. For follow up patients, the nutritionist spends about half an hour in her office discussing patient concerns and their progress.

The psychologist helps patients to have a good outlook and attitude towards weight control. Seeing the psychologist is considered an important element in this clinic these visits deal with underlying psychological issues. These issues including eating habit, depression, academic underperformance, poor body image, psychosomatic complaints and dysfunctional family relationships. If the patient’s insurance does not cover this service, then the patient needs to pay out of his or her own pocket. Usually, patients spend 30 to 40 minutes seeing the psychologist during any particular visit.

A.3.1.2 PATIENT FLOW AT THE CLINIC

Patients need to make an appointment before visiting the clinic. For the new patients, they need to call the receptionist and fill out some forms before visiting the clinic. Follow up patients need to make their next appointment before they leave the clinic. In general, patients come to the clinic once each month.

Figures 3 and 4 illustrate the process flow at the clinic for new and follow up patients, respectively.

New patients, check in at the registration desk to fill out form in the waiting room until being called in. This usually takes about 20 minutes. Before seeing the physician, they first see the nurse. After seeing the physician, typically visit with the nutritionist. If the staff which they want to see is busy, they return to the waiting room. In a normal situation, it will take patients about 20 minutes to be taken in by the nurse, and about 30 minutes each for interaction with the physician and the nutritionist. After these interactions, patients check out and schedule their next appointment in a month or so. This whole process usually requires that new patients spend about two hours in the clinic.

For follow up patients, as indicated in Figure 4, upon arrival, they first spend approximately 10 minutes checking in and then wait to be taken in by the nurse. After interacting with the nurse, people visit the staff that they are scheduled to see. Before patients see the physician and exercise physiologist, they need to see the nurse. Finally, patients schedule next appointment for about a month into the future, which takes about 5 minutes.

Typically, follow up patients require about 20 minutes for intake, 16 minutes to see the physician, 45 minutes to see the psychologist, 45 minutes to see the exercise physiologist and 30 minutes to see the nutritionist. In normal situations, follow up patients will stay in the clinic about one hour.

Table 4 lists typical service times for each staff with both types of patients. As can been seen from Table 4, staff will spend more time with new patients. The clinic is open from 8am to 5pm on weekdays. However, after 4pm, the clinic has exercise classes for children. So the staff should finish their treatment by 4pm.

Table 4 Process Time for Staffs

	New patients	Follow Up Patients
Physician	30 minutes	16 minutes
Nurse Practitioner	30 minutes	16 minutes
Exercise Physiologist	45 minutes	45 minutes
Nutritionist	30 minutes	30 minutes
Psychologist	45 minutes	45 minutes
Nurse	20 -25 minutes	20 -25 minutes

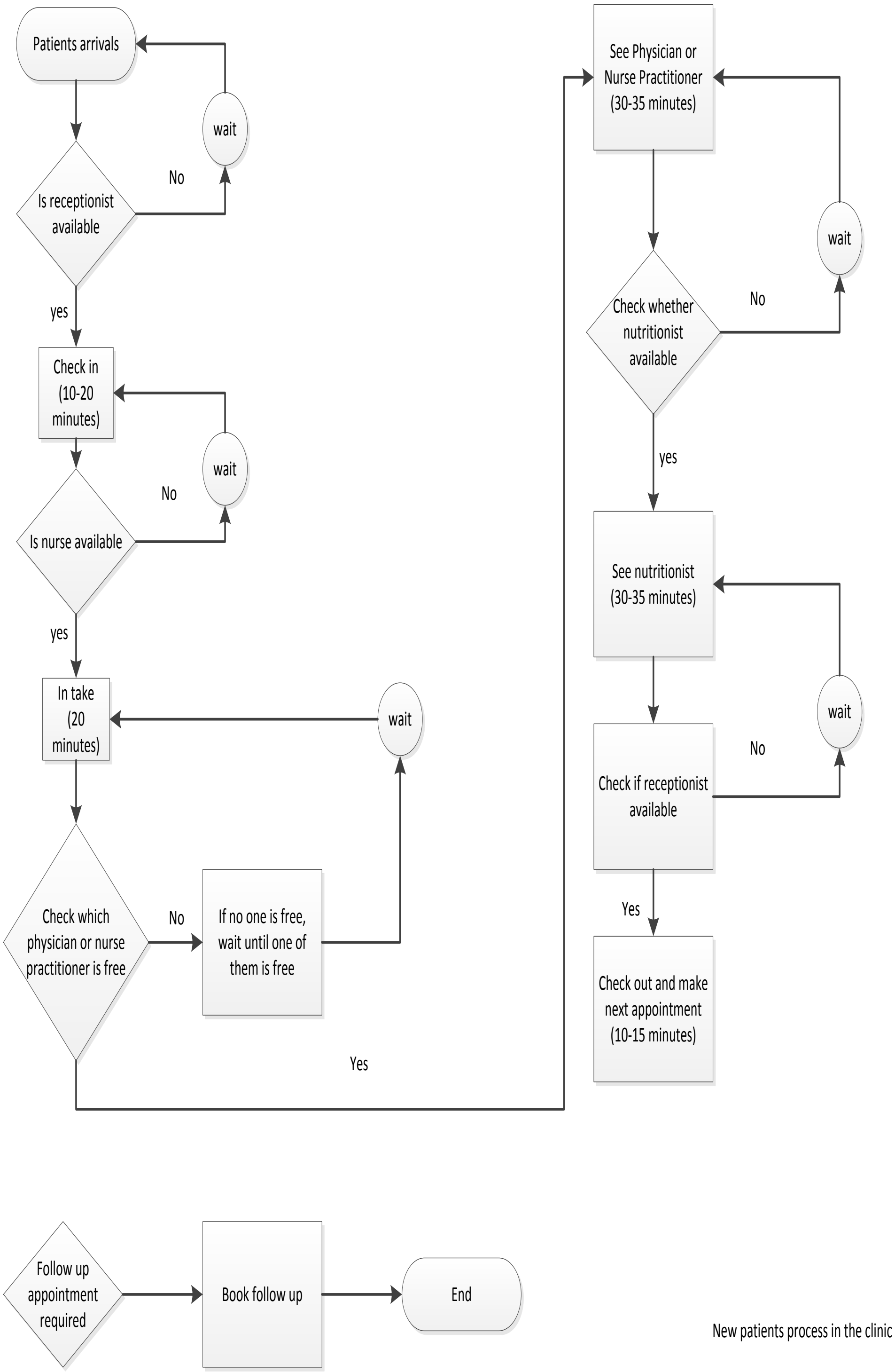

Figure 3. Process of new patients

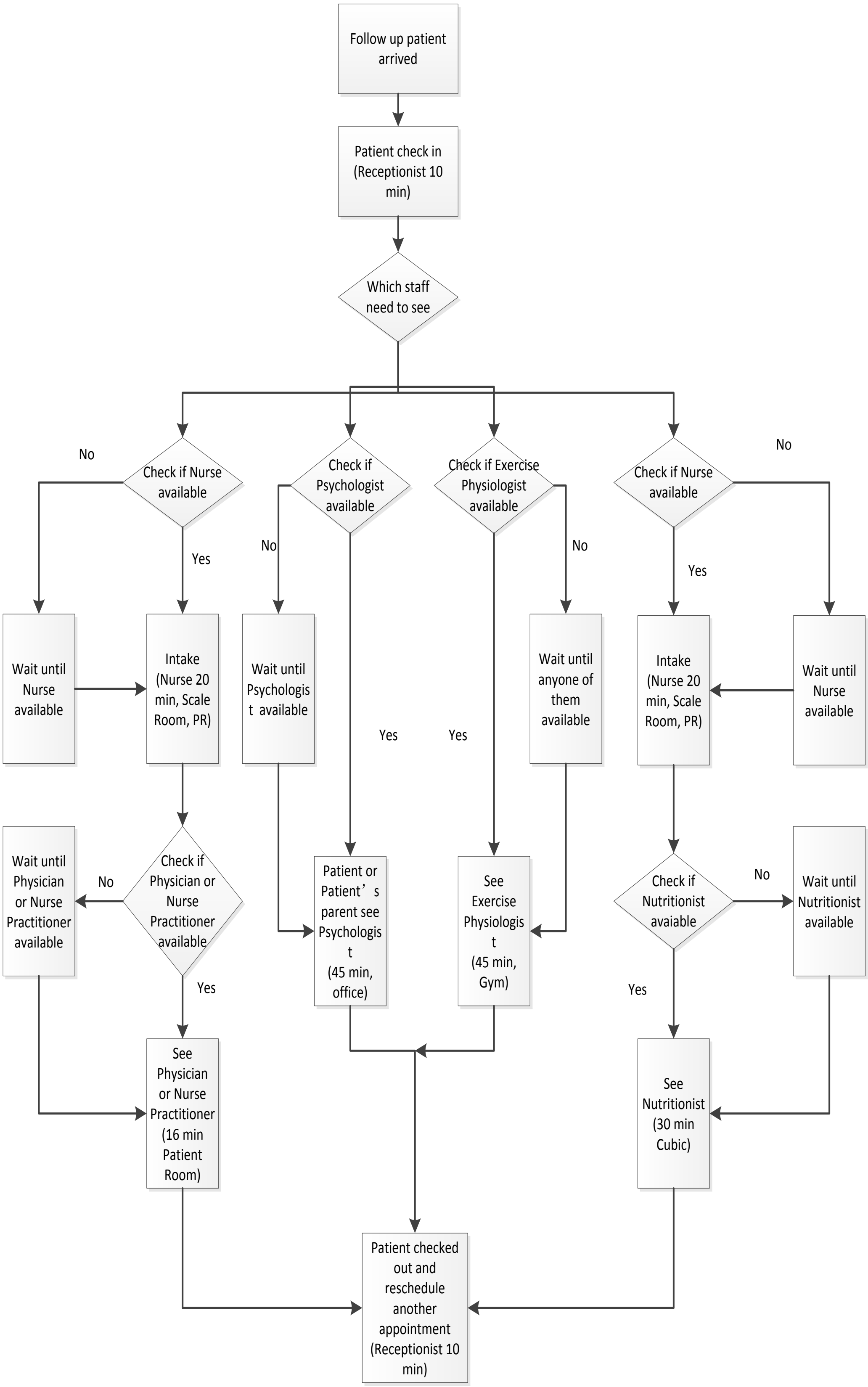

Figure 4. Process of follow up patients

A.3.1.3 CLASSIFICATION OF THE PATIENTS

In this multiple–resources clinic, new patients interact with the physician and the nutritionist during their first visit to the clinic. However, during subsequent visits patients are scheduled to see different staff. We classify patients into five types by visit times, and this classification leads to the following groupings of patients:

- New patients
- Follow up patients to see the nutritionist
- Follow up patients to see the physician
- Follow up patients to see the psychologist
- Follow up patients to see the exercise physiologist

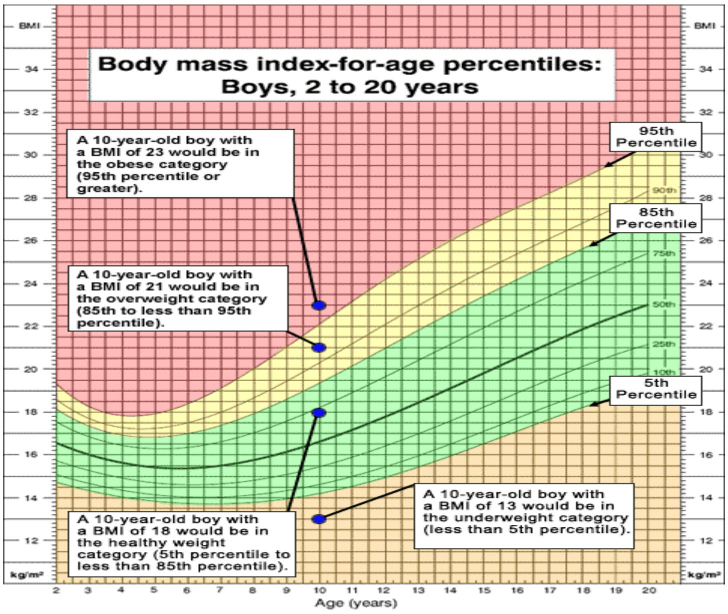

Figure 5. The BMI weight status category

Because this clinic is for overweight children, we also need to consider another factor: the BMI of each child. BMI is widely accepted to estimate body composition which correlates an individual's weight and height to lean body mass. It is thus an index of weight adjusted for stature. Consequently, it can be used to categorize an individual as healthy, underweight, overweight, or obese. (Yang et al., 2013). High values of BMI can indicate excessive fat, while low values can indicate reduced fat. Figure 5 is the BMI weight status category. When a child's BMI is greater than or equal to the 95th percentile, this child will be categorized as obese. In this clinic, most of the children's BMI are above 85%.

