3-26-2015

A Process Improvement Study on a Military System of Clinics to Manage Patient Demand and Resource Utilization Using Discrete-Event Simulation, Sensitivity Analysis, and Cost-Benefit Analysis

Michael Q. Corpuz

A PROCESS IMPROVEMENT STUDY ON A MILITARY SYSTEM OF CLINICS TO MANAGE PATIENT DEMAND AND RESOURCE UTILIZATION USING DISCRETE-EVENT SIMULATION, SENSITIVITY ANALYSIS, AND COST-BENEFIT ANALYSIS

THESIS
MARCH 2015

Michael Q. Corpuz, Captain, USAF

AFIT-ENV-MS-15-M-199

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

AFIT-ENV-MS-15-M-199

A PROCESS IMPROVEMENT STUDY ON A MILITARY SYSTEM OF CLINICS TO MANAGE PATIENT DEMAND AND RESOURCE UTILIZATION USING DISCRETE-EVENT SIMULATION, SENSITIVITY ANALYSIS, AND COST-BENEFIT ANALYSIS

THESIS

Presented to the Faculty

Department of Systems Engineering and Management

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the

Degree of Master of Science in Systems Engineering

Michael Q. Corpuz, BS

Captain, USAF

March 2015

DISTRIBUTION STATEMENT A.
APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.

AFIT-ENV-MS-15-M-199

A PROCESS IMPROVEMENT STUDY ON A MILITARY SYSTEM OF CLINICS TO MANAGE PATIENT DEMAND AND RESOURCE UTILIZATION USING DISCRETE-EVENT SIMULATION, SENSITIVITY ANALYSIS, AND COST-BENEFIT ANALYSIS

Michael Q. Corpuz, BS
Captain, USAF

Committee Membership:

Maj C. F. Rusnock, PhD
Chair

Lt Col K. F. Oyama, PhD
Member

Maj V. V. Valencia, PhD
Member

AFIT-ENV-MS-15-M-199

Abstract

Inefficiencies in the healthcare system are a growing concern. Long wait-times are a concern at military clinics because they take servicemembers away from performing their duties. Managing wait-times is particularly challenging due to frequent relocations of servicemembers and variable patient demands that are less likely to be experienced by civilian clinics. Military clinics must be capable of meeting increasing demand when servicemembers require a Deployment Health Assessment; they also need to be capable of handling an instantaneous surge of walk-ins when a medical incident occurs in the local area. They must be able to meet these demands in a fiscally austere environment.

Existing research primarily focuses on stand-alone clinics, whereas this research takes a novel approach of examining a system of clinics, in which some resources are shared. This research evaluates the impacts of variable staffing levels on total wait-time for the system of clinics at baseline demand and when demand increases, using discrete-event simulation, sensitivity analysis, and cost-benefit analysis. This research finds misallocated resources; the wait-time of alternative systems are sensitive to deployment and medical incident demands; and hiring an optometrist while removing an occupational medicine doctor provides the highest savings in baseline, deployment, and medical incident demand environments.

Acknowledgments

I would like to express my sincere gratitude to my thesis advisor, Major Christina F. Rusnock, for her tremendous support and guidance from the initial conception of this thesis to the final revision. Her valuable insight and expertise helped guided me throughout the process. I would also like to thank my committee members, Lieutenant Colonel Kyle F. Oyama, and Major Vhance V. Valencia, in extending their support and guidance to me as well. Their highly appreciated insights and expertise in their specialized areas provided a different perspective on ideas. I would like to thank Colonel Anthony P. Tvaryanas, from the 711th Human Performance Wing at Wright-Patterson Air Force Base, OH, for sponsoring this research as well as Lieutenant Colonel John W. Woltz and to all of the medical staff of the 88th Aerospace Medicine Squadron located at Area B of Wright-Patterson Air Force Base, Building 675. They provided me crucial insights into the normal operations of the system of clinics as well as their assistance in the data collection effort. Finally, I would like to thank my family and friends who supported me throughout this endeavor.

Michael Q. Corpuz

Table of Contents

List of Figures

List of Tables

Page

A PROCESS IMPROVEMENT STUDY ON A MILITARY SYSTEM OF CLINICS TO MANAGE PATIENT DEMAND AND RESOURCE UTILIZATION USING DISCRETE-EVENT SIMULATION, SENSITIVITY ANALYSIS, AND COST-BENEFIT ANALYSIS

I. Introduction

Chapter Overview

This chapter provides an overview of the thesis topic. It provides a background of the healthcare system as well as states the issues within the system of clinics. It also presents the research question, defines the focus of the research to a system of clinics at Wright-Patterson Air Force Base, and establishes three investigative questions. It then declares the method to answer the investigative questions using discrete-event simulation, sensitivity analysis, and cost-benefit analysis, addresses the limitations of the study, and illustrates the assumptions made. Finally, it comments on the potential implications of the study to the military healthcare system and describes the subsequent chapters of this thesis.

Background

Inefficiencies in the healthcare system are receiving nationwide public attention through the media. The Associated Press (2012) reports that healthcare systems waste billions of dollars. Even President Barack Obama (2014) has concerns over the inefficiencies in the healthcare system. With variable demands of healthcare services, inefficiencies in the system have to be eliminated in order to sustain healthcare services over the next decade. For the military, long wait-times are of particular concern for active duty personnel since the long wait-times take these personnel away from their official duties.

Due to the uncertainty of future crises, military service members can expect short-notice deployments. Ideally, military readiness needs to be at 100% at all times. If a crisis occurs requiring the military to deploy, then military healthcare clinics must be capable of medically clearing personnel for deployment in a timely fashion. Not only do military clinics need to meet the demand of deployments, they also need to be capable of handling an instantaneous surge of walk-ins when a mild medical incident occurs on the military installation.

Unfortunately, the military currently faces a fiscally austere environment. The military's budget is being reduced by billions of dollars over the next two years and personnel end strength reduced by tens of thousands (Simeone, 2014). As defense budgets become constricted, senior leaders of the military healthcare system need to find ways to improve current healthcare processes in order to maintain its level of performance as patient demand changes. The 711th Human Performance Wing from the Air Force Research Laboratory is sponsoring this research to acquire solutions in improving the military healthcare system at Wright-Patterson Air Force Base.

Research Question

How can the total wait-time patients experience in the military system of clinics be cost-effectively reduced during baseline demand and when patient demand increases as the clinics within the system of clinics compete for scarce resources? A system of clinics is defined as a group of clinics co-located in one building where certain medical resources are shared. A military environment is defined as situations where active duty military personnel are deployed as a normal aspect of daily working conditions.

Investigative Questions

There are three investigative questions that must be addressed in order to answer the research question:

1.) How can staffing levels be adjusted to improve the patient's overall wait-time in the system of clinics? The patient's overall wait-time in the system of clinics is the dependent variable. Staffing levels are the independent variables that could potentially affect the overall wait-time of the patient.

Hypothesis: One or more staffing levels will have statistically lower wait-times than the baseline staffing level of the system.

2.) Which staffing level solution is the most robust as patient demand increases? Robustness is defined as the ability to maintain the level of performance of the system of clinics' as patient demand changes.

Hypothesis: One or more staffing levels will have statistically lower wait-times than other staffing levels when exposed to a surge in patient demand.

3.) Which system improvement solution has the lowest cost to implement? Cost to implement includes two variables. First, monthly salary being paid to the staff member, based on type, is accounted for. Second, the cost equivalent of wait-time reduced or wait-time increased is calculated. A reduction in wait-time is a desired effect of an alternative system implementation so such an implementation has a positive dollar equivalent. Conversely, an increase in wait-time is considered an adverse effect of an alternative system implementation so this implementation has a negative dollar equivalent.

Hypothesis: One or more staffing levels will have a statistically lower cost to implement than other staffing level alternatives.

Research Focus

The focus of this study is to model the behavior of a current process in a system of clinics located at Wright-Patterson Air Force Base (WPAFB) and to identify alternative processes that will improve the overall performance of the system of clinics. The study will focus primarily on patient processing through the system of clinics. Five clinics are investigated utilizing shared resources all co-located in a single building. These five clinics are the Flight Medicine Clinic, the Occupational Medicine Clinic, the Hearing Conservation Clinic, the Audiology Clinic, and the Optometry Clinic.

Methodology Overview

The overarching research goal is to identify feasible solutions to the research question. To accomplish this, this research uses a five-step process. The first step is to assess the operational behavior of the system of clinics. To achieve this objective, a data collection effort must be conducted. The span of this effort spanned one month in August 2014.

Data is collected for each of the studied clinics by having the medical staff collect time data of the patient as they process through the different stations of various clinics. The second step is to build a baseline discrete-event simulation model. The model is based on the data collected. It is verified with the medical staff to acknowledge that the model is an adequate representation of the system of clinics. It is also validated using data collected from the system of clinics. The third step is to perform experiments using the model. The experiments aid in identifying where the efforts should be focused in order to affect the desired outcome. The experiments evaluate alternative systems that can affect the patient wait-time. The fourth step is to perform a sensitivity analysis on the feasible solutions. Sensitivity analysis is used to evaluate the robustness of a feasible solution when subjected to changing patient demand. The fifth step is to perform a cost-benefit analysis on the feasible solutions. Cost-benefit analysis is used to evaluate the costs to implement on alternative systems when subjected to changing patient demand. After the five steps are met, the results stemming from these tasks are used to formulate a solution to the overall research question in the form of a recommendation which is presented in Chapter V of this thesis.

Methodology Details

To address each investigative question, this study utilizes discrete-event simulation (DES), sensitivity analysis, and cost-benefit analysis. First, DES is used to answer the first investigative question. A conceptual model of the system of clinics is created in order to build a DES. A baseline model is then created in ARENA 14.0 using data collected by the staff of the system of clinics. It is then verified and validated against the actual system. The baseline model is revised until there is statistical evidence that the model is a close representation of the real system. Once the baseline model is statistically similar to the real system, alternative scenarios of the system are simulated in order to minimize the patient wait-time.

A sensitivity analysis is conducted next to evaluate the robustness of the solutions. The analysis explores the effect of patient demand changes in terms of a 200% demand increase due to increased military personnel deployments (deployment demand). A 200% increase in demand equates to 54 additional patients being seen throughout the day. A second sensitivity analysis is conducted in terms of a surge in patient demand from a mild medical incident occurring on the military installation (medical incident demand). The same level of increase, 200% or 54 additional patients, as "walk-ins" to the clinic for the first three hours of operation is studied for this analysis. Finally, a cost-benefit analysis is conducted to evaluate the cost and benefit trade-offs of implementing the alternative solutions. The analysis looks at three different environments. The first environment looks at the system of clinics when demand is at baseline level. The second environment looks at the system of clinics when demand increases due to an increase in military deployments. The third environment looks at the system of clinics when there is a medical incident demand for the first three hours of operation.

Limitations and Assumptions

Due to resource constraints, limitations are imposed upon this study. One limitation is the shortened data collection period. Time data of the patient arriving to the system of clinics, as well as the service rate data of each of the stations, are not readily available. Because data are not currently available, a data collection process is vital to answer the research question. The data collection period is limited to one month, August 2014, because the time needed to process more data is unavailable for this research. If the data collection period is over the entire year, then all the months of the year can be characterized leading to a more complete study. Since only a month's worth of data is collected, it is assumed that the other months have the same characteristics as the month of August. Another limitation to the study is the sample of the study. Due to limited funding, the researchers were not authorized a Temporary Duty (TDY) assignment to travel to other clinics at other military installations. To overcome this limitation, this study focuses on a system of clinics located at WPAFB; system of clinics at other military installations may behave differently, but since it is currently not feasible to characterize their behavior, it is assumed that they have the same characteristics as the system of clinics at WPAFB.

With the inherent complexity of a system of clinics, this study makes several assumptions. These assumptions are necessary in order to create a simplified model that can be analyzed towards the understanding of the general behavior of the system of clinics. First, the analysis assumes that only patients with either an appointment or an acute medical condition that is urgent, but not serious enough to go to the emergency room (ER) at a hospital, will enter the clinic. Another assumption is that the patient will not pre-maturely leave upon entering the clinic. This is known as balking. These resource constraints are the reason why limitations are imposed upon this research.