A.3.1.4 NO-SHOW RATES

We collected the data from the clinic in 2011. There were 160 new patients' appointments from January 2011 and 86 of these new patients did not show up. As mentioned earlier, new patients will see the physician and the nutritionist. Thus, the average no show rate is 46.25%, i.e., nearly half of the appointments are canceled or rescheduled. $\text{No Show Rate} = \frac{Cancel+No\ Show}{Total}$ After their first visit, new patients will become follow up patients. Follow up patients were scheduled for 505 appointments, of which 268 were "no shows". Hence, the no show rate for follow up patients was 53.06%.

From Table 5, it can be seen that the no show rate for follow up patients who see the psychologist is low. Also, most of the follow up patients prefer to see physician and psychologist in their following visits.

Table 5 No Show Rate for Different Types of Patients

	Arrival	Cancel	No show	Total	no show rate
New	86	39	35	160	*46.25%*
FP See Physician	105	73	55	233	*54.94%*
FP See Nutritionist	25	24	12	61	*59.02%*
FP See Psychologist	85	49	23	157	*45.86%*
FP See Exercise Physiologist	22	21	11	54	*59.26%*

A.3.2 SIMULATION OVERVIEW

This simulation model was built in Arena 14.0 as a discrete-event, stochastic model. Epstein' research (2000) on four treatment methods for overweight showed that children a significant change in weight was possible through the first two years of treatment, with decreases in percent overweight of 22.7% at the end of 6 months and a decrease of 10.9% overweight at 2 years. Figure 6 shows the overweight change in percent from baseline for obese children in the experimental groups at 6, 12, and 24 months.

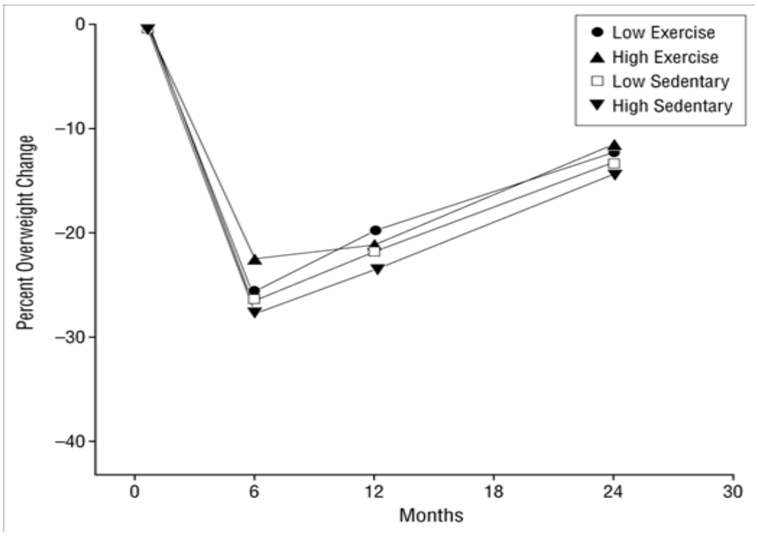

Figure 6. Overweight changing in percent with months

In this dissertation, we assume that overweight children can lose weight, and that BMI decreases after six months. We build simulation models to represent treatment over a six months period and observe the patient flow during this time period.

The scheduled patients include new and follow up patients. The process of scheduling appointments differs for these two categories of patients. New patients make appointments one week in advance and follow up patients make appointments one month in advance. We assume that each patient has their own preferred time. When the patients want to make an appointment, the receptionist will check whether the requested staff is available at the patient's preferred time. If staff is not available, the receptionist will check the next half hour slot. This process repeats until the first available slot is found with the requested staff. If staff is not free during the patients prefer time, we will see whether staff is free in another time period and record the numbers of patients that cannot see staff during their preferred time. We want to assign most of the patients' appointments to their preferred time slots.

The model do not consider the urgent or emergency patients who need to be treated immediately. We only consider the appointment schedule for patients who call in advance. In this long term model, new patients see two staff in their first visits and follow up patients see one staff during one visit. We consider half an hour to be one unit of time. The model represents simulation period of half a year.

A.3.2.1 MODELING ASSUMPTION

The following assumptions are made in the simulation model.

- The waiting room has unlimited capacity.
- Processing times follow the same distribution for the same type of patient.
- Unlimited queue lengths are allowed at all processes.
- The order of processing is first-in-first-out (FIFO).
- One week has five days and every day has nine hours.
- Assume patients will get better in half a year, so the model runs for half a year.

A.3.2.2 MODEL CONSTRUCTION AND APPROACH

Features from the Basic and Advanced Process template and the Blocks template of Arena are used. The model can be divided into three sections. One section is time flow, the second one is for patients to make appointments with the clinic and the third section represents the process of the patients seeing staff in the clinic.

- *TIME ENTITY FLOW MODEL:*

In this long term model, time flow process is an important part. First, we assign all the variable values to 1 including' time of day', 'day of week', 'week of month'. We assume half an hour as a unit. When half an hour passed, we add 1 to the variable 'time of day'. We assume that one day begins at 8am and has 9 hours. So when the time of day equal to 18, we need to add 1 to the variable 'day of week' and change the variable 'time of day' back to 1. For example, the "TNOW" is 8 pm on Monday. After nine hours passed, the "TNOW" is 8 pm on Tuesday.

When the variable 'day of week' is equal to 5, we need to add one to the variable 'week of month' and let the other variables 'time of day' and 'day of week' equal to 1. For example, when the 'week of month' equal to 2 , 'day of week' equal to 1 and 'time of day' equal to 1, it means it is the second week 8am on Monday. Figure 7 explains time entity flows.

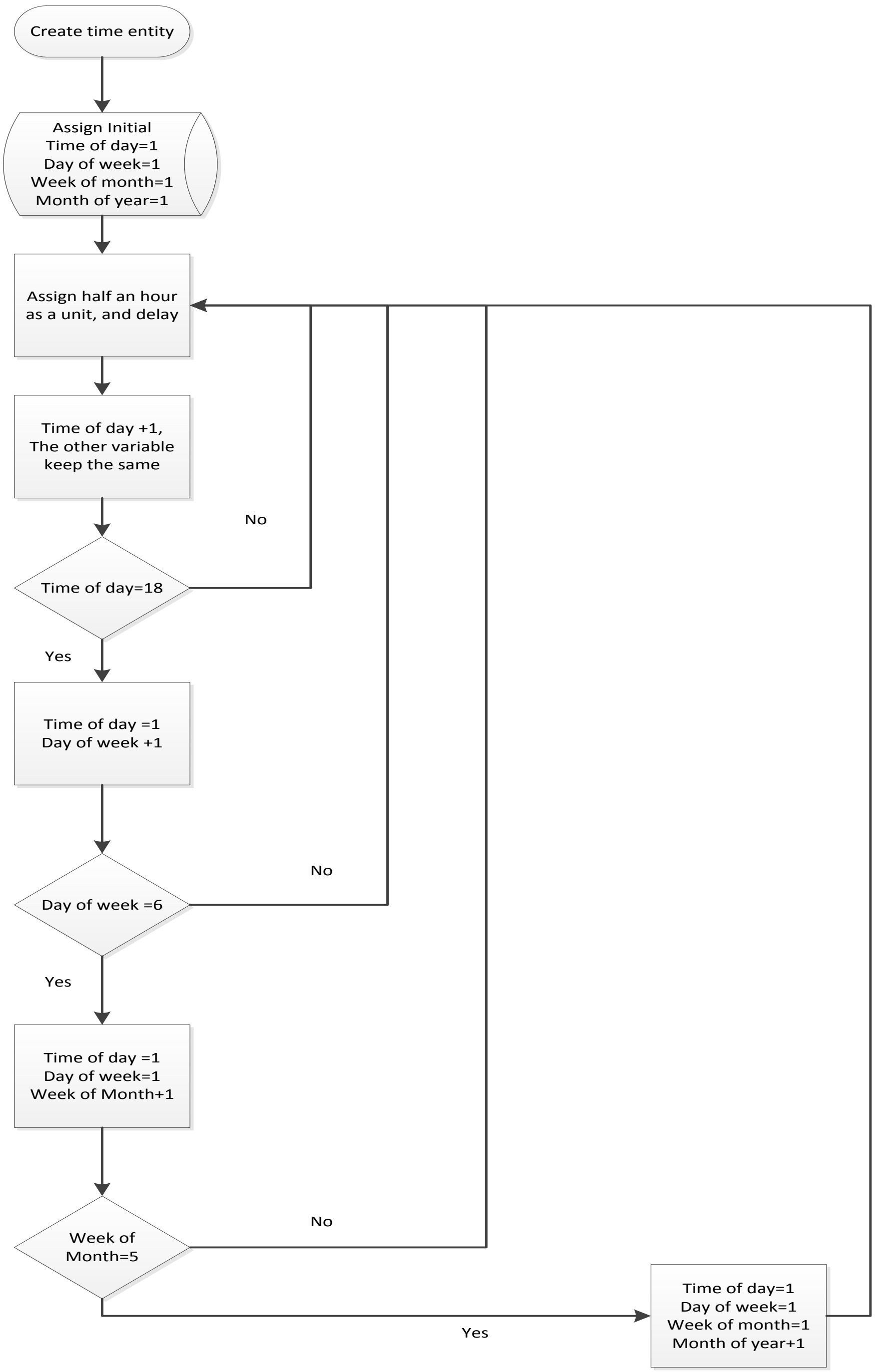

Figure 7. Explain time entity flows

- *APPOINTMENTS MODEL FOR NEW PATIENTS:*

Every day, there are many calls to the receptionist including the new patients who want to make appointment, patients who want to cancel or reschedule their appointment, patients who want to know the information about the clinic. When new patients make appointments, the receptionist checks the schedule book. Because there is only one nutritionist in the clinic, the receptionist will check which time slot the nutritionist has available one week later. If the nutritionist is free, the receptionist will schedule the appointment at that slot precluding other patients from that time slot.

- *PROCESS MODULE FOR RECEPTIONIST CHECKS THE NUTRITIONIST SCHEDULE:*

The receptionist will check five days later from 9 am to 3:30 pm to determine whether the nutritionist is free. The reason that the check starts from 9 am is that the new patients have to check in, intake and see physician which will use nearly one hour and the nutritionist works from 8 am. The reason appointments end at 3:30 pm is that the nutritionist needs to see new patients for half an hour and the staff end work at 4pm. We will avoid staff overtime work in this model.

If the nutritionist is free at the slot, the receptionist will schedule the appointment at that time slot. If the nutritionist has been scheduled at that time slot, the receptionist will continue checking time slots until 3:30pm. If the nutritionist's whole day schedule is busy, the receptionist can check the next day. See Figure 8.

- *PROCESS FOR THE NEW PATIENTS IN THE CLINIC:*

For new patients, upon arrival they check in at the registration desk to complete forms and then stay in the waiting room until called. Before seeing the physician, they first see the nurse. The two physicians and one nurse practitioner perform the same duties, so patients can see any of them depending on who is free. After this, patients check out and schedule their next appointment in a month or so. This whole process usually takes new patients about two hours in the clinic. Figure 8 shows the process of the new patients making appointments in the clinic.