Implications

The results of this study will aid the WPAFB system of clinics to implement economical alternatives, identify bottlenecks in the system, reduce patient wait-time and increase the utilization of its medical personnel. If this study is replicated throughout other clinics on military installations across the United States, then it may ultimately improve the military healthcare system. It will assist the United States government to utilize taxpayer' funding more effectively.

Preview

This chapter has described the research topic and provided: pertinent information on the current problem, the objective of this study, the approach to produce a solution and the potential impacts of the results to this study. The following chapter of this thesis will follow a traditional format for Chapter II, Literature Review. The remaining chapters of this thesis follow a scholarly format with one conference paper article (Chapter III) and one peer-reviewed journal article (Chapter IV) followed by Chapter V, Conclusions and Recommendations Chapter.

II. Literature Review

Chapter Overview

The purpose of this chapter is to review the literature that fosters an understanding of the topics discussed in subsequent thesis chapters. This chapter explains a generalized overview of the healthcare industry, simulation in healthcare, sensitivity analysis in healthcare, cost-benefit analysis in healthcare, and the research gap that this thesis addresses. In summary, this chapter establishes the intellectual foundation of the subject areas necessary to follow the discussion throughout the thesis chapters.

The Healthcare Industry Overview

The healthcare system is one of the most important systems in modern societies. Without the healthcare system in place, members of society would find it a challenge to maintain their health when they have the misfortune to experience sickness or disease. The expansion of the healthcare system has become ubiquitous in American society; it is "one of the most complex business models in American industry given the uniqueness of the marketplace in which it operates" (Kudyba & Temple, 2010). More and more people are relying on the healthcare system to help them find relief for their bodily ailments, and healthcare providers are increasingly being forced to carry the financial responsibility of these people as reimbursements for healthcare services rendered are dwindling (Kudyba & Temple, 2010). As a result, the healthcare industry is not profiting due to its influx of patients. There are more demands for healthcare services than there are solutions in place to meet those demands.

Simulation in Healthcare

Simulation is widely used in the field of healthcare to discover potential solutions to the issue of system inefficiencies (Giachetti, 2008; Kim, et al., 2013; Cote, 1999; Huschka, Narr, Denton, & Thompson, 2008; Connelly & Bair, 2004; Swisher, Jacobson, Jun, & Balci, 2001; Jacobson, Hall, & Swisher, 2006). For example, Giachetti (2008) looks at using simulation to combat long wait-times patients face for scheduled appointments. Long wait-times due to overbooking cause patient dissatisfaction. Patient dissatisfaction increases patient no-shows the next time an appointment is booked and, in turn, cause a reduced output of clinical care; patient no-shows are missed opportunities for other patients to see the doctor. Giachetti found that removing multiple appointment types can reduce patient wait-time. Giachetti further suggests that minimizing patient wait-time would increase patient satisfaction and decrease no-shows.

DES is a useful tool in improving and establishing individual clinics. Kim, et al. (2013) found that adding an additional psychiatrist and extending daily hours of an operation by two hours can effectively reduce the service time by 14.6 minutes, on average, in order to improve access to mental health services at a mental health clinic. Cote (1999) used DES to determine the capacity of examination rooms as healthcare demands increase, finding that it is the physician, not the number of examination rooms that influences the quality of care. Despite the physician influencing the quality of care, if physicians are consistently over utilized, then the quality of care diminishes. This is due to reduced time spent by the physician with each patient in order to meet patient demand (Cote, 1999). When physicians are being rushed, they also increase the risk of making errors which result in patient needs not being met. Physicians typically belong to independent clinics where they do not share resources with other clinics. Huschka, et al. (2008) used DES to establish an Outpatient Procedure Center (OPC). An increase of patient demand resulted in long wait-times at the current OPC; this is what drives the creation of another OPC. Using DES, Huschka, et al. (2008) suggested clinic improvements to better utilize resources, increase patient satisfaction, and more efficiently use healthcare providers.

DES is also useful for studying healthcare facilities larger than a clinic. Connelly and Bair (2004) analyzed the average treatment times patients receive when checking in at an emergency department at a hospital. Swisher, et al. (2001) reallocated some of the provider's tasks to a centralized information center. This centralized information center services a network of clinics across the United States and its primary purpose is to take administrative, clerical, and scheduling tasks away from the provider so the provider can focus more on patient care. Unlike a system of clinics, a network of clinics are independent clinics not co-located in a single building that share administrative tasks through a centralized function. Because the scope of the Swisher, et al. study focuses on the clinical environment, only one clinic is studied; the operation of the network as a whole has yet to be studied (Swisher, Jacobson, Jun, & Balci, 2001). The current literature on simulation in healthcare presents a research opportunity to expand these studies beyond the single-clinic level to a system of clinics.

Sensitivity Analysis in Healthcare

In any system, there are certain properties that are desired by the decision maker. One such property that would be of interest to a military healthcare decision maker is the robustness of the system. There are various definitions of robustness (de Weck, Ross, & Rhodes, 2012; Ryan, Jacques, & Colombi, 2013). For this specific research, robustness is defined as "the measure of how effectively a system can maintain a given set of capabilities in response to external changes after it has been fielded (Ryan, Jacques, & Colombi, 2013)." In this case, the system would be the system of clinics and the measure of capability is the patient wait-time. The external changes are the increase in patient demand due to an increase in military personnel deployments or a mild medical incident happening on the military installation. Mild medical incidents can range from flu/cold incidents that do not require hospital care to food poisoning at a local restaurant that is mild enough to not warrant an emergency room visit. Simulated experiments of alternative systems are used to evaluate alternate systems being fielded.

To test the robustness of a system, sensitivity analysis is performed. There are several studies showing how sensitivity analysis is used to test the robustness of a healthcare system (Aktas, Ulengin, & Sahin, 2007; Hashimoto & Bell, 1996; Dorr, Horn, & Smout, 2005; Doubilet, Begg, Weinstein, Braun, & McNeil, 1985; Angus, Kelley, Schmitz, White, & Popovich, 2000). One such study is performed by Aktas, Ulengin, and Sahin (2007). Aktas, et al. performed a sensitivity analysis on a case study involving a private hospital in Turkey. The tomography section in the radiology department had a problem with the process time because lengthy time spent on the tomography machines have high operating costs; additional tomography machines also have a high cost to purchase. Also, the longer a doctor spends time on the tomography machines, the more dissatisfied the patients will be due to patients having to wait in long queues. In order to affect change in this system to reduce patient wait-times, a sensitivity analysis was conducted to identify the variables that are the most sensitive to change in affecting the process time. Aktas, et al. found that the process time is very sensitive to the process type; if different process types are offered on different days, then it can solve this issue with the exception of one type. They found that the whole abdomen process time is exceptionally long by itself. Additionally, Aktas, et al. (2007) found that the process time is not sensitive to technicians; improving the technicians will have no effect, if any, on the process time.

While Aktas, et al. (2007) used sensitivity analysis to look at reducing the process time, Dorr, Horn, and Smout (2005) took a different approach and used sensitivity analysis to evaluate the robustness of cost estimates ranging from hospitalization costs to registered nurse cost per hour. Dorr, et al. (2005) found that hospitalization costs are most sensitive to perturbations from nursing home residents.

Hashimoto and Bell (1996) conducted a sensitivity analysis on clinic staffing to evaluate the patient time in the clinic, session length, and idle times of the doctor for a single clinic. Hashimoto and Bell (1996) showed that patient total time in the clinic is sensitive to number of doctors in the clinic; increasing the doctor staffing level decreased the average patient time in system by 18.3 minutes.

Cost-Benefit Analysis in Healthcare

Comparable to cost-value analysis and cost-effectiveness analysis, cost-benefit analysis studies have also been performed in the healthcare field (Brown, Brown, Sharma, & Landy, 2003; Nord, 1993). The overarching structure of these analyses stems from costs incurred in relation to gains realized. Brown, Brown, Sharma, and Landy (2003) define cost-benefit analysis as a measure of "both the costs and the outcomes of alternative interventions in terms of dollars (resources)."

Several studies analyze the relationship of the costs to gains in other healthcare systems (Nord, 1993; Eichler, Kong, Gerth, Mavros, & Jonsson, 2004; van den Bemt, et al., 2002). Nord (1993) compared the costs of different medical interventions to the effect treatments have on patients. This resulted in giving medical decision makers the ability to prioritize healthcare programs in terms of cost per one Saved Young Life Equivalent (SAVE) (Nord, 1993). Eichler, Kong, Gerth, Mavros, and Jonsson (2004) took a different approach in prioritizing healthcare resources by analyzing the cost to gain ratio in terms of an acceptable threshold to allocate scarce resources. Van den Bemt, Postma, van Roon, Chow, Fijn, and Brouwers (2002) looked into reducing prescription errors by hospital pharmacy staff by conducting a cost-benefit analysis. In order to save money, money must first be spent. Van den Bemt et al. (2002) demonstrated that when the hospital invested more time to properly prescribe medication to patients, a net cost of €285 to a benefit of €9867 is attributed to a reduction of prescribing errors.

Research Gap

Despite the growing proliferation of simulation studies in healthcare, little has been done in using DES to model a system of clinics in the private practice and no study was found in military healthcare. Existing research primarily focuses on stand-alone clinics, whereas this research takes a novel approach of examining a system of clinics, in which some resources are shared. Evaluating the individual clinics in a system of clinics does not reveal how the performance of one clinic affects the performance of other clinics. This research evaluates the impacts of various staffing levels on patient wait-time for the system of clinics at Wright-Patterson Air Force Base (WPAFB), Ohio. This research uses DES to identify the system of clinic's bottlenecks, assess the system of clinic's overall wait-time and throughput, and investigates the effects of altering the staffing levels. Because resources are shared in the existing system of clinics, this study hypothesizes that rebalancing the staffing levels of individual clinics can reduce the average patient wait-time of the system of clinics as a whole.

Despite the various studies conducted on sensitivity and cost-benefit analysis, no work has been found to study the effects of increasing patient demand have on a system of clinics. In particular, no study is found that analyzes this effect due to (1) increased military deployments or (2) a surge of patient "walk-ins" due to a mild medical incident in the local area. This research takes a novel approach of using both sensitivity analysis and cost-benefit analysis to evaluate the simulated effects of an increase in patient demand on a system of clinics where some resources are shared. This research evaluates the robustness of different staffing level combinations when the system is subjected to deployment demand as well as a medical incident demand. This study hypothesizes that scenarios with increased patient demand will be most negatively impacted (longer patient wait-times) for alternative scenario(s) that decrease the number of flight medicine doctors.

This research also evaluates the savings estimates in implementing alternative scenarios: where the staffing levels vary in the system of clinics while maintaining a zero-sum manning level when the system of clinics is subjected to deployment and medical incident demands. This study hypothesizes that one or more staffing level will have a statistically lower cost to implement than the remaining staffing levels.

Summary

This chapter provided an overview of the healthcare industry, simulation in healthcare, sensitivity analysis in healthcare, and cost-benefit analysis in healthcare. This chapter also identified the gap in the literature that this research addresses. DES has become a well-established tool for evaluating clinic processes. Sensitivity analysis is a common tool to evaluate the robustness of a system where a system maintains its level of performance in a changing environment is highly desired. Cost-benefit analysis is common in businesses, but healthcare decision makers are starting to utilize this technique in aiding their decisions. The next two chapters address the research question through a conference paper that answers the first investigative question and a journal article that answers the second and third investigative questions.