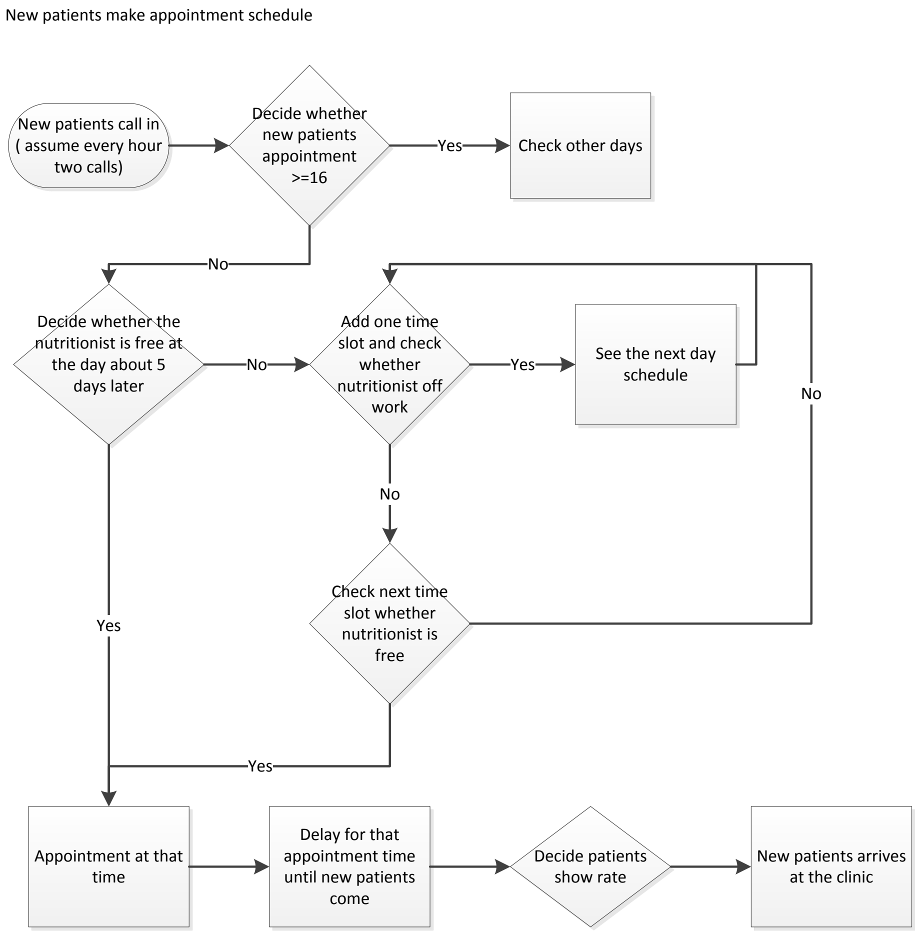

Figure 8. Process of new patients make appointment

- PREFERRED TIME ASSIGNMENT MODULE

When new patients finish their first visit, they need to make their next appointment before they leave the clinic. Every patient has their own preference time. Some of them prefer an appointment on the day they call or sooner, and the day of the week or the time of the appointment is not important to them. Others prefer a particular day of week and a specific convenient time. Some of them prefer a particular provider, even if the time is not convenient to them or they have to wait.

Based on a literature review, patients prefer to arrive at the clinic according to a “dome” shaped distribution, see Wang (1997), Robinson and Chen (2001), and Denton and Gupta (2001). So we assume that 20% of the patients prefer appointments between 8am and 10am, 35% prefer appointments between 10am and 12am, 35% prefer appointments between 1pm and 3pm and the reminder prefer appointments between 3pm and 4pm. In the model, we assume that if patients prefer a particular time period initially, they will continue to prefer this time period in subsequent visits.

- *DECIDING WHICH STAFF TO SEE IN THE FOLLOWING VISITS*

From the data we collected from the clinic, we can see that most of the patients prefer to see the physician at their first and second visit, and on their third visit, some patients would see psychologist. On their fourth visit, patients would see the exercise practitioner, or the nutritionist. We also observe that typically patients visit the psychologist after their second appointments. Based on data collected from the clinic, we estimated the cumulative probability associated with appointments with each staff according to the visit number. In the simulation model, we randomly generated follow up patients visit times in the simulation model, we used these cumulative probabilities to decide which staff member patients will see. Table 6 shows these cumulative probabilities. Columns shows the staff member patients will see. Row shows patients visit times. Table 6 shows the cumulative probabilities of patients see particular staff in their visit times. For example, if this is the third times of this patient come to the clinic, we will use the random probability to compare to the cumulative probability in the third row. If the random probability is 0.5, then this patient will see the physicians in his/her third visit.

Table 6 Cumulative Probability to See Each Staff in Different Visits

% see each staff	2nd	3rd	4th	5th	6th	7th	8th
Nutritionist	0.050847	0.090909	0.096774	0.065217	0.27027	0.212121	0.107143
Physician	0.813558864	0.636364	0.467742	0.326087	0.621621	0.393939	0.464286
exercise physiologist	0.906779203	0.738636	0.66129	0.521739	0.702702	0.515151	0.535714
psychologist	1	1	1	1	1	1	1

Table 7 Ten Configurations for the Interarrival Times (minutes)

Configuration	Interarrival time (minutes)				
	New patients	FP See Nut	FP See Phy	FP See Exe	FP See Psy
1	15	30	30	30	30
2	15	45	45	30	30
3	30	30	30	15	15
4	30	30	30	30	30
5	30	45	45	30	30
6	45	30	30	15	15
7	45	30	30	30	30
8	45	45	45	30	30
9	60	45	45	15	15
10	60	45	45	45	30

- *CHECK TO DETERMINE WHETHER A PARTICULAR STAFF MEMBER IS FREE AT THE PATIENT'S PREFERRED TIME PLOT*

As mention earlier, different patients have different preferred appointment times. The receptionist checks whether the staff member is available at the patient's preferred time. Normally, this day is one month from the visit day. If the staff member has an appointment with another patient during this preferred time slot, the receptionist will check whether this staff is free at other times. However, the model will record this situation as one where a patient did not see staff during their preferred time. If the staff member is busy the whole day, the receptionist will check the following days in sequence until this patient is scheduled. The model records the number of patients scheduled in their preferred time slots and the number of patients scheduled at other times.

Figure 9 shows the process associated with making an appointment with the nutritionist for follow up patients.

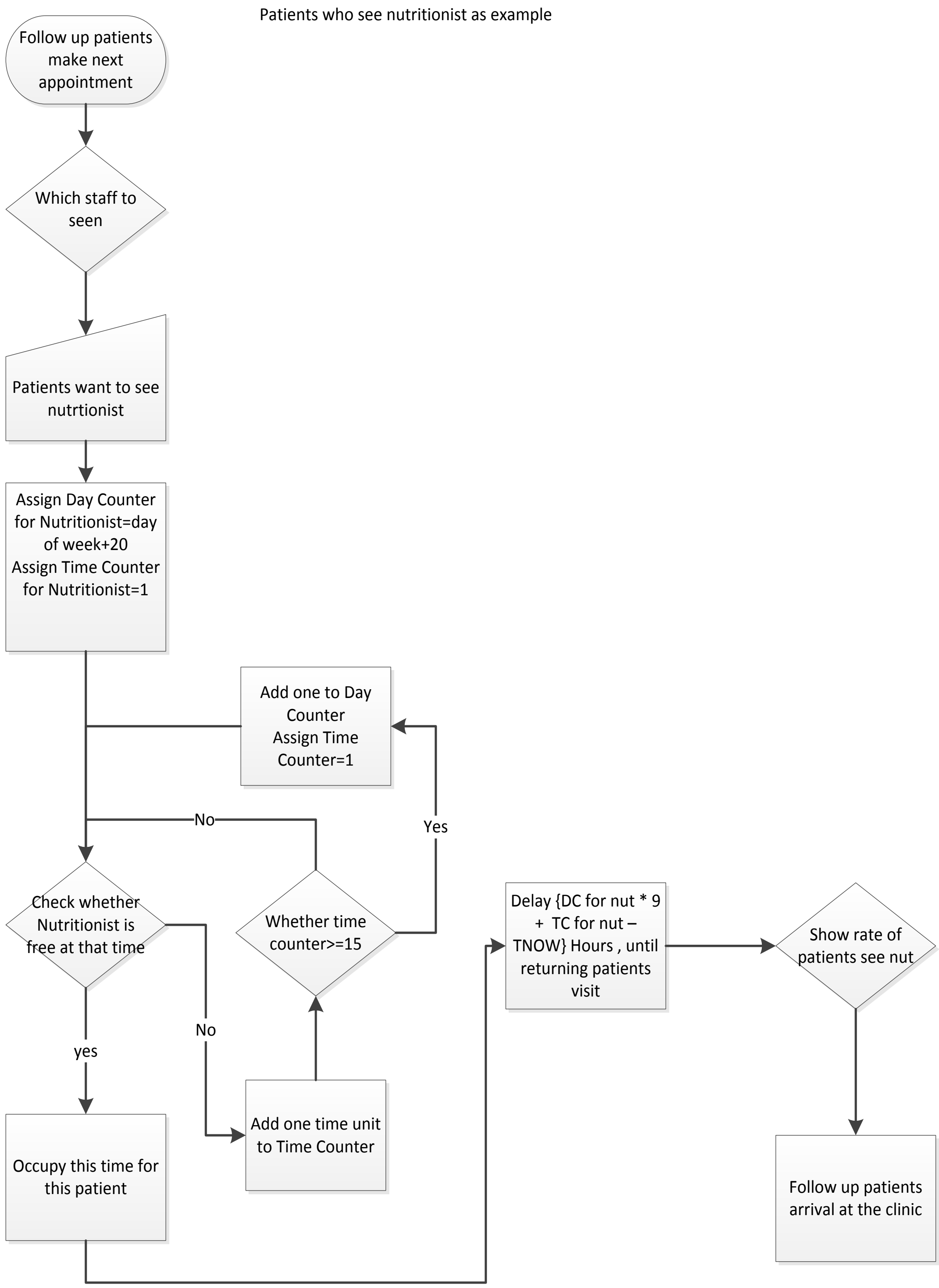

Figure 9. The process of follow up patients make appointment

- *THE PROCESS FOR THE FOLLOW UP PATIENTS IN THE CLINIC:*

Follow up patients first spend approximately 10 minutes checking in and then see the staff that they are scheduled to visit. In addition, before patients see the physician or nutritionist, they are taken in by the nurse. Note that follow up patients just see one staff person during each visit. Finally, these follow up patients make their next appointment for next month before they leave, which takes about 10 minutes.

A.4 SIMULATION RESULTS

There are many methods to assign patients appointment. Some clinics overbooked appointments by double-booking patients into common appointments times and relying on no-shows to allow the schedule to catch up (Chung, 2002). One type of overbooking involves scheduling an appointment every 30 minutes when the facility can serve patients every 45minutes. The goal of overbooking is to minimize the negative effect of no-shows. Also, some researchers have studied changing the interarrival time for patients. One method is to use different interarrival based on different patient types (Lau, 2000).