III. Industrial and Systems Engineering Research Conference Paper

Reducing Wait-Time of a System of Clinics Using Discrete-Event Simulation

Michael Q. Corpuz, Christina F. Rusnock, Vhance V. Valencia, and Kyle F. Oyama

Department of Systems Engineering and Management

Air Force Institute of Technology

Wright-Patterson AFB, OH 45433 USA

Abstract

Inefficiencies in the U.S. healthcare system are a growing concern. Long wait-times are of particular concern for active duty military personnel, as long waits at military clinics unnecessarily take active duty personnel away from performing their military duties. Managing wait-times can be particularly challenging not only due to variable patient demands, but also due to variability in the number of providers caused by frequent relocations of military personnel. Existing research primarily focuses on stand-alone clinics, whereas this research takes the novel approach of examining a system of clinics, in which some resources are shared. This research evaluates the impacts of variable staffing levels on patient wait-time for a system of clinics at Wright-Patterson AFB, using Discrete-Event Simulation (DES) to identify bottlenecks within the system of clinics, assess the overall wait-time and throughput of the system of clinics, and investigate the effects of altering the staffing levels. This study finds that resources are misallocated

within the system of clinics, with too few resources devoted to the optometry clinic and too many resources devoted to the other clinics. To effectively manage resources and patient wait-times, this study recommends a rebalancing of military manning allocations.

Keywords

discrete event simulation; military healthcare; system of clinics; healthcare staffing levels

1. Introduction

Inefficiencies in the U.S. healthcare system are receiving nationwide public attention. It is reported that healthcare systems waste billions of dollars [1]; even President Barack Obama has concerns over the inefficiencies in the healthcare system [2]. With variable demand for healthcare services, inefficiencies in the system, particularly inefficiencies in military clinics, must be eliminated in order to sustain healthcare services in the coming decades. Long wait-times for healthcare are of particular concern for active duty personnel because the long wait-times take these personnel away from performing their official duties. To address this ongoing issue, this research uses discrete-event simulation (DES) to investigate the effects of changing staffing levels. Of particular interest is to understand the effect of such changes on process wait-times while maintaining the overall manning level of the entire system. This study hypothesizes that adjusting staffing levels of different clinics within the system of clinics will reduce the wait-times experienced by patients at various processes within the system, while maintaining an overall zero-sum manning level. This study evaluates a system of clinics located on Wright-Patterson Air Force Base, Ohio. This system of clinics consists of five separate clinics: Flight Medicine Clinic, Occupational Medicine Clinic, Hearing Conservation Clinic, Audiology, and Optometry. This group of clinics is considered a system of clinics because they are co-located in a single building sharing staffing and room resources.

2. Background

DES is a type of simulation that mimics the operation of a real-world system at discrete points over time [3]. Given its capability, DES is an effective tool in studying healthcare systems because it is particularly suited to analyzing systems with queues, variable processing times, and emergent system behavior. DES can be used to analyze numerous healthcare system problems: reducing patient wait-times; managing utilization rates; identifying bottlenecks; and evaluating alternative system effectiveness.

2.1 Literature Review

Simulation is widely used in the field of healthcare to discover potential solutions to the issue of system inefficiencies [4-10]. For example, Giachetti [4] looks at using simulation to combat long wait-times patients face for scheduled appointments. Long wait-times due to overbooking cause patient dissatisfaction. Patient dissatisfaction increases patient no-shows the next time an appointment is booked and, in turn, cause a reduced output of clinical care; patient no-shows are missed opportunities for other patients to see the doctor. Giachetti found that removing multiple appointment types can reduce patient wait-time. Giachetti further suggests that minimizing patient wait-time would increase patient satisfaction and decrease no-shows.

DES is a useful tool in improving and establishing individual clinics. Kim, et al. [5] found that adding an additional psychiatrist and extending daily hours of an operation by two hours can effectively reduce the service time by 14.6 minutes, on average, in order to improve access to mental health services at a mental health clinic. Cote [6] used DES to determine the capacity of examination rooms as healthcare demands increase, finding that it is the physician, not the number of examination rooms that influences the quality of care. Despite the physician influencing the quality of care, if physicians are consistently over utilized, then the quality of care diminishes. This is due to reduced time spent by the physician with each patient in order to meet patient demand [6]. When physicians are being rushed, they also increase the risk of making errors which result in patient needs not being met. Physicians typically belong to independent clinics where they do not share resources with other clinics. Huschka, et al. [7] used DES to establish an Outpatient Procedure Center (OPC). An increase of patient demand resulted in long wait-times at the current OPC; this is what drives the creation of another OPC. Using DES, Huschka, et al. [7] suggested clinic improvements to better utilize resources, increase patient satisfaction, and more efficiently use healthcare providers.

DES is also useful for studying healthcare facilities larger than a clinic. Connelly and Bair [8] analyzed the average treatment times patients receive when checking in at an emergency department at a hospital. Swisher, et al. [9] reallocated some of the provider’s tasks to a centralized information center. This centralized information center services a network of clinics across the United States and its primary purpose is to take administrative, clerical, and scheduling tasks away from the provider so the provider can focus more on patient care. Unlike a system of clinics, a network of clinics are independent clinics not co-located in a single building that share administrative tasks through a centralized function. Because the scope of the Swisher, et al. study focuses on the clinical environment, only one clinic is studied; the operation of the network as a whole has yet to be studied [9]. The current literature on simulation in healthcare presents a research opportunity to expand these studies beyond the single-clinic level to a system of clinics.

2.2 Research Gap

Despite the growing proliferation of simulation studies in healthcare, little has been done in using DES to model a system of clinics in the private practice and no study was found in military healthcare. Existing research primarily focuses on stand-alone clinics, whereas this research takes a novel approach of examining a system of clinics, in which some resources are shared. Evaluating the individual clinics in a system of clinics does not reveal how the performance of one clinic affects the performance of other clinics. This research evaluates the impacts of various staffing levels on patient wait-time for the system of clinics at Wright-Patterson Air Force Base (WPAFB), Ohio. This research uses DES to identify the system of clinic's bottlenecks, assess the system of clinic's overall wait-time and throughput, and investigates the effects of altering the staffing levels. Because resources are shared in the existing system of clinics, this study hypothesizes that rebalancing the staffing levels of individual clinics can reduce the average patient wait-time of the system of clinics as a whole.

3. Baseline Discrete-Event Simulation Model

To evaluate the hypothesis, this study begins with the development of a baseline DES model. The first step in developing a baseline model is to formulate a conceptual model of the system in order to ensure that system tasks, resources, and work flows are accurately captured. Next, the required input data are collected and fitted to probability distributions. Analysis of the input data is combined with the conceptual model of the system into a task network that forms the baseline simulation model. The baseline simulation model features the task flows, arrival rates, process probability distributions, system resources, and probabilistic events. Finally, time in system (TIS) data from the baseline simulation model are validated against the TIS data from the real world system. This method is further described in the subsections that follow.

3.1 Conceptual Model

The first step in creating a usable baseline simulation model is to understand the system of clinics being studied. In order to understand the system of clinics, a conceptual model of daily operations is developed. To develop this framework, staff members of the system of clinics provided a general description of daily operations, graphically depicted in Figure 1. A typical daily operation starts when patients check in at the front desk upon arrival. Patients are given paperwork to fill out, if needed. Then, patients visit other stations where a nurse or technician perform various tasks on them (e.g., check vitals/preparation, laboratory work, electrocardiogram (ECG), X-ray, visit other clinics, and additional visits to nurses or technicians) if they are required prior to visiting the doctor. After these preparatory tasks, patients wait until the doctor is available. When patients are waiting, the current queuing strategy of the system of clinics at WPAFB is a priority queue: Patients with a scheduled appointment have priority to see the doctor over walk-in patients. After visiting with the doctor, a follow-up appointment is scheduled if an additional visit is required. Patients then exit the system of clinics.

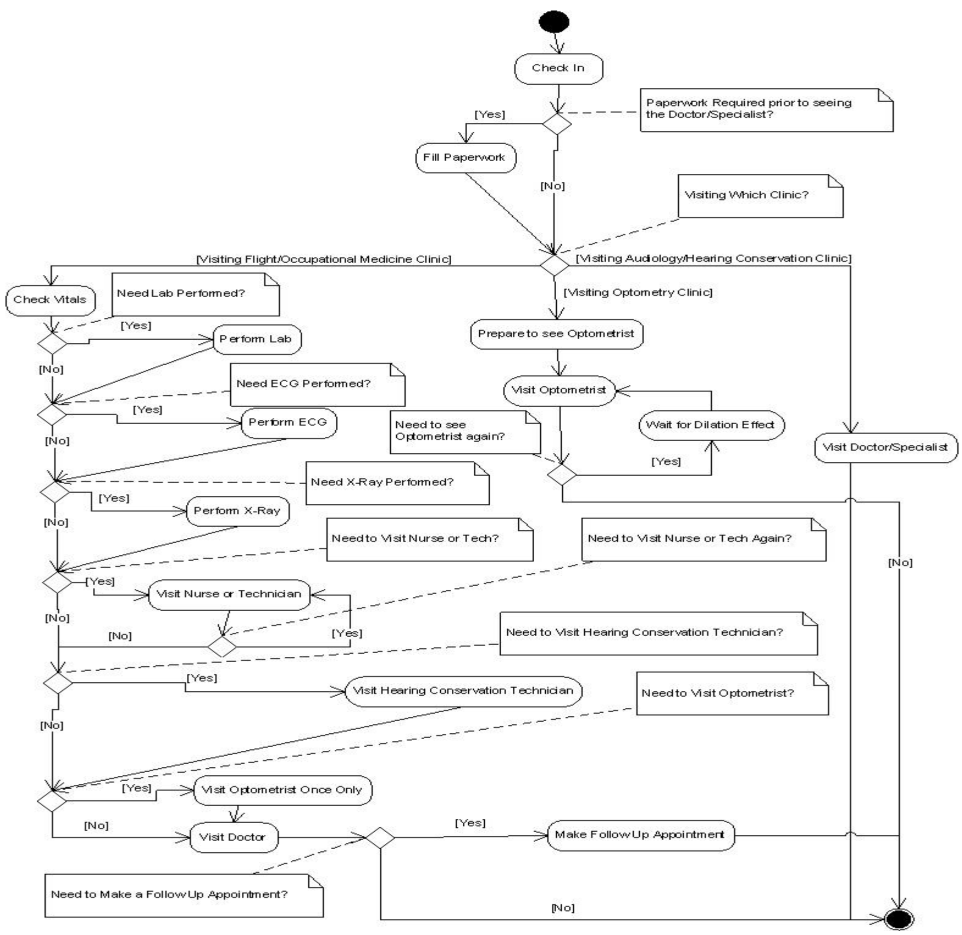


Figure 1: System of Clinics Task Network

3.2 Data Collection

For each activity described in the conceptual model, timing and decision data are required in order to build the simulation model. These data were collected by the clinic medical staff by first performing a trial data collection effort during the month of July 2014 to become familiar with the data collection process. The official data collection effort was conducted in August 2014. The start and end times for each process were collected using a clipboard with an integrated clock and a data collection sheet. The data collection sheet records the following general information about the patient's visit: clinic type (audiology, flight medicine clinic, hearing conservation clinic, occupational medicine clinic, or optometry), patient type (military, civilian, or dependent), status (scheduled appointment or walk-in), date, appointment time (if applicable), and appointment type. The data collection sheet also records the start and end time of each process the patient undergoes which includes: patient check-in, filling out paperwork, hearing conservation visit, checking vitals/preparing patient, nurse or technician visit, laboratory tasks, X-ray examination, ECG, provider visit, additional provider visits, and scheduling a follow-up appointment. Annotating the start and end times on the sheet have negligible impact on the performance of the medical staff's duties. A few of the processes were performed infrequently, thus failing to provide an adequate number of observations during the August 2014 collection period. Thus, the data collection effort was extended to include the trial data from July 2014 and an additional collection from September 2014 for these infrequent tasks: laboratory tasks, X-ray examination, ECG, and visits to additional nurses or technicians. It is reasonable to include some data from the trial period in July 2014 for these processes because the times for these tasks were accurately collected.

3.3 Input Analysis

Upon completion of the data collection effort, input data modeling was performed on the patient arrivals and process times in order to form probability distributions. These probability distributions were tested for independence, homogeneity, and goodness-of-fit. All of the final distributions in the baseline model either successfully passed these tests or were replaced by an empirical distribution directly representing the data. Table 1 summarizes the frequency for each process and possible patient path flows within the system of clinics; this information is used to establish the decision logic for the simulation model. Table 2 summarizes the frequency counts for the clinic visited, patient type, and status of the patient; these frequencies are used to establish the decision logic for the simulation model. Table 3 summarizes the likelihood of an optometry patient seeing the optometrist twice in a single visit; this is unique from other processes in that the patient visits the optometrist again whereas the patient visits other processes only once. Table 3 is used to establish the decision logic for the simulation model. Table 4 summarizes the probability distribution for each of the datasets being fitted; these distributions are used in the simulation model to determine inter-arrival times for patients entering the system, as well as process times for each process visited by a patient as they go through the system.

Table 1: Flight/Occupational Medicine Clinic Process Frequency Counts

Assign Flight/Occupational Medicine Paperwork

	Paperwork Count	Total Count	Paperwork	No Paperwork
Flight Medicine	98	104	94%	6%
Occupational Medicine	95	179	53%	47%

Need to Visit Hearing Conservation? (For Flight/Occupationa Medicine Patients)

	Obs Count	Total Count	TRUE	FALSE
Flight Medicine	27	104	26%	74%
Occupational Medicine	35	179	20%	80%

Need to Visit Nurse or Tech 2nd Time? (For Flight/Occupationa Medicine Patients)

	Obs Count	Total Count	TRUE	FALSE
Flight Medicine	1	104	1%	99%
Occupational Medicine	3	179	2%	98%

Need to Visit Nurse or Tech 3rd Time? (For Flight/Occupationa Medicine Patients)

	Obs Count	Total Count	TRUE	FALSE
Flight Medicine	1	1	100%	0%
Occupational Medicine	1	3	33%	67%

Need to See Optometrist? (For Flight/Occupationa Medicine Patients)

	Obs Count	Total Count	TRUE	FALSE
See Optometrist	7	283	2%	98%

Need Follow Up Appointment? (For Flight/Occupationa Medicine Patients)

	Obs Count	Total Count	TRUE	FALSE
Schedule Follow Up	17	283	6%	94%

Need to Visit Lab or ECG or X Ray?

	Count	TRUE
Lab	18	6%
ECG	2	1%
X Ray	13	5%
No Visit Needed	250	88%

Also Need ECG or X Ray? (After Lab Assigned)

	Count	TRUE
ECG	2	11%
X Ray	1	6%
No Visit Needed	15	83%

Also Need X Ray? (After ECG Assigned)

	Count	TRUE
X Ray	1	50%
No Visit Needed	1	50%

Table 2: Patient Attribute Frequency Counts

Clinic Visited	Count	Percent
Audiology	68	13%
Flight Medicine	104	20%
Hearing Conservation	37	7%
Occupational Medicine	179	34%
Optometry	133	26%

Patient Type	Count	Percent
Civilian Employee	177	34%
Dependent	88	17%
Military	252	49%

Status	Count	Percent
Scheduled Appointment	474	91%
Walk In	45	9%

Table 3: Optometry Clinic Frequency Count

See Optometrist Twice?

	Obs Count	Total Count	TRUE	FALSE
See Optometrist Twice	18	133	14%	86%

Table 4: Probability Distribution Summary Table of Inter-Arrival/Process Times (in seconds)

Create/Process Node	Distribution	Parameters	K-S Test p-value	Sample Mean	Sample Std. Dev.
Arrive System of Clinics	Weibull	k = 0.778 Lambda = 844	> 0.15	994	1550
Check In	Empirical	N/A	N/A	20	26
Prepare to See Optometrist with Nurse or Tech	Erlang	ExpMean = 292 k (int) = 2	0.0606	599	488
Visit Optometrist	Erlang	ExpMean = 790 k (int) = 2	0.0604	1700	1100
Dilation Effect Delay	Weibull	k = 0.616 Lambda = 1320	> 0.15	2020	2680
Visit Audiologist	Weibull	k = 1.34 Lambda = 1220	0.131	1870	833
Visit Hearing Conservation Technician (Hearing Conservation Clinic Only)	Exponential	Mean = 532	> 0.15	1080	495
Visit Hearing Conservation Technician (Non Hearing Conservation Clinics)	Beta	Alpha1 = 1.79 Alpha2 = 5.2	0.136	861	328
Fill Flight Medicine Paperwork	Weibull	k = 1.71 Lambda = 311	> 0.15	289	155
Fill Occupational Medicine Paperwork	Exponential	Mean = 454	> 0.15	463	472
Check Vitals	Gamma	Alpha = 575 Beta = 1.34	0.113	822	722
Perform Lab	Erlang	ExpMean = 261 k (int) = 2	0.119	574	321
Perform ECG	Exponential	Mean = 384	> 0.15	577	408
Perform X Ray	Beta	Alpha1 = 0.926 Alpha2 = 2.28	> 0.15	817	492
2nd Session with Flight Medicine Nurse or Tech	N/A	Constant = 377	N/A	N/A	N/A
2nd Session with Occupational Medicine Nurse or Tech	Exponential	Mean = 68.8	> 0.15	548	90.6
3rd Session with Flight Medicine Nurse or Tech	N/A	Constant = 634	N/A	N/A	N/A
3rd Session with Occupational Medicine Nurse or Tech	N/A	Constant = 818	N/A	N/A	N/A
See Flight Medicine Physician	Weibull	k = 1.19 Lambda = 1170	> 0.15	1260	917
See Occupational Medicine Physician	Weibull	k = 1.49 Lambda = 801	> 0.15	984	480
Make Follow Up Appointment	Weibull	k = 0.595 Lambda = 130	> 0.15	171	188

3.4 Arena Model

The input data described above are combined with the process flows to form a task network. Figure 1 in Section 3.1 provides a task network which is a visual representation of the conceptual model. The conceptual model is translated into a task network by representing decision logic as decision nodes, processes as task nodes, and the order of these tasks and decisions as directional arcs. When a patient goes through the system, the individual will process through the various nodes established in the task network and will follow the decision logic throughout the model. For example, all patients go through the check-in node, followed by decision logic to determine (1) if the patient needs to fill out paperwork and (2) which clinic the patient will visit: Audiology/Hearing Conservation Clinics, Optometry Clinic, or Flight/Occupational Medicine Clinics.

If the clinic to be visited is Audiology or Hearing Conservation, the task flow is simple. The patient will go to the respective node of Visit Doctor/Specialist to process through a visit with the audiologist or hearing conservation technician. Once completed, the patient exits the system.

If the clinic to be visited is Optometry, then the optometry nurse or technician prepares the patient to see the optometrist. The patient then visits the optometrist. Decision logic is used to determine if the patient needs to see the optometrist again. If the patient needs to see the optometrist again, it is because their eyes need to be dilated for examination. The patient waits for the dilation drug to take effect before visiting the optometrist a second time; the patient waiting for the dilation drug to take effect is counted as value-added time and not attributed to wait-time because this is a necessary process. Once completed, the patient exits the system.

If the clinic to be visited is Flight Medicine or Occupational Medicine, the nurse or technician of their respective clinic checks the vitals of the patient. A series of decision nodes is created to determine if the patient needs to perform various tasks. If the patient needs to perform a laboratory task, ECG, X-ray, see a nurse or technician numerous times, visit hearing conservation technician, and/or visit the optometrist once, then the patient will go to the needed process nodes in any order based upon availability. If the process node is using up all the resources to perform the task, then the patient proceeds to the next task and returns to the previous node when it becomes available. When completed, the patient will visit the doctor of the respective clinic. A decision node determines if the patient makes a follow up appointment. Once completed, the patient exits the system.

In addition to capturing the process flows, decision logic, and timing data, the clinic staff also annotated the type and quantity of resources used. Table 5 summarizes the resources used in the system of clinics. There are unique characteristics associated with a few of the resources. These characteristics are listed here:

- There is a front desk station at the entrance of the building that can only be manned by one administration technician.
- The Hearing Conservation technician is being treated as a provider for this clinic.
- The Flight Medicine and Occupational Medicine clinics share 6 examination rooms.
- The laboratory and ECG rooms are operated by the nurse or technicians of either the Flight Medicine or Occupational Medicine clinic, depending on which clinic the patient belongs to.
- The ECG room is co-located with one of the optometry examination rooms.
- The X-Ray room is manned by an X-Ray technician.

Once the resources were incorporated into the model, it was then validated.

Table 5: System of Clinic Resources

	Rooms	Providers	Nurse/Tech
Front Desk Station	1	Not Applicable	1
Audiology	3	2	0
Flight Medicine	shared 6 with occupational medicine	4	shared 8 with Lab and ECG
Hearing Conservation	1	1	Not Applicable
Occupational Medicine	shared 6 with flight medicine	4	shared 4 with Lab and ECG
Optometry	1 dedicated to optometry with 1 shared with ECG	1	1
Lab	2	Not Applicable	performed by respective clinic's nurse/tech
ECG	1 shared with optometry	Not Applicable	performed by respective clinic's nurse/tech
X Ray	1	Not Applicable	1

3.5 Validation

Validation is an important step in creating a baseline simulation model. It provides statistical evidence that the model adequately reflects the real world system. For satisfactory validation, a confidence interval range that is within 10% above and below the mean is desired. For this system, the average time in system is 54.13 minutes, thus a half-width of 5.4 min or less is required. A 99% confidence interval for this system produced a half-width of 3.16 minutes, thus a 99% confidence interval level was deemed sufficient for use in validation. A tradeoff in using a 99% confidence interval level is that, although it provides a high level of confidence, it does so at the risk of an unacceptably large half-width. Because the 99% confidence interval level has a half-width that is considerably less than the desired ±10% of the mean, the 99% confidence interval's half-width is deemed to be acceptably narrow.

Upon establishing a confidence interval level, real world data is compared to simulation data using a 99% confidence interval. In order to determine the number of replications needed to run the model, an approximation equation is used [11]:

$$n \cong n_0 \frac{h_0^2}{h^2} \tag{1}$$

Where n is the number of replications needed, n_0 is the number of replications in the initial production run, h_0 is the half-width of the initial production run, and h is the desired half-width. An initial run on the model is conducted with n_0=10 as an arbitrary initial number of replications. It produces an initial half-width of h_0 = 6.03 min. Based on the desired half-width of $h = 3.16$ min (taken from the real world half-width of 3.16 minutes), an estimate on the number of replications needed, *n*, is evaluated; first iteration: $n=10(6.03^2/3.16^2) = 36.49$. This process is repeated three more times to determine a reasonable number of replications; second iteration: $37(3.31^2/3.16^2) = 40.68$; third iteration: $41(3.21^2/3.16^2) = 42.39$; fourth iteration: $43(3.09^2/3.16^2) = 41.20$. It is determined that at least 41.20, rounded up (to be conservative) to 42 replications, is required to achieve the desired half-width. The confidence intervals of the real world data and simulation data reveal that there is no statistical difference between the model and the real world system, see Figure 2. This is demonstrated by the overlap of both confidence intervals, thus validating the baseline model. Note that the average time in system of the simulation is 49.29 minutes. This indicates that the simulation is, on average, 4.84 minutes faster than reality. To account for this difference, it is hypothesized that the exclusion of transit time in the model is what is causing a slightly faster time in system. This is of negligible concern for the purpose of this study as the patient wait-time is the focus of this investigation, not the total time in system, and transit time is not expected to impact wait-time.