In this model, we assigned ten different configurations for new patients' and follow up patients' interarrival times. We changed each type of patients' interarrival time and observed the patients average waiting time and staff average utilization. We considered each type of patients' process time and show up rate to set up the experiment. After running the simulation model for 10 replications, we obtained output for two attributes as shown in Table 8. (FP=follow up patients)

Attribute x_1 ------ patients' average waiting time in the clinic

Attribute x_2 ------ staff utilization (the average utilization for over all the staff in the clinic)

Table 8 $\boldsymbol{n_0}$ = 10

Configuration	Sample mean Waiting Time	Sample mean Utilization	Individual attribute utility function value for X_1 $u_1(x_1)$	Individual attribute utility function value for X_2 $u_2(x_2)$	half width of $u_1(x_1)$	half width of $u_2(x_2)$
1	22.99	0.22	0.66	0.34	0.04	0.01
2	22.14	0.22	0.68	0.34	0.05	0.01
3	23.00	0.22	0.66	0.34	0.04	0.01
4	22.99	0.22	0.66	0.34	0.04	0.01
5	22.14	0.22	0.68	0.33	0.05	0.01
6	11.26	0.15	0.87	0.21	0.03	0.01
7	11.26	0.14	0.87	0.21	0.03	0.01
8	8.95	0.15	0.90	0.21	0.02	0.01
9	10.20	0.09	0.88	0.14	0.04	0.01
10	9.55	0.10	0.89	0.14	0.03	0.01

B. CASE STUDY TWO: AMBULATORY INTERNAL MEDICINE CLINIC

B.1 INTRODUCTION

Ambulatory care is a personal health care consultation, treatment or intervention using advanced medical technology. The patients do not need to stay overnight in the hospital. They stay at the clinic from the time of registration to discharge.

This clinic is a teaching clinic, which belongs to University of Louisville. Normally, residents of doctor will see the patients firstly and then talk to the attending physician. The attending physician will guide them and give them some suggestions. This clinic offers a fee card which called the Gold Card. This card can reduce the cost of medicine. The minimum fee to receive treatment with the card is $20. This is one of the reasons that more patients prefer to come this clinic.

The University of Louisville Ambulatory Internal Medicine (AIM) clinic operates with different specialties according to the day of the week. The patients need to make an appointment with clinic and show up on time. If the patients are more than 15 minutes late, they cannot be treated.

The clinic has one waiting room, one front desk, two residents, an attending physician office, five triage desks and fifteen examination rooms. It is divided into two sides. On the large side, there are nine examination rooms and three triage desks. Some of second year residents and all of the third year residents work on the large side. On the small side, there are two triage desks and six examination rooms. Some of second year residents and all the first year residents work on the small side. The examination room will be assigned to the residents. Figure 10 shows a layout of the clinic.

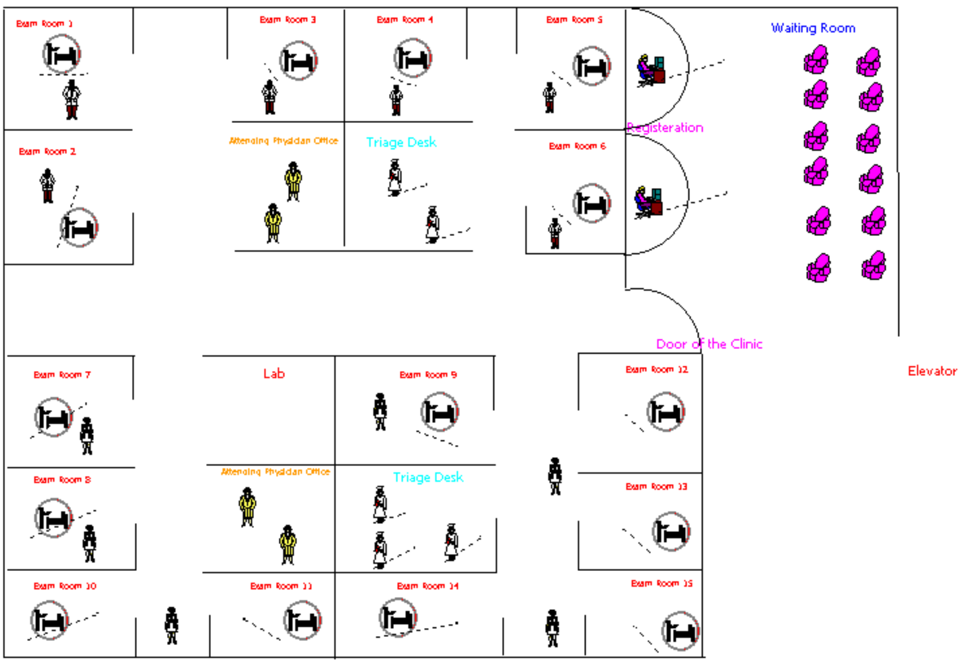

Figure 10. Layout of “AIM” clinic

B.2 PROBLEM STATEMENT

The basic problem addressed for this clinic involved the scheduling of resources (including attending physician, residents and examination rooms) in order to improve the utilization of these resources and decrease the waiting time for the patients. The director of the clinic wants to minimize the waiting time for patients in the examination room and waiting rooms and reduce the over-time for the staff. The residents leave the clinic when the last patient has been seen. If the overtime lasts more than one hour on Tuesday morning, it will influence the next shift of residents on Tuesday afternoon.

This case is different from the case involving the “Healthy for Life” clinic in that the no show rate for patients is not a major concern. The clinic manager wanted to shorten patients’ waiting time so that more patients could be seen. The resources in their clinic are fixed. We need to make a good assignment for each resource and keep every resource busy and efficiency. Finding a good assignment method when resources interact with each other is our goal in this case.

B.3 DATA COLLECTION

B.3.1 STAFFING AND SCHEDULING OPERATIONS AT AIM CLINIC

We use a typical Tuesday morning for our case study. The resources available for Tuesday morning include twelve of residents of varying experience levels, four attending physicians, two receptionists, five nurses and 15 examination rooms. Among these 12 residents, four of them are first year residents, five are second year residents and three are third year residents.

These residents are medical school graduate students undergoing “on the job” training. They completed eight years of higher education before entering the resident program. The resident program ranges from three years to seven years in duration, depending on the specialty. In this clinic, the program lasts three years. Treatment times are longer for first year residents than for second or third year residents.

The residents treat patients and are supervised by the attending physicians who check whether the treatments are correct. For the first year residents (especially for the first six months), the attending physician will supervise them during the entire patient interaction. For the second and third year residents, permission of the attending physician is needed before giving patients the results. In this clinic, one attending physician will supervise of four residents.

At the front desk, there are two receptionists who are responsible for check in and checkout of as well as some paper work. In addition, two days before the appointment day, a receptionist makes reminder phone calls to the patients.

The nurse is responsible for taking in patients and recording the basic physical data; these activities require about twenty minutes. Both new and follow up patients see the nurse before they see the residents. Each nurse is assigned to a particular resident.

B.3.2 PATIENTS FLOW AT THE CLINIC

Patients make an appointment before visiting the clinic. New patients call the receptionist and complete some forms before going to the clinic. Patients who apply for a gold card bring their documents to the Financial Counselor office. Follow up patients make their next appointment, if needed, before they leave the clinic. In general, patients come to the clinic two or three times in one year.

Table 9 Check in Time for Different Types of Patients

(Use Triangular Distribution)

Patients type	Minimum value	Most Likely Value	Maximum Value
New	4	6	8
Follow up	3	5	7

Table 9 shows the check in times by patient types. Clinic manager gave us the data and explain the patients flow of the “AIM” clinic. Then we went to the clinic and observe the whole process for four “Tuesday Morning”. Also, we talked to the patients and got complains about the clinic. After that, we concluded the problems from data and patients talk. When the patients arrive, they need to check in at the front desk to fill the form out and then stay in the waiting room until being called in. The check in time varies between new patients and follow up patients, but both correspond to a triangular distribution. For new (old) patients the most likely check in time is 6(5) minutes.

After patients check in, they wait until the assigned nurses are free for giving triage vitals. There are five nurses in the clinic and each is assigned to particular resident. After the patients receives triage vitals, they return to the waiting room until an examination room is free. When an examination room becomes available, the patient enters the room to wait for their assigned resident. New patients are assigned to the next available resident, while follow up patients see the particular resident who treated them on their previous visit.

Residents see the patients by themselves first. Table 10 shows the process time for the initial interaction with residents. Note that these times are distribution according to a triangular distribution. As indicated in Table 10, third year residents should see more patients than second year residents or first year residents during the morning shift.

Table 10 Treatment Time for Patients See Residents

(Use Triangular Distribution)

Residents Type	New patients (minutes)	Follow up patients (minutes)
1st year Resident	TRIA(55,60 65)	TRIA(45,50 55)
2nd year Resident	TRIA(45,50,55)	TRIA(20,25,30)
3rd year Resident	TRIA(35,40,45)	TRIA(15,20,25)

When a resident finishes seeing a patient, they will talk to an attending physician. The attending physician consider the resident's experience and decide whether it is necessary to check the patient himself/herself in the examination room. If necessary, both of the resident and attending physicians will come back to the examination room and talk to the patients again. If not, the residents will return to the examination room by themselves without the attending physician.

After treatment, the patient waits in the examination room for the reports and lab results. At the same time, the residents completes the relevant the forms. When these activities are completed, the patient can exit the examination rooms to check out and make next appointment if needed. This also depends on which receptionist is free or whose queue is shorter. The "time of check out" corresponds to triangular distribution -TRIA (13, 17, 20) minutes. Figure 11 illustrates the patients flow in AIM clinic.

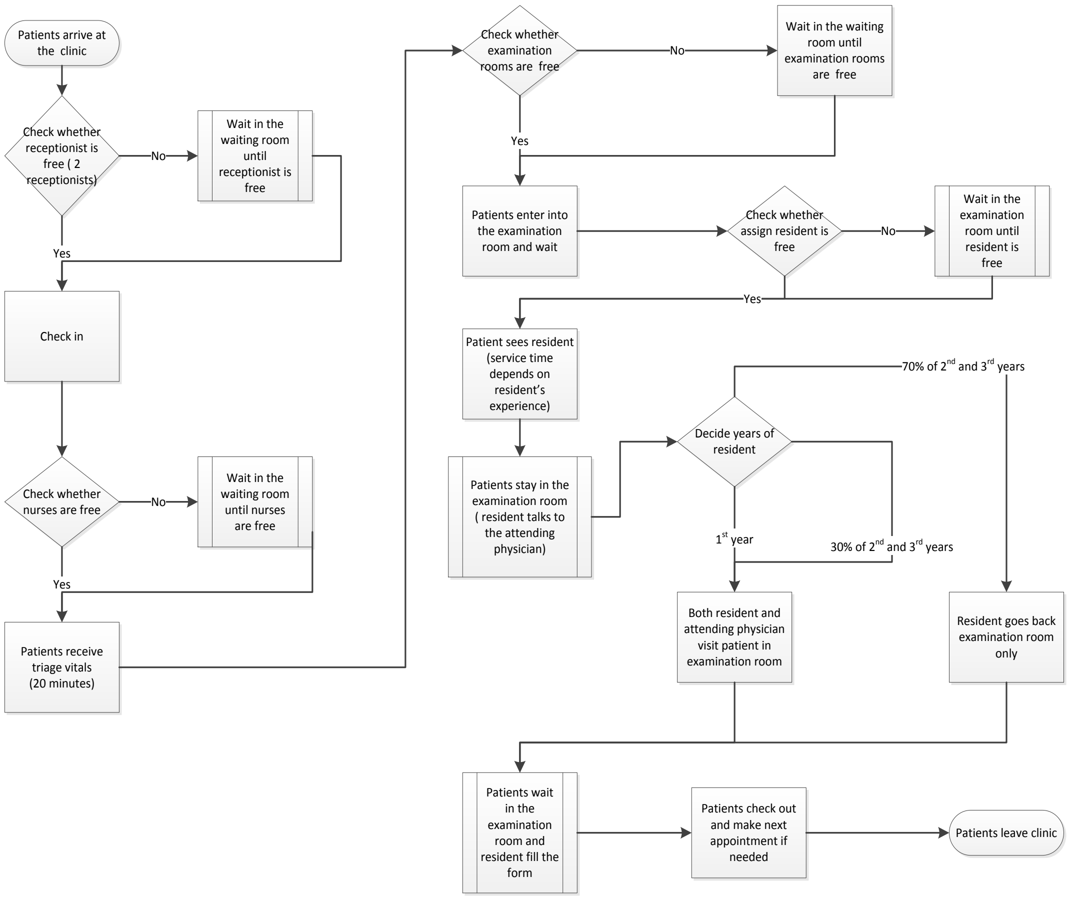

Figure 11. Process of patients flow

B.4 SIMULATION MODEL

B.4.1 OVERVIEW

This simulation model is also built in Arena Version 14.0 as a discrete-event, stochastic model.