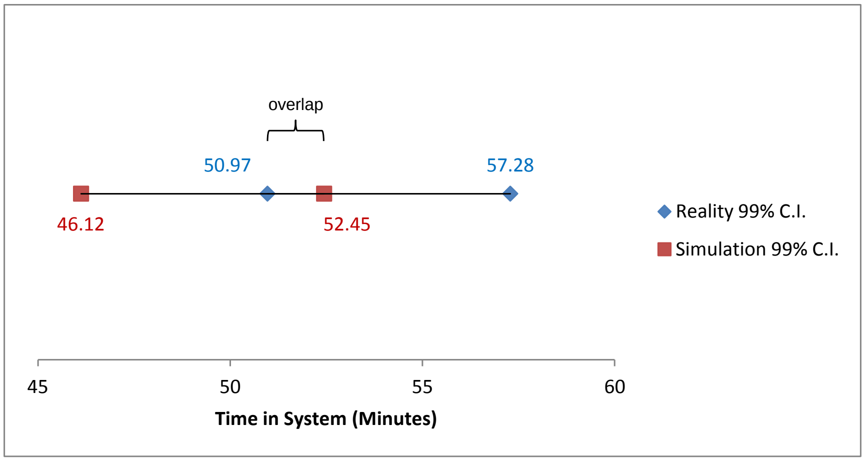


Figure 2: Real-World versus Simulation TIS with a 99% Confidence Interval

3.6 Average Wait Time Analysis of Individual Processes

After the baseline model is validated, the average wait-time associated with each individual process is analyzed in order to identify potential bottlenecks in the system. Potential bottlenecks are processes that have a significant average wait-time. In this case, all processes had an average wait-time that was less than 2 minutes except “Visit Optometrist”. The “Visit Optometry” process has an average wait-time of 18.17 minutes and is clearly the bottleneck in the system. Figure 3 further shows that the Optometrist is the highest utilized resource in the system; it is currently utilized at 50.9%. In this case, utilization rate is equal to the time spent with patient divided by time available. The utilization rates in Figure 3 only include data from patient interactions and thus do not include information about additional tasks performed by the clinic staff that do not involve the patient. It is hypothesized that adding an optometrist to the staff will greatly reduce the average wait-time of that process. However, military units often struggle to gain additional staffing positions. Instead, this study proposes recoding one of the currently under-utilized positions to change it into an optometrist position. This provides a zero-sum manning level to the system of clinics that essentially removes a staff member from one of the clinics and adds an additional optometrist to the optometry clinic. This research assumes that this under-representation of optometrists is local to this clinic and does not indicate a shortage of optometrists in the U.S. military medical service. Thus, the additional optometrist comes from an optometry clinic from a different military installation (presumably one that has too many optometrists). Potential shortages to particular medical staffing types is outside the scope of this research, but is worthy of further investigation.

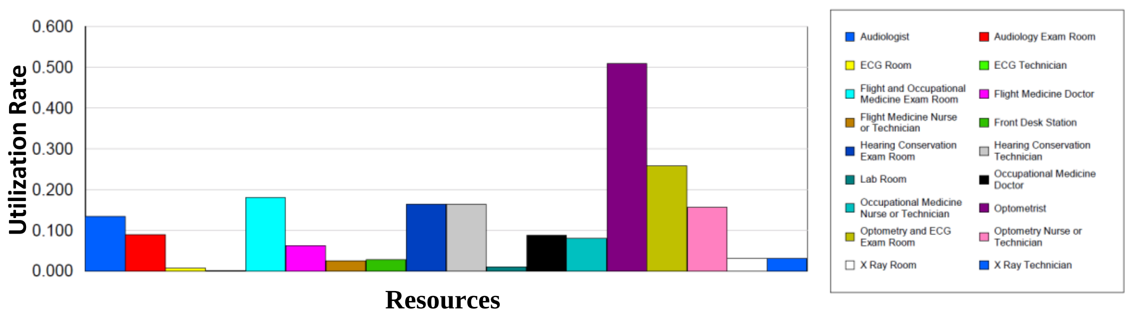


Figure 3: Baseline Scenario Resource Utilization Rates

4. Alternative Systems

To implement this zero-sum manning level recoding, the validated baseline simulation model is modified to incorporate varying staffing levels from each of the clinics in order to determine which position recoding will minimize the average wait-time in the system of clinics. The staffing levels serve as the independent variables and the patient wait-time serves as the dependent variable for this experiment. The experimental design is described in greater detail below.

4.1 Experimental Design/Methodology

Table 6 summarizes the simulation experiments that are conducted. In the table, “BS” represents the baseline scenario and “AS” represents alternative scenarios. There are five distinct alternative scenarios. Because the staffing positions are being recoded to bring in an additional optometrist, the optometrist value is increased by one optometrist to two optometrists in all alternative scenarios (highlighted in green). While the optometrist is increased by one, a different staff type must be reduced by one to maintain a zero-sum manning level. The hearing conservation technician, optometry nurse or technician and the x-ray technician cannot be reduced because all staff types must be manned by at least one person. There are five staff types that can potentially be reduced (highlighted in red). A reduction of a staff member from each feasible staff type constitutes an alternative scenario:

- AS1 reduces the audiologist by one and incrementing the optometrist by one while holding all else constant;
- AS2 reduces the flight medicine doctor by one and incrementing the optometrist by one while holding all else constant;
- AS3 reduces the flight medicine nurse or technician by one and incrementing the optometrist by one while holding all else constant;
- AS4 reduces the occupational medicine doctor by one and incrementing the optometrist by one while holding all else constant;
- and AS5 reduces the occupational medicine nurse or technician by one and incrementing the optometrist by one while holding all else constant.

Each alternative scenario is a separate model, and each model is run individually, using the pre-determined sample size of 42 replications.

Table 6: Experimental Design

STAFF TYPE	BS	AS1	AS2	AS3	AS4	AS5
Audiologist	2	1	2	2	2	2
Flight Medicine Doctor	4	4	3	4	4	4
Flight Medicine Nurse or Technician	8	8	8	7	8	8
Hearing Conservation Technician	1	1	1	1	1	1
Occupational Medicine Doctor	4	4	4	4	3	4
Occupational Medicine Nurse or Technician	4	4	4	4	4	3
Optometrist	1	2	2	2	2	2
Optometry Nurse or Technician	1	1	1	1	1	1
X Ray Technician	1	1	1	1	1	1

5. Analysis and Results

The output data from the 5 alternative scenarios are presented in Table 7 and Table 8. Table 7 shows the average wait-time, along with a 95% confidence level half-width, of the individual processes the patients go through in the system of clinics. For example, when a patient visits the optometrist, they have to wait 18.17 minutes, on average, before seeing the optometrist. Table 8 shows the average total wait-time, along with a 95% confidence level half-width, of the patients when looked at from the system of clinics perspective. For example, in the baseline scenario, patients wait 7.49 minutes, on average, when they process through the entire system. Figure 4 is a statistical analysis (two-sample t-test) that tests if the mean of the baseline scenario is significantly different from the mean of each of the alternative scenarios. If the value of zero is included in the range, then this indicates that the particular alternative scenario being analyzed has a statistically similar mean to the baseline scenario. Figure 4 shows that the mean of all alternative scenarios are statistically significant from the baseline scenario with a 95% level of confidence. Further investigation shows that reducing the audiologist staffing by one (AS1) would increase the average wait-time for the audiologist visit to 4.3 minutes, compared to .3 minutes in the baseline scenario (see "Visit Audiologist," Table 7). AS2, AS3, AS4, and AS5 show little impact on the reduction of their respective staff type to the average wait-time of the respective processes. AS2 and AS4 would be recommended solutions in reducing inefficiencies in the system of clinics since the cost savings by reducing these staff types from the payroll is significantly higher than a nurse or technician. Further analysis of AS2 indicates that reducing the flight medicine doctor by one has little impact on its utilization rate from the baseline; the utilization rate rose from 6.2% to 8.8%, see Figure 5. Similarly, further analysis of AS4 indicates that reducing the occupational medicine doctor by one has little impact on its utilization rate from the baseline; the utilization rate rose from 8.7% to 11.4%, see Figure 6.

Table 7: Average Wait-Time of the Individual Processes for All Scenarios

Process Node with Queues-Average Wait-Time in Minutes (Half-Width)	BS	AS1	AS2	AS3	AS4	AS5
2nd Session with Flight Medicine Nurse or Tech	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
2nd Session with Occupational Medicine Nurse or Tech	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
3rd Session with Occupational Medicine Nurse or Tech	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Check In	0.12 (0.14)	0.14 (0.15)	0.13 (0.15)	0.13 (0.15)	0.13 (0.15)	0.13 (0.15)
Check Vitals_Flight Medicine	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Check Vitals_Occupational Medicine	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Make Follow Up Appointment	0.17 (0.34)	0.18 (0.34)	0.18 (0.34)	0.18 (0.34)	0.18 (0.34)	0.18 (0.34)
Perform ECG_Flight Medicine	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Perform ECG_Occupational Medicine	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Perform Lab_Flight Medicine	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Perform Lab_Occupational Medicine	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Perform X Ray	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Prepare to See Optometrist with Nurse or Tech	1.2 (0.62)	1.32 (0.56)	1.33 (0.56)	1.33 (0.56)	1.37 (0.55)	1.34 (0.56)
See Flight Medicine Physician	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
See Occupational Medicine Physician	0 (0)	0 (0)	0 (0)	0 (0)	0.03 (0.04)	0 (0)
Visit Audiologist	0.33 (0.34)	4.3 (2.24)	0.29 (0.3)	0.29 (0.3)	0.29 (0.3)	0.29 (0.3)
Visit Hearing Conservation Technician (Hearing Conservation Clinic Only)	1.46 (1.01)	1.23 (0.72)	1.24 (0.73)	1.24 (0.73)	1.39 (0.77)	1.58 (0.96)
Visit Hearing Conservation Technician(Non Hearing Conservation Clinics)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Visit Optometrist	18.17 (7.52)	1.77 (0.99)	1.58 (0.99)	1.58 (0.99)	1.83 (1.06)	1.57 (0.99)

Table 8: Average Total Wait-Time for All Scenarios

	BS	AS1	AS2	AS3	AS4	AS5
System of Clinics-Average Total Wait Time in Minutes (Half-Width)	7.49 (3.3)	2.29 (0.71)	1.4 (0.53)	1.4 (0.53)	1.51 (0.55)	1.41 (0.54)

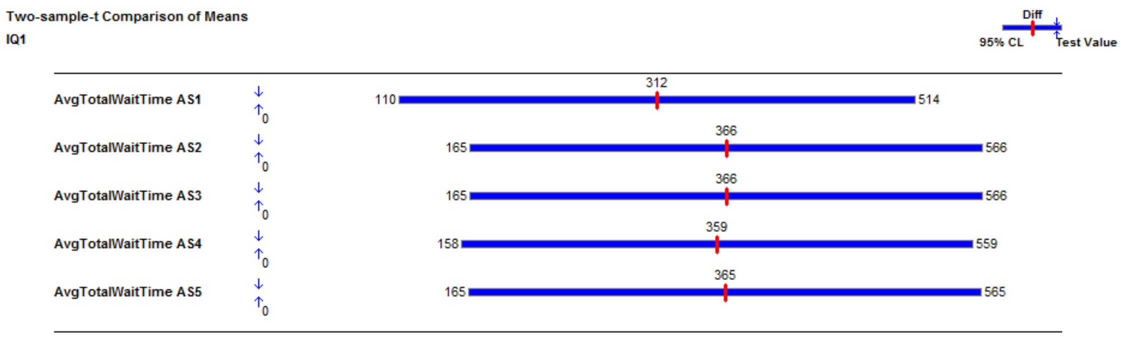


Figure 4: Two-Sample t-Test Comparison of the Difference between Baseline System and Each Alternative System