This model is a one morning model, with a simulation duration of four hours. The AIM clinic operates with different specialties each day of the week. The residents of University of Louisville take turns to be in "AIM" clinic one day a week in the morning or afternoon. We simulate the entire process associate with the patients stay in the clinic.

Patients arrive to the clinic according to "dome" distribution which means most of patients arrive in the middle of the morning (from 9am to 11am). This is one of the reasons for the long waiting time for patients.

B.4.2 MODELING ASSUMPTION

The following assumptions are made in the simulation model

- The waiting room has unlimited capacity.
- Processing times follow the same distribution for the same type of patient.
- Unlimited queue lengths are allowed at all processes.
- The order of processing is first-in-first-out (FIFO).
- Patient is late no more than 5 minutes, or we will define this patient as no show.

B.4.3 MODEL CONSTRUCTION AND APPROACH

Constructs from the Basic and Advanced Process Templates and the Blocks Template of Arena are used for this model. The following sections describe the construction of the Model.

We follow the clinic rules and the data we collected to build the model. Although from the clinic manager and patients, we know the main problem of this clinic is long waiting time. We still need to build simulation model and find the bottle neck from the clinic operation. Below is the basic idea of simulation model.

The arrival rate for patients corresponds the data we collected from the clinic. Patients are divided into two categories: new (80%) and follow up (20%),

When the first patients come into the clinic, we will assign this patient as the number one patient. The number one patient will see the number one resident, and there are 12 residents in the clinic. We do not use resident's name and assign them a number from one to twelve. The second patients see the number two resident and so on. Number thirteen patients will see number one resident again. We can change the sequence of resident to see the patients to let third years residents see more patients than the other year's residents.

Each nurse is assigned to particular resident. The patients wait until the nurses are free and receive triage vitals which nearly use 20 minutes.

When the examination room are free, the patients can stay in the examination rooms to wait residents. Firstly, the residents see patients by themselves. After they finish seeing patients, they need to talk to the attending physician outside the examination rooms. There are four attending physicians. Residents talk to the attending physicians depends on which attending physicians are free. While the residents talk to the attending physicians, the patients still wait in the examination rooms.

After talking to the attending physicians, the first year residents, 30% of second year residents and third year residents will go back to the examination rooms with attending physicians. They talk to the patients again. The whole process follows triangular distribution-- TRIA (30, 35, 40) minutes. For other second year and third year residents (70% of them), the residents will go back examination room by themselves. The whole process follow triangular distribution---TRIA (13, 15, 20) minutes. Then the residents need to fill the forms.

After patients finish the treatment and obtain all the results, they can leave the examination rooms and check out.

The first patient will arrive at the clinic at 8:00am and the last patient will arrive at the clinic at 11:20 am.

B.5 SIMULATION RESULTS FOR "AIM"

We follow the clinic rules and collected data to build model. We considered each year of residents' process time and patients interarrvial time to set up the experiment. After running the simulation model for 10 replications, we obtained output as shown in Table 11, Table 12, Table 13. We got new patients' and follow up patients' average service time, average waiting time, average total time and average over time showed in Table 11. From Table 11, the results can be accepted, except over time is longer. However, we observed Table 12 which showed the top longest average waiting time for different activity. We found that waiting for examination rooms always take patients more time. Therefore, we need to change examination room assignment. Table 13 shows different examination room utilization. From Table 13, we conclude that examination room 13 and examination room 15 have low utilization. The reason is third year residents have two examination rooms. From the results, we conclude that examination rooms' assignment is not reasonable. We need to try to reassign examination rooms.

From the results seen in Tables 11, 12 and 13, we determine the problems of the AIM clinic.

Table 11 Process Time for Different Type of Patients

Patients Type	Process time (minutes)	Waiting time (minutes)	Total Time (minutes)	Over time (minutes)
New patients	93.57	38.12	157.57	91.76
Follow up patients	79.28	32.37	136.83	

Table 12 Average Longest Waiting Time for Different Activity

Activity	Waiting time(minutes)
Waiting for examination room 6	34.16
1st year resident fill the form	24.4
Waiting for examination room 7	19.36
Waiting for examination room 3	13.75
Waiting for examination room 4	13.64
Waiting for examination room 1	10.76
Waiting for examination room 2	10.54
2nd year resident fill the form	8.13

Long waiting time for examination rooms, especially for the first year residents.

Table 13 Average Lowest Utilization of Facility

Examination room	Utilization
exam room 15	0.00466216
exam room 13	0.01528925
exam room 8	0.1489
exam room 12	0.2309
exam room 14	0.2352
exam room 11	0.2505
exam room 9	0.2842
exam room 5	0.4003
exam room 10	0.4697

- Long waiting time for residents to complete the forms.
- The utilization associated with nurses is much lower than the utilizations for residents and the attending physicians.
- Long over time, especially for the first year residents (first year resident service time is longer)

Analysis of these simulation results and discussion with the clinic's management led to the following suggested solution alternatives:

- Change the numbers of patients assigned to different year residents.
- Change the patient interarrival times
- Allow flexible use of some examination rooms for residents

Corresponding to these suggestions, we changed the simulation model. First, we increased the number of patients assigned to second and third year residents. In particular, third year residents were assigned to more patients than second year residents and second year residents were assigned to more patients than first year residents. From the data we collected, we found that the number of patients see each years of residents are equal. However, the first year residents need more service time than the other years of residents. Therefore, we increased the number of patients assigned to second and third year residents.

Secondly, we changed the interarrival time for patients. In particular, we experimented with interarrival times of 3, 4, 5, 6 and 7 minutes.

Thirdly, we allowed flexible use of examination rooms for all of the residents. The rule of the clinic is third year residents have two examination rooms, while the other resident just have one examination rooms. From the observation, we found that some patients need to wait examination rooms, however at the same time, other examination rooms are available. Also, we hear one patient complained she had waited in the examination rooms for an hour. The feeling of waiting in the examination room is worse than waiting room. Therefore, we assign that residents were allowed to use and available examination room.

These changes led to 20 alternative configurations, as indicated in Table 14.

Table 14 Twenty Configurations Based on Suggestions

Configuration	Interarrival Time (minutes)	Assign Examination Room	Sequence of residents
1	3	Yes	original
2	3	No	original
3	3	Yes	change
4	3	No	change
5	4	Yes	original
6	4	No	original
7	4	Yes	change
8	4	No	change
9	5	Yes	original
10	5	No	original
11	5	Yes	change
12	5	No	change
13	6	Yes	original
14	6	No	original
15	6	Yes	change
16	6	No	change
17	7	Yes	original
18	7	No	original
19	7	Yes	change
20	7	No	change

There are four attributes to be considered, the sample mean waiting time of patients, sample mean utilization of staff, sample mean utilization of examination room and sample mean over time. Ten replications were run. The simulation results are shown in Table 15.

Table 15 Simulation Results for Twenty Configurations

Configuration	Average Waiting Time	Average Staff utilization	Average Examination room utilization	Over Time
1	58.84	0.55	0.43	162
2	62.94	0.57	0.54	164
3	52.46	0.61	0.46	173
4	52.45	0.59	0.51	172
5	35.87	0.53	0.39	120
6	36.79	0.53	0.43	122
7	25.17	0.59	0.41	112
8	25.01	0.59	0.43	96
9	18.8	0.48	0.34	80
10	20.48	0.47	0.35	76
11	11.84	0.49	0.32	65
12	11.84	0.49	0.32	65
13	10.8	0.37	0.25	89
14	11.48	0.37	0.26	90
15	5.28	0.39	0.25	76
16	5.28	0.39	0.25	76
17	7.5	0.32	0.21	116
18	7.56	0.33	0.21	97
19	3.69	0.34	0.21	84
20	3.69	0.34	0.21	84

From the results, we concluded that when the interarrival time is set to three minutes (configurations 1 though 4), the over time is almost three hours. One of the rules of clinic is that it closes when the last patient leaves. A long overtime period influences the afternoon schedule. When the interarrival time was set to seven minutes, the utilizations of staff and facility were low. After comparing these results, 12 configurations were chosen for future analyses, as shown in Table 16.

Table 16 Twelve Configurations and Simulation Results

Configuration	Interarrival Time	Assign Examination Room	Sequence of residents	Average Waiting Time	Average Staff utilization	Average Examination room utilization	Over Time
1	4	Yes	original	35.87	0.53	0.39	120
2	4	No	original	36.79	0.53	0.43	122
3	4	Yes	change	25.17	0.59	0.41	112
4	4	No	change	25.01	0.59	0.43	96
5	5	Yes	original	18.8	0.48	0.34	80
6	5	No	original	20.48	0.47	0.35	76
7	5	Yes	change	11.84	0.49	0.32	65
8	5	No	change	11.84	0.49	0.32	65
9	6	Yes	original	10.8	0.37	0.25	89
10	6	No	original	11.48	0.37	0.26	90
11	6	Yes	change	5.28	0.39	0.25	76
12	6	No	change	5.28	0.39	0.25	76

V. UTILITY FUNCTIONS USED IN RANKING AND SELECTION

A. RESULTS FOR “HEALTHY FOR LIFE” CLINIC

A.1 MULTIPLE ATTRIBUTE UTILITY FUNCTION FOR THE “HEALTHY FOR LIFE” CLINIC:

In the long period “Healthy for Life” simulation model, the main goal is to choose a policy for scheduling patients that will satisfy both the clinic’s manager and the clinic’s patients. The candidate policies involve varying interarrival times for patients.

Two performance measures, the waiting time of patients and the staff utilization are considered. An ideal result will have low mean waiting time and high mean utilization. However, we need to tradeoff between these two attributes in order to find a better policy. We denote waiting time as X_1, and utilization as X_2.

A single attribute utility function form is given by:

$$u_i(x_i) = A_i - B_i e^{x_i RT_i} \tag{19}$$

where RT_i is the decision maker’s (DM’s) assessed risk tolerance and A_i and B_i are scaling constants.

A particular single attribute utility function for the waiting time is given by:

$$u_1(x_1) = 1.309 - 0.309\exp(0.03208x_1) \tag{20}$$

The range of waiting time is (0, 45) minutes. The midpoint is 30 minutes as its utility value is 0.5. A graph of this function is shown in Figure 12.

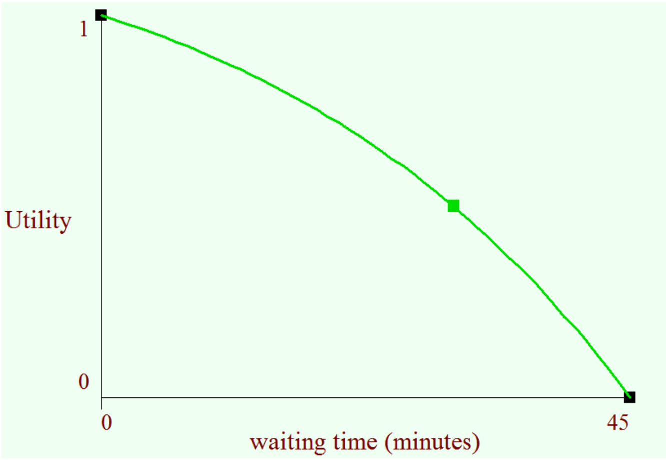

Figure 12. Utility function for waiting time

A particular single attribute utility function for utilization is given by:

$$u_2(x_2) = -0.7841 + 0.7841\exp(1.644x_2) \tag{21}$$

The range of utilization is (0, 0.5). The midpoint is 0.3 as the utility value is 0.5. The reason for using a maximum utilization value of 0.5 is that the staff has activities to perform other than what is represented in the model. A graph for this function is shown in Figure 13.