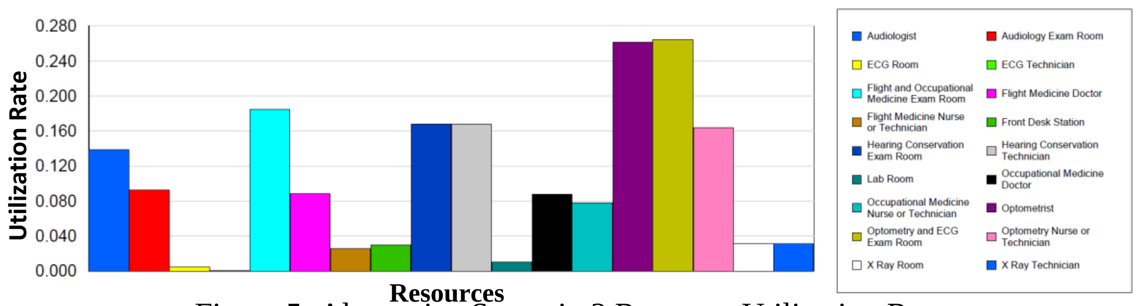


Figure 5: Alternative Scenario 2 Resource Utilization Rates

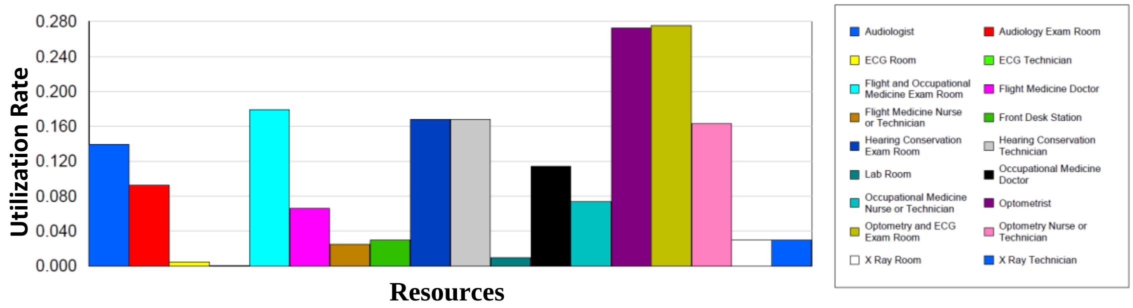


Figure 6: Alternative Scenario 4 Resource Utilization Rates

6. Conclusion

The results of the simulation experiments indicate that adding an additional optometrist can reduce the average wait-time of the optometry clinic and the total wait-time for the system of clinics. Adding one more optometrist can reduce the wait-time patients visiting the optometry clinic in a system of clinics by as much as 16.6 minutes, on average. In a military setting, that is 16.6 minutes of time that the patients could be using to perform official military duties.

Due to difficulties in increasing military unit manpower requirements, this study investigated alternatives that achieved zero-sum manning for the system of clinics. Simulation of five staffing level changes reveals that there are four options that equally reduce total average wait-time in the system with insignificant impacts to the individual process average wait-times. These options are reducing a flight medicine doctor, flight medicine nurse/technician, occupational medicine doctor, or occupational medicine nurse/technician. Reducing a flight medicine doctor or an occupational medicine doctor would be the most effective in reducing cost since these staffing types cost the most to be kept on the payroll.

Future work includes developing other alternative scenarios that can reduce the average wait-time. For example, reducing the average wait-time could be achieved by increasing the number of examination rooms available, by alternating the process flow, by changing the current queuing strategy of a priority queue to a first come first served queue, or by changing the appointment scheduling process. Additional future work includes adding or removing more staff, performing the same analysis on other military installations, and doing an Air Force-wide assessment to determine if optometry has a career field shortage.

Acknowledgements

This work was supported in part by the 88th Aerospace Medicine Squadron, Wright-Patterson AFB, OH. The views expressed in this paper are those of the authors and do not reflect the official policy or position of the United States Air Force, Department of Defense, or the United States Government.

References

1. "Report: Health care system wastes $750B a year," The Associated Press, on the Internet at http://www.cbsnews.com/news/report-health-care-system-wastes-750b-a-year/ (visited *Apr 5, 2014*).

2. Obama, B., 21 May 2014, "Statement by the President on Veterans Health Care," The White House, on the Internet at http://www.whitehouse.gov/the-press-office/2014/05/21/statement-president-veterans-health-care (visited *May 25, 2014*).

3. Banks, J., Carson II, J.S., Nelson, B.L., & Nicol, D.M., 2010, Discrete-Event System Simulation, 5th Edition, Prentice Hall, New Jersey.

4. Giachetti, R.E., 2008, “A Simulation Study of Interventions to Reduce Appointment Lead-Time and Patient No-Show Rate,” *Winter Simulation Conference*, 1463-1468.

5. Kim, B., Elstein, Y., Shiner, B., Konrad, R., Pomerantz, A. S., & Watts, B.V., 2013, “Use of discrete event simulation to improve a mental health clinic,” *General Hospital Psychiatry*, 35(2013), 668-670.

6. Cote, M. J., 1999, “Patient flow and resource utilization in an outpatient clinic,” *Socio-Economic Planning Sciences,* 33(3), 231-245.

7. Huschka, T, R,, Narr, B.J., Denton, B.T., Thompson, A. C., 2008, “Using Simulation in the Implementation of an Outpatient Procedure Center,” *Winter Simulation Conference,* 1547-1552.

8. Connelly, L. G., & Bair, A. E., 2004, “Discrete Event Simulation of Emergency Department Activity: A Platform for System-level Operations Research,” *Academic Emergency Medicine*, 11(11), 1177-1185.

9. Swisher, J. R., Jacobson, S. H., Jun, J. B., & Balci, O., 2001, “Modeling and Analyzing a Physician Clinic Environment Using Discrete-Event (Visual) Simulation,” *Computers & Operations Research*, 28, 105-125.

10. Jacobson, S.H., Hall, S.N., & Swisher, J.R., 2006, “Discrete-event simulation of health care systems,” Patient flow: Reducing delay in healthcare delivery, 211-252.

11. Kelton, W.D., Sadowski, R.P.,Zupick, N.B., 2015, Simulation with Arena, 6th Edition, McGraw-Hill Education, New York.

IV. Journal Article

Using Sensitivity Analysis and Cost-Benefit Analysis to Evaluate the Effects of Increasing Patient Demand on a System of Clinics

Michael Q. Corpuz, Christina F. Rusnock, Vhance V. Valencia, and Kyle F. Oyama

Department of Systems Engineering and Management

Air Force Institute of Technology

Wright-Patterson AFB, OH 45433 USA

Abstract

Unexpected deployments are a normal part of military operations. When a crisis arises, military personnel must be ready to deploy at a moment's notice. For military readiness to be at 100%, military clinics must be capable of meeting the surge in demand when military personnel require a Deployment Health Assessment prior to deploying.
Not only do military clinics need to meet the demand of deploying military personnel, they also need to be capable of handling a surge of walk-ins when a mild medical incident occurs on the military installation. Additionally, recent fiscal environments of austere government funding raise another issue to consider when evaluating healthcare demand. This research evaluates the impacts of various staffing levels on patient wait-time while maintaining a zero-sum manning level for the system of clinics at Wright-Patterson AFB when there is a 200% surge in patient demand due to mass deployments.

This evaluation is conducted using discrete-event simulation to estimate patient wait-times and performs a sensitivity analysis of the increased patient demand. This research also evaluates the cost associated with changing staffing levels using a cost-benefit analysis to determine the most cost-effective alternative scenario. It is found that the average total wait-time of alternative systems is sensitive to deployment demand and medical incident demand. Hiring an optometrist while removing an occupational medicine doctor provides the lowest cost to implement in baseline, deployment, and medical incident demand environments.

Keywords

discrete event simulation; sensitivity analysis; cost benefit analysis; military healthcare; system of clinics

1. Introduction

Due to the uncertainty of future crises, military service members can expect short-notice deployments. Ideally, military readiness needs to be at 100% at all times. Unfortunately, the military currently faces a fiscally austere environment. The military's budget is being reduced by billions of dollars over the next two years and military personnel end strength reduced by tens of thousands (Simeone, 2014). If a crisis occurs requiring military personnel to deploy, then military healthcare clinics must be capable of medically clearing personnel for deployment in a timely fashion.

This research studies the impact of a 200% increase (54 additional patients) in patient demand due to increased deployments (deployment demand) as well as a surge of the same level of 54 additional patients walking in during the first 3 hours due to a mild medical incident on a military installation (medical incident demand) on a system of clinics located at Wright-Patterson Air Force Base. The study is carried out using a discrete-event simulation model to perform a sensitivity analysis. This research also conducts a cost-benefit analysis on the patient wait-time and costs associated with varying staffing levels while maintaining a zero-sum staffing level. This cost-benefit analysis is conducted with the same patient demand scenarios used in the sensitivity analysis.

Given a surge in patient demand (either deployment demand or medical incident demand), this study hypothesizes that one or more staffing levels will have statistically lower wait-times than other staffing level scenarios. This study also hypothesizes that one or more staffing levels will have a statistically lower cost to implement than the other staffing level scenarios on all three conditions of the patient demand (baseline demand, deployment demand, and medical incident demand).

2. Literature Review

In any system, there are certain properties that are desired by the decision maker. One such property that would be of interest to a military healthcare decision maker is the robustness of the system. There are various definitions of robustness (de Weck, Ross, & Rhodes, 2012; Ryan, Jacques, & Colombi, 2013). For this specific research, robustness is defined as “the measure of how effectively a system can maintain a given set of capabilities in response to external changes after it has been fielded (Ryan, Jacques, & Colombi, 2013).” In this case, the system would be the system of clinics and the measure of capability is the patient wait-time. The external changes are the increase in patient demand due to an increase in military personnel deployments or a mild medical incident happening on the military installation. Mild medical incidents can range from flu/cold incidents that do not require hospital care to food poisoning at a local restaurant that is mild enough to not warrant an emergency room visit. Simulated experiments of alternative systems are used to evaluate alternate systems being fielded.

To test the robustness of a system, sensitivity analysis is performed. There are several studies showing how sensitivity analysis is used to test the robustness of a healthcare system (Aktas, Ulengin, & Sahin, 2007; Hashimoto & Bell, 1996; Dorr, Horn, & Smout, 2005; Doubilet, Begg, Weinstein, Braun, & McNeil, 1985; Angus, Kelley, Schmitz, White, & Popovich, 2000). One such study is performed by Aktas, Ulengin, and Sahin (2007). Aktas, et al. performed a sensitivity analysis on a case study involving a private hospital in Turkey. The tomography section in the radiology department had a problem with the process time because lengthy time spent on the tomography machines have high operating costs; additional tomography machines also have a high cost to purchase. Also, the longer a doctor spends time on the tomography machines, the more dissatisfied the patients will be due to patients having to wait in long queues. In order to affect change in this system to reduce patient wait-times, a sensitivity analysis was conducted to identify the variables that are the most sensitive to change in affecting the process time. Aktas, et al. found that the process time is very sensitive to the process type; if different process types are offered on different days, then it can solve this issue with the exception of one type. They found that the whole abdomen process time is exceptionally long by itself. Additionally, Aktas, et al. (2007) found that the process time is not sensitive to technicians; improving the technicians will have no effect, if any, on the process time.

While Aktas, et al. (2007) used sensitivity analysis to look at reducing the process time, Dorr, Horn, and Smout (2005) took a different approach and used sensitivity analysis to evaluate the robustness of cost estimates ranging from hospitalization costs to registered nurse cost per hour. Dorr, et al. (2005) found that hospitalization costs are most sensitive to perturbations from nursing home residents.

Hashimoto and Bell (1996) conducted a sensitivity analysis on clinic staffing to evaluate the patient time in the clinic, session length, and idle times of the doctor for a single clinic. Hashimoto and Bell (1996) showed that patient total time in the clinic is sensitive to number of doctors in the clinic; increasing the doctor staffing level decreased the average patient time in system by 18.3 minutes.

Comparable to cost-value analysis and cost-effectiveness analysis, cost-benefit analysis studies have also been performed in the healthcare field (Brown, Brown, Sharma, & Landy, 2003; Nord, 1993). The overarching structure of these analyses stems from costs incurred in relation to gains realized. Brown, Brown, Sharma, and Landy (2003) define cost-benefit analysis as a measure of "both the costs and the outcomes of alternative interventions in terms of dollars (resources)."