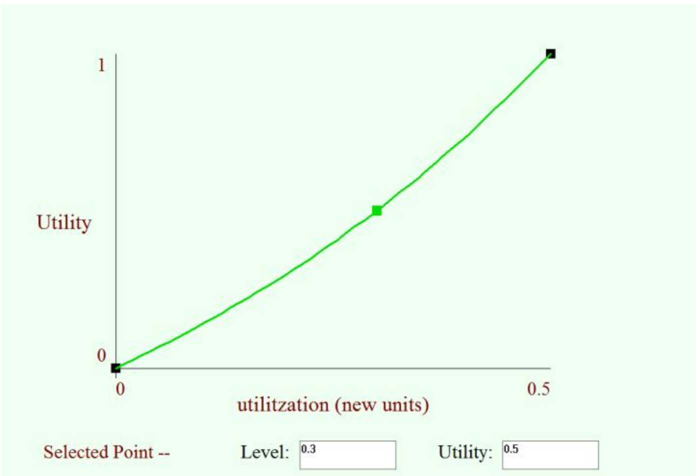

Figure 13. Utility function for utilization

Using these two attributes X_1 and X_2, an additive multiple attribute utility function is given by equation (22).

$$\mathrm{U}(x_1, x_2) = w_1 u_1(x_1) + w_2 u_2(x_2) \tag{22}$$

$$\text{Let } w_1 = 0.6 \quad w_2 = 0.4\,, \tag{23}$$

Substituting (20) (21) and (23) into the (22), one obtains

$$\mathrm{U}(x_1, x_2) = 0.6 * [1.309 - 0.309\mathrm{exp}(0.03208x_1)] + 0.4 * [-0.7841 + 0.7841\mathrm{exp}(1.644x_2)]$$

A.2 SELECTION OF $\boldsymbol{\delta}^*$ FOR “HEALTHY FOR LIFE” CLINIC

A.2.1 UTILITY EXCHANGE

We studied ten configurations for new patients’ and follow up patients’ interarrival time. We change each type of patients’ interarrival time and observe the patients average waiting time and average utilization of staff. We considered each type of patients’ process time and show up rate to set up the experiment. Details associated with the ten configurations are shown in Table 7, and associated output from the simulation model are shown in Table 8.

Butler et al. (2001) proposed a “utility exchange” where one sets the utilization at a common level, and hence only needs to adjust the waiting time with the fixed utilization level.

The first step is to determine the standard measure which is utilization of staff. Then, select a common level of utility, denoted as c_i for the attribute which is assigned to be the standard measure. The last step is utility exchange. Based on the value of c_i, we change the value of waiting time from x_{k1} to x'_{k1}. We want to make two alternatives equally preferred, which means that the respective expected utility values associated with the two alternatives will be equal.

As noted earlier, there are two attributes and ten configurations in this study.

So K=10. We define x_{k1} as the average waiting time, and x_{k2} as the average utilization. We chose utilization as the standard measure and let $\mathrm{u}(x'_{k2}) = c_2$. Then we changed waiting time x_{k1} to x'_{k1}, where k denote the alternative (in this project, k=1, 2, 3, 4...10) and the index 1 in x'_{k1} denote the first attribute.

Butler et al. (2001) provide three propositions, which allows one to extend to an indifference zone for an attribute to an indifference zone for expected utility. We mentioned in Chapter III (P.27). Applying Propositions to the project: Let the utilization be the standard measure, and assume that the utilization is fixed at 0.22. Then $c_2 = 0.35$.

Table 17 shows the sample mean waiting time, the sample mean utilization, the individual attribute utility function value for x_1 and x_2, the fixed utility function value for x_2 and rescaled utility value of x'_1 for the various configurations.

Table 17 Utility Value for the Average Waiting Time, Utilization and Rescaled Utility of Waiting Time Value

Configuration	Sample mean Waiting Time	Sample mean Utilization	Individual attribute utility function value for x_1 $u_1(x_1)$	Individual attribute utility function value for x_2 $u_2(x_2)$	Fixed utility function value for x_2 c_2	Rescaled utility function value for x_1 $u_1(x_1')$
1	22.99	0.22	0.66	0.34	0.35	0.66
2	22.14	0.22	0.68	0.34	0.35	0.67
3	23.00	0.22	0.66	0.34	0.35	0.65
4	22.99	0.22	0.66	0.34	0.35	0.66
5	22.14	0.22	0.68	0.33	0.35	0.67
6	11.26	0.15	0.87	0.21	0.35	0.77
7	11.26	0.14	0.87	0.21	0.35	0.77
8	8.95	0.15	0.90	0.21	0.35	0.81
9	10.20	0.09	0.88	0.14	0.35	0.74
10	9.55	0.10	0.89	0.14	0.35	0.75

A.2.2 DETERMINING THE INDIFFERENCE ZONE

The next step is that the decision maker needs to determine $\delta_1{}^*$. We discussed $\delta_1{}^*$ in Section III, and we chose one of the indifference zones to calculate. We set $\delta_1{}^* = 0.1$ which means that the decision maker is indifferent between a waiting time of 20 minutes and a waiting time of 25 minutes, as shown in Table 3.

A.3 TWO STAGE RANKING AND SELECTION FOR THE "HEALTHY FOR LIFE" CLINIC

In order to make a final comparison between alternative configurations, we determined the number of additional replications for the simulation results shown in Table 18. We used a half width of the confidence interval as output from the simulation runs in order to calculate the variance of each utility function, then we used the variance of the utility function to calculate the number of replications needed to allow a valid determination. Setting $P^* = 0.95, h = 4.29, n_0 = 10, K = 10, c_2 = 0.7, \delta_1{}^* = 0.1$ and then using equation (7) yields the results shown in Table 18. After running additional replications, we obtained the average waiting time, utilization, utility value of waiting time and utility value of utilization in Table 19. Then we performed a utility exchange to calculate exchanged utility waiting time on these additional replications. After that, we calculated the weighted of two stage sample mean using formulation (9). Finally, we obtained the weighted sample means of utility value through the use of (10). The final results are shown in Table 20.

Table 18 Calculate Numbers of More Replications Needed According Variance

Configuration	Rescaled Average Waiting Time $u_1(X_{k1})'$	Fix Utility C_2 Utilization	Half Width of $u_1(x_1)$	Half Width of $u_2(x_2)$	Total Replications (N_k)	More Replications $(N_k - n_0)$
1	0.66	0.35	0.04	0.01	23	13
2	0.67	0.35	0.05	0.01	36	26
3	0.65	0.35	0.04	0.01	23	13
4	0.66	0.35	0.04	0.01	23	13
5	0.67	0.35	0.05	0.01	36	26
6	0.77	0.35	0.03	0.01	13	3
7	0.77	0.35	0.03	0.01	13	3
8	0.81	0.35	0.02	0.01	6	0
9	0.74	0.35	0.04	0.01	23	13
10	0.75	0.35	0.03	0.01	13	3

Table 19 Calculated Rescaled Exchanged Utility of Waiting Time on More Replications and Weight w_{k1}

Configuration	$N_k - n_0$	$x_k(N_k - n_0)$	$u_1(N_k - n_0)$	$u_2(N_k - n_0)$	$u_1'(N_k - n_0)$	Define the Weights w_{k1}
1	13	22.57	0.67	0.34	0.66	0.43
2	26	21.98	0.68	0.33	0.67	0.28
3	13	22.57	0.66	0.33	0.65	0.43
4	13	22.57	0.66	0.33	0.65	0.43
5	26	21.98	0.68	0.33	0.67	0.28
6	3	11.37	0.86	0.20	0.76	0.74
7	3	11.37	0.86	0.20	0.76	0.74
8	0					1.00
9	13	10.42	0.87	0.15	0.74	0.43
10	3	8.61	0.89	0.14	0.75	0.74

Table 20 Utility Value of the Final Results

Configuration	W_{k1}	W_{k2}	U_1'(x_1)	U_1'$(N_k - n_0)$	final results
1	0.43	0.57	0.66	0.66	0.66
2	0.28	0.72	0.67	0.67	0.67
3	0.43	0.57	0.65	0.65	0.65
4	0.43	0.57	0.66	0.65	0.65
5	0.28	0.72	0.67	0.67	0.67
6	0.74	0.26	0.77	0.76	0.77
7	0.74	0.26	0.77	0.76	0.77
*8	1.00	0.00	0.81		0.81
9	0.43	0.57	0.74	0.74	0.74
10	0.74	0.26	0.75	0.75	0.75

Table 20 indicates that policy 8 is the best. For the policy, the interarrival times for new patients and follow up patients to see the physician and nutritionist are each 45 minutes respectively, and for follow up patients to see the exercise physiologist and psychologist are 30 minutes respectively.

B.SENSITIVITY ANALYSIS ON UTILITY FUNCTION WEIGHTS FOR "HEALTHY FOR LIFE"

We changed the weight of waiting time (w_1) in increments of 0.1 from 0.9 to 0.1. Since $w_1 + w_2 = 1$, w_2 was also appropriately changed in value.

When $w_1 = 0.9, w_2 = 0.1,$ the multiple attribute utility function is given by

$$U(x_1, x_2) = 0.9 * [1.309 - 0.309\exp(0.03208x_1)] + 0.1 * [-0.7841 + 0.7841\exp(1.644x_2)]$$

From the formula for the utility exchange:

$$w_1 u_1(x_{k_1}) + w_2 u_2(x_{k_2}) = w_1 u_1(x_{k_1}{}') + w_2 c_2$$

Thus, we obtain the required utility exchange for k=1, 2, 3…... K as follows:

$$u_1(x'_{k1}) = u_1(x_{k1}) + \frac{w_2}{w_1}(u_2(x_{k2}) - c_2).$$

We concluded that $u_1(x'_{k1})$ is influenced by the weight. We followed the steps as we mentioned above and obtained the final results shown in Table 21.

Since the utility function is scaled from 0 to 1, its expected value should be between 0 and 1. Morrice (1999) mentioned that the utility value was only a convention and would not necessarily attain a value between 0 and 1. Hence, we ignored the configurations with utility values smaller than one. We mark these values as N/A in Table 21.

Table 21 Utility Value of Final Results on Different Weights

configuration	w1=0.9	w1=0.8	w1=0.7	w1=0.6	w1=0.5	w1=0.4	w1=0.3	w1=0.2	w1=0.1
1	0.67	0.66	0.66	0.66	0.66	0.65	0.63	0.62	0.56
2	0.68	0.68	0.67	0.67	0.66	0.65	0.63	0.59	0.50
3	0.66	0.66	0.65	0.65	0.66	0.64	0.63	0.62	0.47
4	0.66	0.66	0.65	0.65	0.66	0.64	0.63	0.62	0.47
5	0.68	0.68	0.67	0.67	0.66	0.65	0.63	0.58	0.49
6	0.85	0.83	0.80	0.77	0.73	0.65	0.54	0.31	N/A
7	0.85	0.83	0.80	0.77	0.72	0.65	0.54	0.31	N/A
8	0.88	0.86	0.84	0.81	0.76	0.69	0.57	0.33	N/A
9	0.85	0.71	0.79	0.74	0.67	0.57	0.40	0.06	N/A
10	0.87	0.84	0.80	0.75	0.68	0.58	0.41	0.07	N/A

From Table 21, we can conclude that when waiting time has a weight that is larger than or equal to 0.4, the configuration 8 is best. This optimal configuration states that the interarrival times for new patients and follow up patients to see the physician, nutritionist are each 45minutes respectively, in addition, the interarrival times for follow up patients who see exercise physiologist and the psychologist are 30 minutes. When $w_2 = 0.9$, configuration 1 is the best. This optimal configuration corresponds to interarrival times for new patients as 30 minutes, and for follow up patients who see the physician, nutritionist, exercise physiologist the interarrival times are 15 minutes.

C. RESULTS FOR THE "AIM" CLINIC

C.1 MULTIPLE ATTRIBUTE UTILITY FUNCTION FOR "AIM" CLINIC:

In the single morning "AIM" clinic simulation model, the main goal is to choose an optimal policy for scheduling patients with respect to satisfaction of the goal of the clinic's manager and the clinic's patients. The candidate policies involves varying interarrival times for patients, assignment of differing numbers of patients be to respective assigned to residents of different experience, flexibly assigned examination rooms.

There are four performance measures: the waiting time of patients, the staff utilization, the examination room utilizations and the amount of over time. The ideal result will be low mean waiting time, high mean utilization of staff and examination rooms and low over time. However, tradeoffs are needed between these four attributes in order to determine a better policy. We denote waiting time as X_1, utilization of staff as X_2, utilization of examination room as X_3 and over time as X_4.

The single attribute utility function form is given by:

$$u_i(x_i) = A_i - B_i e^{x_i RT_i},$$

where RT_i is the decision maker's (DM's) assessed risk tolerance and A_i and B_i are scaling constants.

A single attribute utility function for the waiting time is given by (24):

$$u_1(x_1) = 1.425 - 0.4248\exp(0.01729x_1) \quad (24)$$

The range of waiting time is (0, 70) minutes. The midpoint is 45 minutes as the utility value is 0.5.

A single attribute utility function for the utilization of staff is given by (25):

$$u_2(x_2) = 1.784 - 1.784\exp(-0.8222x_2) \qquad (25)$$

The range of utilization is (0,1). The midpoint is 0.4 as the utility value is 0.5.

A single attribute utility function for the utilization of examination room is given by (26):

$$u_3(x_3) = 1.198 - 1.198\exp(-1.801x_3) \qquad (26)$$

The range of utilization is (0, 1). The midpoint is 0.3 as the utility value is 0.5.

A single attribute utility function for the overtime is given by (27):

$$u_4(x_4) = 2.028 - 1.028\exp(0.005661x_4) \qquad (27)$$

The range of waiting time is (0, 120) minutes. The midpoint is 70 minutes as the utility value is 0.5.

Using the four attributes, an additive multiple attribute utility function is given in (28).

$$\mathrm{U}(x_1, x_2) = w_1u_1(x_1) + w_2u_2(x_2) + w_3u_3(x_3) + w_4u_4(x_4) \qquad (28)$$

Let $w_1 = 0.4, w_2 = 0.3, w_3 = 0.2, w_4 = 0.1$, then the multiple attribute utility function is given by:

$$\begin{aligned} \mathrm{U}(x_1, x_2, x_3, x_4) & \\ &= 0.4 * [1.425 - 0.4248\exp(0.01729x_1)] + 0.3 \\ &* [1.784 - 1.784\exp(-0.8222x_2)] + 0.2 \\ &* [1.198 - 1.198\exp(-1.801x_3)] + 0.1 \\ &* [2.028 - 1.028\exp(0.005661x_4)] \end{aligned}$$

C.2 SELECTION OF $\boldsymbol{\delta}^*$ FOR “AIM” CLINIC

C.2.1 UTILITY EXCHANGE

We considered different years of residents’ service time, different types of patients’ service time and show up rate to set up the experimental. We assigned twelve configurations and observe the patients average waiting time, average utilization of staff, average utilization of examination rooms and amount of over time. Twelve configurations and simulation results are shown in Table 16, (Chapter IV).

In this project, we have four attributes and twelve configurations. So K=12. We define x_{k1} is the average waiting time, x_{k2} is the average utilization of staff, x_{k3} is the average utilization of examination rooms, and x_{k4} is the over time. We choose utilization of staff, utilization of examination rooms, over time these three attributes as the standard measures and let $\mathrm{u}(x'_{k2}) = c_2, \mathrm{u}(x'_{k3}) = c_3, \mathrm{u}(x'_{k4}) = c_4$. Then we need to change waiting time x_{k1} to x'_{k1}, k is the alternative (in this project, k=1, 2, 3, 4...12) and the index 1 in x'_{k1} is the first attribute.

We applied Propositions which mentioned in Chapter III to the project: Let the utilization of staff, utilization of examination rooms, and over time be the standard measure. We need to define $c_2, c_{3,} and\ c_{4.}$ from the formulas (25), (26) and (27), we get that: when $X_2 = 0.5$, then $u_2(x_2) = 0.6 = c_2$; when $X_3 = 0.4$, then $u_3(x_3) = 0.6 = c_3$; when $X_4 = 66$, then $u_4(x_4) = 0.53 = c_4$.

Table 22 shows the individual attribute utility function value for x_1, x_2, x_3 and x_4, fixed utility function value for $x_{2,}x_3$ and x_4 and rescaled utility value of x'_1.

Table 22 Utility Value of Each Attribute and Rescaled Utility Value for Waiting Time

Configuration	Individual attribute utility function value for x_1 $u_1(x_1)$	Individual attribute utility function value for x_2 $u_2(x_2)$	Individual attribute utility function value for x_3 $u_3(x_3)$	Individual attribute utility function value for x_4 $u_4(x_4)$	Fixed utility function value for X_2 C_2	Fixed utility function value for X_3 C_3	Fixed utility function value for X_4 C_4	Rescaled utility function value for X_1 $u_1(x_1')$
1	0.64	0.63	0.604511	0.01168	0.6	0.6	0.53	0.530474
2	0.62	0.63	0.645762	0.056824	0.6	0.6	0.53	0.549722
3	0.77	0.69	0.625508	0.277767	0.6	0.6	0.53	0.782549
4	0.77	0.69	0.645762	0.336217	0.6	0.6	0.53	0.809102
5	0.84	0.58	0.548587	0.355263	0.6	0.6	0.53	0.753948
6	0.82	0.57	0.560178	0.447326	0.6	0.6	0.53	0.757986
7	0.90	0.59	0.524769	0.542754	0.6	0.6	0.53	0.862959
8	0.90	0.59	0.524769	0.542754	0.6	0.6	0.53	0.862959
9	0.91	0.47	0.434312	0.326612	0.6	0.6	0.53	0.680249
10	0.91	0.47	0.447943	0.316954	0.6	0.6	0.53	0.678595
11	0.96	0.49	0.434312	0.447326	0.6	0.6	0.53	0.773134
12	0.96	0.49	0.434312	0.447326	0.6	0.6	0.53	0.773134

C.2.2 DETERMINING THE INDIFFERENCE ZONE

The next step is that the decision maker needs to determine $\delta_1{}^*$. We assume the clinic manager believes that the waiting time of 30 minutes and 37 minutes are indifference. After calculation, we get $\delta_1{}^* = 0.09$.

C.2.3 TWO STAGE RANKING AND SELECTION FOR “AIM” CLINIC

In order to make a final comparison between alternative configurations, we determined the number of additional replications for the simulation in Table 24. We used the half widths of the 95% confidence intervals to calculate the variance of each expected utilities, then used these variances to calculate the additional numbers of replications needed. Setting $P^* = 0.95, h = 4.29$, $n_0 = 10$, $K = 12$, $c_2 = 0.7$, $\delta_1{}^* = 0.09$ and then using equation (7) yields the results in Table 23.

Table 23 Calculate the Number of More Replications Needed According Variance

Configuration	half width of $u_1(x_1)$	half width of $u_2(x_2)$	half width of $u_3(x_3)$	half width of $u_4(x_4)$	Rescaled variances of waiting time utility $u_1(x_1)'$	Total Replications (N_k)	More Replications $(N_k - n_0)$
1	0.20	0.03	0.03	0.33	0.1236	281	271
2	0.17	0.05	0.02	0.23	0.0876	199	189
3	0.05	0.03	0.03	0.15	0.0121	27	17
4	0.05	0.04	0.04	0.11	0.0118	27	17
5	0.05	0.03	0.02	0.06	0.0087	20	10
6	0.05	0.02	0.02	0.10	0.0090	20	10
7	0.07	0.06	0.06	0.07	0.0211	48	38
8	0.07	0.06	0.06	0.07	0.0211	48	38
9	0.04	0.06	0.06	0.16	0.0159	36	26
10	0.04	0.06	0.06	0.15	0.0154	35	25
11	0.01	0.06	0.05	0.11	0.0091	21	11
12	0.01	0.06	0.05	0.11	0.0091	21	11

Table 24 Calculated Rescaled Exchanged Utility of Waiting Time on More Replications and Weight $\boldsymbol{w_{k1}}$

Configuration	$u_1(N_k - n_0)$	$u_2(N_k - n_0)$	$u_3(N_k - n_0)$	$u_4(N_k - n_0)$	$u_1{}'(N_k - n_0)$	define the weights w_{k1}
1	0.72	0.61	0.582743792	0.0116798	0.589200701	0.04
2	0.71	0.61	0.62550799	0.0116798	0.597278185	0.05
3	0.79	0.67	0.615104002	0.269921666	0.787865399	0.37
4	0.79	0.67	0.635726279	0.31152061	0.805079353	0.37
5	0.84	0.59	0.548587064	0.353083695	0.760786976	0.51
6	0.82	0.58	0.560178299	0.279549116	0.723486361	0.49
7	0.92	0.59	0.524768819	0.431046779	0.853881277	0.21
8	0.91	0.59	0.524768819	0.376994895	0.828680148	0.21
9	0.91	0.48	0.447943319	0.341666919	0.691240579	0.28
10	0.90	0.48	0.447943319	0.344623687	0.685833689	0.29
11	0.96	0.51	0.447943319	0.424796737	0.789830477	0.48
12	0.96	0.49	0.43431242	0.402774335	0.764163287	0.48

After running additional replications, we obtained the average waiting times, staff utilizations, utilizations of the examination rooms, over time values, and expected utilities for waiting time, staff utilization, examination rooms utilizations and overtime values. Then we performed the utility exchange procedure to calculate the exchanged utility waiting time on these additional replications. After that, we calculated the weighted of two stage sample mean using formulation (9). Finally, we can obtained the weighted sample means of the expected utility values through the use of (10). The final results are shown in Table 25.

Table 25 The Utility Value of Final Results

Configuration	w_{k1}	w_{k2}	$X_{kn_0} - U_1'(n_0)$	$X_k(N_k - n_0) - U_1'(N_k - n_0)$	final results
1	0.04	0.96	0.53	0.59	0.59
2	0.05	0.95	0.55	0.60	0.59
3	0.37	0.63	0.78	0.79	0.79
4	0.37	0.63	0.81	0.81	0.81
5	0.51	0.49	0.75	0.76	0.76
6	0.49	0.51	0.76	0.72	0.74
7	0.21	0.79	0.86	0.85	0.86
8	0.21	0.79	0.86	0.83	0.84
9	0.28	0.72	0.68	0.69	0.69
10	0.29	0.71	0.68	0.69	0.68
11	0.48	0.52	0.77	0.79	0.78
12	0.48	0.52	0.77	0.76	0.77

From Table 25, we see that policy 7 is the best. Policy 7 has interarrival times for patients as 5 minutes, with two examination rooms assigned to third year residents and more patients assigned to third years residents.

D. SENSITIVITY ANALYSIS ON UTILITY FUNCTION WEIGHT FOR THE "AIM" CLINIC

Using these four attributes X_1, X_2, X_3 and X_4, an additive multiple attribute utility function is given by

$$\mathrm{U}(x_1, x_2) = w_1 u_1(x_1) + w_2 u_2(x_2) + w_3 u_3(x_3) + w_4 u_4(x_4)$$

We categorize the weight values as being as high (value of 0.4), medium (value of 0.3) and low (value of 0.2). Because the utility function is additive. $w_4 = 1 - w_1 - w_2 - w_3$. The ten weight configurations are shown in Table 26.