Several studies analyze the relationship of the costs to gains in other healthcare systems (Nord, 1993; Eichler, Kong, Gerth, Mavros, & Jonsson, 2004; van den Bemt, et al., 2002). Nord (1993) compared the costs of different medical interventions to the effect treatments have on patients. This resulted in giving medical decision makers the ability to prioritize healthcare programs in terms of cost per one Saved Young Life Equivalent (SAVE) (Nord, 1993). Eichler, Kong, Gerth, Mavros, and Jonsson (2004) took a different approach in prioritizing healthcare resources by analyzing the cost to gain ratio in terms of an acceptable threshold to allocate scarce resources. Van den Bemt, Postma, van Roon, Chow, Fijn, and Brouwers (2002) looked into reducing prescription errors by hospital pharmacy staff by conducting a cost-benefit analysis. In order to save money, money must first be spent. Van den Bemt et al. (2002) demonstrated that when the hospital invested more time to properly prescribe medication to patients, a net cost of €285 to a benefit of €9867 is attributed to a reduction of prescribing errors.

2.1 Research Gap

Despite the various studies conducted on sensitivity and cost-benefit analysis, no work has been found to study the effects of increasing patient demand have on a system of clinics. In particular, no study is found that analyzes this effect due to (1) increased military deployments or (2) a surge of patient "walk-ins" due to a mild medical incident in the local area. This research takes a novel approach of using both sensitivity analysis and cost-benefit analysis to evaluate the simulated effects of an increase in patient demand on a system of clinics where some resources are shared. This research evaluates the robustness of different staffing level combinations when the system is subjected to deployment demand as well as a medical incident demand. This study hypothesizes that scenarios with increased patient demand will be most negatively impacted (longer patient wait-times) for alternative scenario(s) that decrease the number of flight medicine doctors.

This research also evaluates the savings estimates in implementing alternative scenarios: where the staffing levels vary in the system of clinics while maintaining a zero-sum manning level when the system of clinics is subjected to deployment and medical incident demands. This study hypothesizes that one or more staffing level will have a statistically lower cost to implement than the remaining staffing levels.

3. Methodology

3.1 Baseline Discrete-Event Simulation Model

In order to evaluate the increase in demand on a system of clinics, a discrete-event simulation (DES) model is developed. A conceptual model of the system of clinics is the first step in creating the model. A one-month data collection effort is conducted to collect the necessary information needed to develop system arrival and process time probability distributions as well as frequency counts for the model. The task network of the model is developed to provide a blueprint for the actual model. The model is then developed and validated. Once the model is validated, it is ready for various simulation experiments. See Chapter 3 for a detailed discussion of this process.

3.2 Data Collection

After the DES baseline model is created and validated, further information is needed to conduct a cost-benefit analysis. Cost information is gathered from the manager of the 88th Aerospace Medicine Squadron, Occupational Medicine Clinic. The manager provided monthly salary, rounded to the nearest five hundred dollars, for each of the different types of staff members. The average monthly salary is calculated for each staff member type.

3.3 Sensitivity Analysis Methodology

In order to evaluate the robustness of alternative systems, a sensitivity analysis is conducted. The performance measure (average total wait-time) is analyzed for each alternative scenario as well as the baseline scenario. The criteria for evaluating the sensitivity analysis occurs when the performance measure crosses a threshold of 15 minutes. When the performance measure is greater than 15 minutes, then the baseline or alternative system is considered sensitive to the respective changing environment. The criteria of greater than 15 minutes stems from military medical facilities using 15 minutes as their indicator for excessive wait-time. Additionally, military medical facilities consider 15-minute delays as a “no-show” for patient late arrivals, and use 15 minutes as the criteria for patients to use when complaining about the long wait-time; other medical facilities even tell patients to show up 15 minutes before their appointment (St. Michael's Emergency Room Commercials, 2015; Peninsula Children's Clinic, 2015). The results are shown on a one-sided tornado diagram in Section 5.1 Sensitivity Analysis Results because it is effective in rank ordering the alternative scenarios from the most sensitive at the top to the least sensitive at the bottom. The tornado diagram is one sided because it is intuitively known that a decrease in demand would not affect the robustness of the alternative scenarios, and thus decreases in demand are not considered in this analysis.

3.4 Cost-Benefit Analysis Methodology

In order to determine the alternative scenario with the lowest cost to implement for the third investigative question, a cost-benefit analysis is conducted. The lowest cost to implement can also imply the highest savings incurred upon implementation. A savings estimate is used as the criteria to determine the best alternative scenario by rank ordering the savings estimates from highest to lowest in dollar amounts. The savings estimate is in terms of the wait-time reduced or gained per month converted to a dollar equivalent plus the monthly savings incurred of removing a staff member from the system of clinics:

Savings Estimate = Reduced Wait-Time Savings + Staff Member Reduction Savings

The wait-time reduction or gain conversion is done by taking the wait-time minutes, divide it by 60, and multiply it by how much an average United States Air Force (USAF) employee earns per hour; according to careerbliss.com, USAF employees earn $23 per hour on average (careerbliss.com, 2015). The savings estimate is calculated for each of the three patient demand environments: baseline, deployment, and medical incident demand environments. Because all of the alternative scenarios add an additional optometrist to the system of clinics, see Section 4.1 Experimental Design, the cost associated with bringing an additional optometrist to the staff is removed from further analysis and the analysis focuses on the savings aspect of removing a different staff type to incur a savings. If an alternative scenario isn't universally ranked first in all three demand scenarios, then to decide on the preferred alternative scenario the three savings estimates are combined into a roll-up savings estimate where all three patient demands environments are given equal weight. By combining the three savings estimates into a combined savings estimate, the sensitivity analysis is accounted for by the cost-benefit analysis.

4. Alternative Systems

To evaluate the effect of deployment demand and medical incident demand has on the average total wait-time of the system of clinics, the validated baseline simulation model is modified to incorporate this increase as well as incorporate varying staffing levels from each clinic in the system of clinics to determine which staff position change is robust against increased patient demand. The staffing levels are the independent variables while the patient wait-time is the dependent variable when evaluating the alternative systems, also known as alternative scenarios. The alternative scenarios are described in greater detail below in the form of an experimental design.

4.1 Experimental Design

Table 9 summarizes the simulation experiments. The table shows the staffing level for each staff type as well as the system of clinics' patient demand level for the baseline scenario (BS) and each of the alternative scenarios (AS). There are 5 distinct alternative scenarios similar to the one shown in Chapter 3, except this experimental design table includes the additional layer of patient demand level, see Chapter 3 for a detailed explanation of each alternative scenario for the varying staffing level. The patient demand level for the baseline scenario, as well as all the alternative scenarios, has a 200% increase of patient demand. This means there are three times as many patients entering the system of clinics than the baseline demand. The total number of additional patients entering the system is the same for both the deployment demand and medical incident demand scenarios.

Table 9: Experimental Design Table

STAFF TYPE	BS	AS1	AS2	AS3	AS4	AS5
Audiologist	2	1	2	2	2	2
Flight Medicine Doctor	4	4	3	4	4	4
Flight Medicine Nurse or Technician	8	8	8	7	8	8
Hearing Conservation Technician	1	1	1	1	1	1
Occupational Medicine Doctor	4	4	4	4	3	4
Occupational Medicine Nurse or Technician	4	4	4	4	4	3
Optometrist	1	2	2	2	2	2
Optometry Nurse or Technician	1	1	1	1	1	1
X Ray Technician	1	1	1	1	1	1

PATIENT DEMAND LEVEL	BS	AS1	AS2	AS3	AS4	AS5
System of Clinics	200%	200%	200%	200%	200%	200%

4.2 Deployment Demand

In order to account for deployment demand, the model is slightly modified. The first modification is a change in the arrival rate. To take into account the 200% increase in patient demand spread throughout the day, two additional *create nodes* of the same Weibull distribution used in Chapter 3 are added at the beginning of the model while keeping the *create node* used in the baseline demand scenario intact; all three *create nodes* have the same Weibull distribution. The *create nodes* represent the interarrival rates of the patients entering the system of clinics.

The second modification is a change in probabilities of patients visiting a particular clinic as well as a change in probabilities in status types within the system of clinics. First, we establish the daily frequency count of how many patients visit each of the five clinics in the model as well as the two status types of “scheduled appointment” and “walk-in”. To establish the daily frequency count of how many patients visit each of the five clinics, the assigned percentages based on the real-world monthly counts are attributed to the average throughput in the model (Table 10). Next, the increased throughput from the patient demand increase of 200% (54 additional patients) is added to the frequency count of the flight medicine clinic since the flight medicine doctors are the only ones who can medically clear military personnel for deployment. The 54 additional patients needing medical clearance prior to deployment have appointment status. The new frequency counts are then used to determine the probability of visiting each of the clinics and status of the patient. The new percentages for each clinic as well as new percentage for the status of patients are integrated into the model decision logic (Table 11). Each alternative model is run for 42 replications; see Chapter 3 for the determination of the required number of replications.

Table 10: Statistics from Baseline Demand to Deployment Demand Part 1

Simulation System Number Out	Baseline
Average	27

From Data Collection		
Clinic	Count	Percent
Audiology	68	13.052%
Flight Medicine	104	19.962%
Hearing Conservation	37	7.102%
Occupational Medicine	179	34.357%
Optometry	133	25.528%

Expected Avg. Daily Patients (Sim_Baseline)		
Clinic	Count	Percent
Audiology	3.524	13.052%
Flight Medicine	5.390	19.962%
Hearing Conservation	1.917	7.102%
Occupational Medicine	9.276	34.357%
Optometry	6.893	25.528%

From Data Collection		
Status	Count	Percent
Scheduled Appointment	474	91%
Walk In	45	9%

Expected Average Daily Patients (Sim_Baseline)		
Status	Count	Percent
Scheduled Appointment	24.659	91%
Walk In	2.341	9%

Table 11: Statistics from Baseline Demand to Deployment Demand Part 2

Simulation System Number Out	Patient Demand Level
Demand Increase	200%
Expected Average	81

CAVEAT: Only Flight Medicine Clinic is affected by DHA Increase in Demand.

Expected Avg. Daily Patients (Sim_Baseline)		
Clinic	Count	Percent
Audiology	3.524	13.052%
Flight Medicine	5.390	19.962%
Hearing Conservation	1.917	7.102%
Occupational Medicine	9.276	34.357%
Optometry	6.893	25.528%

Expected Avg. Daily Patients (Sim_200% Inc.)		
Clinic	Count	Percent
Audiology	3.524	4.351%
Flight Medicine	59.390	73.321%
Hearing Conservation	1.917	2.367%
Occupational Medicine	9.276	11.452%
Optometry	6.893	8.509%

Expected Average Daily Patients (Sim_Baseline)		
Status	Count	Percent
Scheduled Appointment	24.659	91%
Walk In	2.341	9%

Expected Average Daily Patients (Sim_SS1)		
Status	Count	Percent
Scheduled Appointment	78.659	97.110%
Walk In	2.341	2.890%

4.3 Medical Incident Demand

The medical incident demand scenario follows the same experimental design table in Table 9 with the exception of the patient demand level of the system of clinics; it will have a surge of 54 patients over the first three hours of operation. To do this, an additional *create node* is added to the baseline model with an exponential probability distribution with 200 seconds as the mean parameter that stops adding patients into the system after 3 hours of simulation time passes for each replication. The exponential distribution is used because it is the common distribution for interarrival times (Kelton, Sadowski, & Zupick, 2015).

The second modification to the baseline model to evaluate the effects of a medical incident demand is a change in probabilities of patient visiting a particular clinic as well as a change in probabilities in status types within the system of clinics. First, we establish the daily frequency count of how many entities visit each of the five clinics in the model as well as the two status types. To do this, the assigned percentages based on the real-world monthly counts are attributed to the average throughput in the model (Table 12). Next, the increased throughput from the patient demand increase of 54 patients in the surge is equally split and added to the frequency count of the flight and occupational medicine clinics since they are both equally affected by this surge. Fifty-four patients are also added to the walk-in status since this is an incident that occurred that same day as when the patient enters the system of clinics. The new frequency counts are then used to determine the probability of visiting each of the clinics and status of the patient. The new percentages for each clinic as well as new percentage for the status of patients are integrated into the model decision logic (Table 13). Each alternative model is run for 42 replications; see Chapter 3 for the determination of the required number of replications.