Table 26 Assign Weight on Different Level

	w_1	w_2	w_3	w_4
1	High	Medium	Low	1-High-Medium-Low
2	High	Low	Medium	1-High-Medium-Low
3	High	Low	Low	1-High-Low-Low
4	Medium	High	Low	1-High-Medium-Low
5	Medium	Low	High	1-High-Medium-Low
6	Medium	Low	Low	1-Medium-Low-Low
7	Medium	Medium	Medium	1- Medium- Medium- Medium
8	Low	High	Medium	1-High-Medium-Low
9	Low	Medium	High	1-High-Medium-Low
10	Low	Medium	Medium	1- Medium -Medium-Low

Table 27 shows these configurations more explicitly.

Table 27 Assign the Level of Weight to the Number

	w_1	w_2	w_3	w_4
1	0.4	0.3	0.2	0.1
2	0.4	0.2	0.3	0.1
3	0.4	0.2	0.2	0.2
4	0.3	0.4	0.2	0.1
5	0.3	0.2	0.4	0.1
6	0.3	0.2	0.2	0.3
7	0.3	0.3	0.3	0.1
8	0.2	0.4	0.3	0.1
9	0.2	0.3	0.4	0.1
10	0.2	0.3	0.3	0.2

The first step in the process is utility exchange:

$$w_1 u_1\left(x_{k_1}\right) + w_2 u_2\left(x_{k_2}\right) + w_3 u_3\left(x_{k_3}\right) + w_4 u_4\left(x_{k_4}\right) = w_1 u_1\left(x_{k_1}{}'\right) + w_2 c_2 + w_3 c_3 + w_4 c_4$$

Thus, we obtain the required utility exchange for k=1, 2, 3, 4 as follows:

$$u_1(x'_{k1}) = u_1(x_{k1}) + \frac{w_2}{w_1}(u_2(x_{k2}) - c_2) + \frac{w_3}{w_1}(u_3(x_{k3}) - c_3) + \frac{w_4}{w_1}(u_4(x_{k4}) - c_4).$$

The second step of the process involves adjusting the variance due to adjustment of utility values. This is required for the calculation of the number of replications needed. The rescaled variance for the first attribute (x_{k1}) is as follows:

$$var(u_1(x'_{k1})) = var\left[\frac{U(X_k) - w_2c_2 - w_3c_3 - w_4c_4}{w_1}\right] = \frac{var\big(U(X_k)\big)}{{w_1}^2}$$

The third step of the process involves is setting the following values: ${\delta_1}^* = 0.09$ $P^* = 0.95$, $h = 4.29$, $n_0 = 10$, $K = 10$, $c_2 = 0.6, c_3 = 0.6$, $c_3 = 0.53,$ to calculate the number of replications needed. After running additional replications, the utility exchange is done again. Then the use two-stage ranking and selection steps are used to calculate the final results. Table 28 shows the expected utility values for each configuration by weight set.

Table 28 Final Results of the Utility Value with Weighted Changed

Configuration \ Weight	1	2	3	4	5	6	7	8	9	10
1	0.59	0.58	0.46	0.55	0.53	0.20	0.54	0.47	0.46	0.19
2	0.59	0.60	0.47	0.56	0.58	0.20	0.59	0.53	0.53	0.24
3	0.79	0.77	0.70	0.81	0.77	0.59	0.78	0.80	0.78	0.67
4	0.81	0.80	0.71	0.83	0.81	0.65	0.82	0.87	0.85	0.74
5	0.76	0.74	0.71	0.69	0.69	0.55	0.69	0.60	0.53	0.50
6	0.74	0.74	0.69	0.69	0.68	0.58	0.68	0.60	0.58	0.51
7	0.86	0.84	0.84	0.83	0.79	0.78	0.81	0.75	0.71	0.70
8	0.84	0.82	0.81	0.81	0.76	0.75	0.78	0.75	0.72	0.70
9	0.69	0.68	0.67	0.76	0.54	0.53	0.57	0.34	0.32	0.29
10	0.68	0.68	0.67	0.57	0.55	0.53	0.56	0.33	0.32	0.30
11	0.78	0.77	0.78	0.70	0.66	0.69	0.68	0.50	0.46	0.49
12	0.77	0.75	0.76	0.68	0.63	0.66	0.66	0.47	0.44	0.44

From the Table 28, we conclude that when the weight associated with waiting time is set to a high value, configuration 7 is the best result. The main goal of this clinic is to reduce the long waiting time problem. So the configuration 7 represents a good solution. In configuration 7, the interarrival times for patients is 5 minutes, two examination rooms assigned to third year residents and more patients are assigned to third years residents. When weight associated with the waiting time is set to a low value, configuration 4 is the best of those tested. In configuration 4, the interarrival time for patients is 4 minutes, the examination rooms are flexible to use for all the residents and more patients are assigned to third year's residents. When the weight associated with the waiting time is at a medium value, the result various among the configurations. We need to consider the weight of the other attributes.

We also consider that when the weight associated with the utilization of staff is set to a high value, the configuration 4 is the best. When the weight associated with the utilization of examination rooms is set to a high value, the configuration 4 is also the best. In configuration 4, the interarrival time for patients is 4 minutes, the examination rooms are flexible to use for all the residents and more patients are assigned to third year's residents. When the weight associated with the utilization of staff and examination rooms is at a low value, the result various among the configurations. We need to consider the weight of the other attributes. Over time is not an important attribute as other, so the weight of associated with the over time is always set to a low value or lower.

VI. CONCLUSIONS AND FUTURE RESEARCH

A.CONCLUSIONS

Clinic managers are under a great deal of pressure to reduce costs and improve quality of service provided. Clinic managers hope to find an optimal scheduling method to improve staff utilization, and also decrease the patients' waiting time in order to satisfy the patients.

In this dissertation, we performed projects for "Healthy for Life" Clinic and "AIM" Clinic in Louisville, KY.

The "Healthy for Life" clinic is a multiple resource clinic for treating overweight children. The main problem in this clinic was the high no show rate. The patients make appointments with the clinic, but do not show up. Our work involved analysis and optimization of the clinic's operation through data collection, simulation modeling and analysis. The steps were as follows:

1. Collected one year raw data from the clinic. Analyzed data and identified opportunities for improvement.
2. Constructed a long period simulation model for this multiple resources clinic. Categorized patients and staff through no show rates and service times.
3. Changed the interarrival time of different types of patients as the configurations. Used multiple attribute utility theory with statistical

ranking and selection procedure to select the best configuration from these configurations with an indifferent zone approach.

4. The clinic managers can decide which level of weight is suitable for the attributes and choose a best scheduling method based on the highest expected utility value.

The animation of the simulation model provided the clinic manager with a good understanding of patient flow and the problems of the clinic. The results gave the clinic manager suggestions to increase the clinic's efficiency and satisfy the patients. Also, we used multiple attribute utility theory with statistical ranking and selection to select the best configuration in health care is one of the contributions in this dissertation. The other contribution is building a long period simulation model in a multiple resource clinic.

The "AIM" clinic is a teaching clinic, which belongs to the University of Louisville. The main problem for the clinic manager is long waiting times. Our work involved the improvement and optimization of the clinic operations by intelligent scheduling of patients and flexible assignment of facilities. The steps were as follows:

1. Collected raw data from the clinic. Analyzed data and identify opportunities for improvement.
2. Built simulation model and assign medical resources including examination rooms and residents in different years. Changed patients' interarrival time and reassign medical resources as configurations. Concluded waiting time, utilization of staff, utilization of examination rooms and over time as the attribute to observe and analyze.
3. Used multiple attribute utility theory with statistical ranking and selection

to select the best configuration from a set of configurations.

4. Provide the decision makers the optimal scheduling policy based on different attitudes to each attribute.

The new strategy optimizes the different years of resident scheduling and examination room assignment. Provide clinic manager suggestions to satisfy the patients and increase the clinic's efficiency.

B.FUTURE RESEARCH

There are several directions available for further research in this area. These areas are discussed below.

For the Simulation Models for the Healthy for Life clinic, there are three areas we like to propose. :

First, in addition to the patient categories employed for the current model, patients could also be categorized by insurance type. Examples of these types of insurance include Passport, United Health Care, and Humana. Patients with Passport Insurance pay nothing for their medical care, while patients with other types of insurance need to co-pay. Some insurance types cover only two visits to the clinic; hence, insurance type is a significant factor influencing the no show rate. Therefore one approach that might be tried would be to investigate overbooking of patients in which the amount of overbooking would be by insurance type. This type of investigation would constitute a contribution to the literature since it has not been studied before.

Second, the model could also be extended by categorizing patients by age. The range of patients' age is from 2 to 19 years old. Patient no show rate varies by age; in particular, younger patients' no show rate is higher than older patients. Hence an investigation in which the amount of overbooking varies by patient age could also be made with the simulation model.

Third, in the current model, patients are randomly assigned to staff at each visit. A different approach would involve using a fixed sequence to assign patients. For example, patients could be assigned to see the psychologist in their second visit; the exercise physiologist in their third visit and so on. Then, we could compare the results of these two methods (random assignment vs. fixed sequence assignment) and choose an optimal one to suggest to the clinic manager.

For the simulation model for the AIM Clinic, the following topics can be further studied.

First, the current Tuesday morning model can be extended to a five-weekday model that considers variabilities in service times among residents, arrival rates for different days of the week, and special operational rules on a certain day during the week. Such a weekly model allows clinic manager to forecast dynamics on patient flow, staff utilization and quality of service. Second, the simulation results in this dissertation show that the utilization of nurses is low. We can modify the shift of nurse or reduce the number of nurse to increase efficiency. Third, the main objective of the current model is to reduce patients' waiting time and overtime for staff. An alternative model can look into economic objectives such as reducing operating costs and increasing revenue. For example, increasing patients' arrival rate will have positive effects on increasing revenue but negative effects on reducing patients' waiting time. Thus, a balanced approach from using multi-attribute utility function can be explored.

Finally, we like to point several future directions on the general methodology for developing simulation model for outpatient clinic operations. First, multiplicative and multilinear multi-attribute utility function can be studied instead of the additive multi-attribute utility function used in the dissertation. Second, the sensitivity analysis conducted in the dissertation mainly varies the weights assigned to different terms in the additive multi-attribute utility function. We like to extend the sensitivity analysis by varying different types of utility function, validate the use of these functions and study varying effects of these utility functions. Finally, we like to integrate the design of experiment into our simulation model. One such technique called “controlled sequential factorial design” (CSFD), by Shen and Wan (2009), is particularly interesting to us. It uses traditional factorial design to control the Type I error and focuses on each factor with heterogeneous variance. We like to use CSFD in our simulation model because it requires a moderate number of factors.

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CURRICULUM VITAE

NAME: Bo Sun

ADDRESS: Department of Industrial Engineering
J.B. Speed School of Engineering
University of Louisville
Louisville, Kentucky 40292

DOB: Beijing, China P.R. – January 28th, 1985

EDUCATION
& TRAINING: B.S., Mechanical Engineering
Beijing Institute of Graphic Communication, China
2003 - 2007

M.S., Industrial Engineering
University of Louisville
2009 - 20011

HYPAA TRANING
2010 - 2015

Ph.D., Industrial Engineering
University of Louisville
2011 -2016

AWARDS: Graduate Fellowship
2011 – 2013

WORKING EXPERIENCE:

Liaoning Urban and Rural Construction and Planning Design Institute, China
2007-2009

Teaching Assistant
Industrial Engineering Department, University of Louisville
2010 – 2011, 2013 – 2015

PROFESSIONAL SKILLS:

Analysis Software: Lingo (mathematical programming), MiniTab (statistics analysis), Arena (simulation), Excel, ArcGis, etc

Common Software: Microsoft Word, PowerPoint, Project, Visio, Access, etc

Programming Languages: Python, JavaScript, SAS, Django, HTML, Visual Basic, UML, SQL, LATEX, etc

OS Platforms: Microsoft Windows, AIX, Solaris, Linux

Database Platforms: SQL, SQLite, Oracle, MySql, Microsoft SQL Server

Languages: Fluent in Chinese and English

Professional Societies and Memberships:

Institute for Operations Research and the Management Sciences

Institute of Industrial Engineers President of INFORMS Student Chapter, University of Louisville