Table 12: Statistics from Baseline Demand to Medical Incident Demand Part 1

Simulation System Number Out	Baseline
Average	27

From Data Collection		
Clinic	Count	Percent
Audiology	68	13%
Flight Medicine	104	20%
Hearing Conservation	37	7%
Occupational Medicine	179	34%
Optometry	133	26%

From Data Collection		
Status	Count	Percent
Scheduled Appointment	474	91%
Walk In	45	9%

Expected Average Daily Patients (Sim_Baseline)		
Clinic	Count	Percent
Audiology	3.524	13%
Flight Medicine	5.390	20%
Hearing Conservation	1.917	7%
Occupational Medicine	9.276	34%
Optometry	6.893	26%

Expected Average Daily Patients (Sim_Baseline)		
Status	Count	Percent
Scheduled Appointment	24.659	91%
Walk In	2.341	9%

Table 13: Statistics from Baseline Demand to Medical Incident Demand Part 2

Simulation System Number Out	Surge Scenario
Instant Demand Increase	54
Expected Average	81

CAVEAT: Only Flight Medicine Clinic and Occupational Medicine Clinic are evenly affected by Instantaneous Increase in Demand.

Expected Average Daily Patients (Sim_Baseline)		
Clinic	Count	Percent
Audiology	3.524	13%
Flight Medicine	5.390	20%
Hearing Conservation	1.917	7%
Occupational Medicine	9.276	34%
Optometry	6.893	26%

Expected Average Daily Patients (Sim_Baseline)		
Status	Count	Percent
Scheduled Appointment	24.659	91%
Walk In	2.341	9%

Expected Average Daily Patients (Sim_SS1)		
Clinic	Count	Percent
Audiology	3.524	4.351%
Flight Medicine	32.390	39.987%
Hearing Conservation	1.917	2.367%
Occupational Medicine	36.276	44.786%
Optometry	6.893	8.509%

Expected Average Daily Patients (Sim_SS1)		
Status	Count	Percent
Scheduled Appointment	24.659	30.443%
Walk In	56.341	69.557%

5. Analysis and Results

The output data from the 5 alternative scenarios for the deployment demand are presented in Table 14. The output data from the 5 alternative scenarios for the medical incident demand are presented in Table 15. In both tables, it is expected to see an increase in average total wait-time in the baseline and alternative scenarios for the medical incident demand because, unlike the deployment demand where 54 additional patients are seen throughout the day, medical incident demand are seeing a surge of 54 additional patients within the first 3 hours of the system of clinics opening. Sensitivity and cost-benefit analysis are conducted and once the analysis is complete, the results of the findings are discussed.

Table 14: Average Wait-Time of the Individual Processes and System of Clinics for All Alternative Scenarios for Deployment Demand

Process Node with Queues: Average Wait-Time in Minutes (Half-Width)	BS	AS1	AS2	AS3	AS4	AS5
2nd Session with Flight Medicine Nurse or Tech	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
2nd Session with Occupational Medicine Nurse or Tech	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
3rd Session with Occupational Medicine Nurse or Tech	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Check In	0.18 (0.08)	0.24 (0.17)	0.15 (0.07)	0.26 (0.18)	0.26 (0.18)	0.26 (0.18)
Check Vitals_Flight Medicine	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Check Vitals_Occupational Medicine	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Make Follow Up Appointment	0.29 (0.36)	0.27 (0.3)	0.18 (0.25)	0.21 (0.23)	0.34 (0.36)	0.34 (0.36)
Perform ECG_Flight Medicine	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Perform ECG_Occupational Medicine	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Perform Lab_Flight Medicine	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Perform Lab_Occupational Medicine	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Perform X Ray	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Prepare to See Optometrist with Nurse or Tech	1.54 (0.6)	1.12 (0.66)	1.52 (0.78)	1.63 (0.78)	1.63 (0.79)	1.63 (0.79)
See Flight Medicine Physician	1.71 (0.28)	1.9 (0.48)	14.66 (3.63)	1.75 (0.36)	1.91 (0.47)	1.91 (0.47)
See Occupational Medicine Physician	0.29 (0.11)	0.37 (0.17)	0.27 (0.15)	0.36 (0.17)	0.36 (0.17)	0.36 (0.17)
Visit Audiologist	0.46 (0.39)	6.47 (2.62)	0.35 (0.31)	0.46 (0.37)	0.46 (0.37)	0.46 (0.37)
Visit Hearing Conservation Technician (Hearing Conservation Clinic Only)	4.86 (1.97)	3.5 (1.53)	4.13 (1.64)	3.44 (1.36)	3.57 (1.48)	3.57 (1.48)
Visit Hearing Conservation Technician(Non Hearing Conservation Clinics)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Visit Optometrist	15.72 (5.42)	1.41 (0.79)	2.21 (1.05)	1.01 (0.68)	0.95 (0.68)	0.95 (0.68)
Average Total Wait-Time for System of Clinics in Minutes (Half-Width)	20.93 (6.98)	19.19 (6.94)	26.56 (6.51)	19.45 (6.28)	20.43 (7.37)	20.44 (7.37)

Table 15: Average Wait-Time of the Individual Processes and System of Clinics for All Alternative Scenarios for Medical Incident Demand

Process Node with Queues: Average Wait-Time in Minutes (Half-Width)	BS	AS1	AS2	AS3	AS4	AS5
2nd Session with Flight Medicine Nurse or Tech	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
2nd Session with Occupational Medicine Nurse or Tech	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
3rd Session with Occupational Medicine Nurse or Tech	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Check In	0.2 (0.12)	0.21 (0.1)	0.24 (0.19)	0.25 (0.19)	0.2 (0.13)	0.23 (0.1)
Check Vitals_Flight Medicine	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Check Vitals_Occupational Medicine	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Make Follow Up Appointment	0.21 (0.19)	0.17 (0.16)	0.14 (0.17)	0.14 (0.18)	0.03 (0.02)	0.2 (0.16)
Perform ECG_Flight Medicine	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Perform ECG_Occupational Medicine	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Perform Lab_Flight Medicine	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Perform Lab_Occupational Medicine	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Perform X Ray	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Prepare to See Optometrist with Nurse or Tech	5.18 (1.71)	3.78 (1.14)	4.51 (1.66)	3.7 (1.26)	4.57 (1.55)	4.2 (1.29)
See Flight Medicine Physician	0.44 (0.15)	0.36 (0.09)	1.52 (0.62)	0.49 (0.13)	0.42 (0.11)	0.47 (0.12)
See Occupational Medicine Physician	0.37 (0.12)	0.43 (0.13)	0.37 (0.1)	0.44 (0.12)	1.34 (0.47)	0.44 (0.11)
Visit Audiologist	1.5 (0.86)	15.69 (5.71)	2.02 (0.93)	1.67 (0.95)	1.53 (0.91)	1.61 (1.15)
Visit Hearing Conservation Technician (Hearing Conservation Clinic Only)	5.94 (1.6)	6.31 (1.68)	6.5 (1.5)	7.24 (1.6)	6.75 (1.7)	6.76 (1.38)
Visit Hearing Conservation Technician(Non Hearing Conservation Clinics)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Visit Optometrist	70.89 (15.79)	10.01 (3.97)	8.64 (2.92)	6.66 (2.7)	7.83 (3.35)	8.87 (3.18)
Average Total Wait-Time for System of Clinics in Minutes (Half-Width)	57.2 (9.66)	49.67 (9.65)	48.91 (9.34)	49.81 (9.54)	49.17 (9.71)	52.38 (9.63)

5.1 Sensitivity Analysis Results

Based on the criteria of greater than 15 minutes established in Section 3.3 Sensitivity Analysis Methodology, all baseline and alternative scenarios indicate that the systems considered are sensitive to deployment demand, see Figure 7. One of the alternative systems clearly stood out from the other alternative systems evaluated. Alternative scenario 2 (AS2), where the optometrist staffing level is increased to one and the flight medicine doctor staffing level is decreased to one, shows to be the most sensitive to the deployment demand when compared to baseline demand. However, the average total wait-time is not statistically significant in relation to the average total wait-time of other alternative scenarios at a 95% level of confidence, see Figure 8. This result failed to support the hypothesis that one or more staffing level scenarios will have statistically lower wait-times than other staffing levels when exposed to an increase in deployment demand.

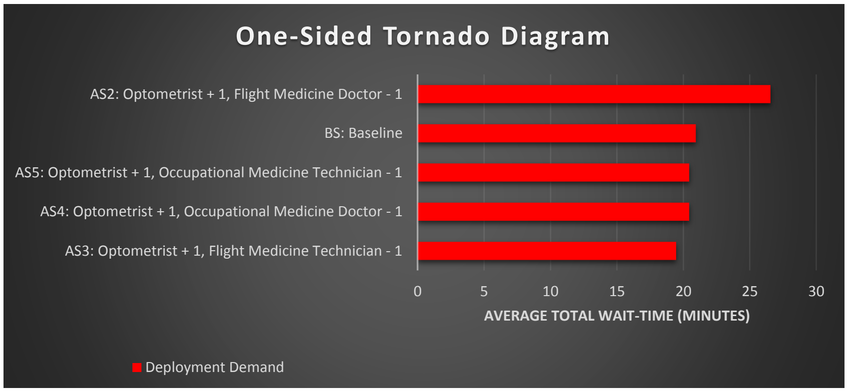
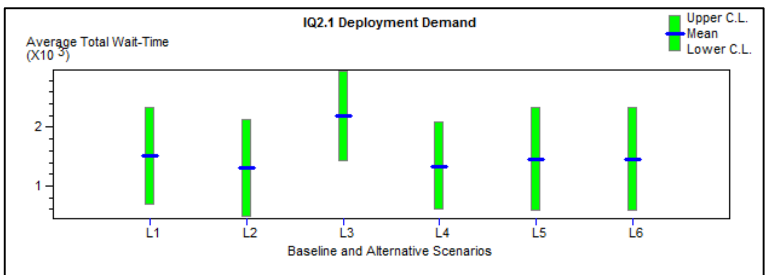


Figure 7: One-Sided Tornado Diagram of Average Total Wait-Time for Deployment Demand




```
            One-Way ANOVA Table : IQ2.1 Deployment Demand

L1  - AvgTotalWaitTime Baseline 200% Increase
L2  - AvgTotalWaitTime AS1 200% Increase
L3  - AvgTotalWaitTime AS2 200% Increase
L4  - AvgTotalWaitTime AS3 200% Increase
L5  - AvgTotalWaitTime AS4 200% Increase
L6  - AvgTotalWaitTime AS5 200% Increase

SOURCE OF VARIATION   SUM SQUARES    DF  MEAN SQUARES     F-EXP
-----------------------------------------------------------------------
BETWEEN TREATMENTS     5.599e+006     5     1.12e+006     0.631
ERROR (W.TREATMENTS)   4.365e+008   246     1.77e+006
-----------------------------------------------------------------------
TOTAL                  4.421e+008   251        F-CRIT     2.251
FAIL TO REJECT  H0  => MEANS ARE EQUAL  AT  0.05 LEVEL
```

Figure 8: Statistical Analysis: One-Way ANOVA of Baseline and Alternative Scenarios Subjected to Deployment Demand

Based on the criteria of greater than 15 minutes established in Section 3.3 Sensitivity Analysis Methodology, all baseline and alternative scenarios indicate that the systems considered are sensitive to medical incident demand, see Figure 9; but, like the deployment demand analysis, the average total wait-time of these alternatives are not statistically significant in relation to each other at a 95% level of confidence, see Figure 10. Figure 10 fails to support the hypothesis that one or more staffing level scenarios will have statistically lower wait-times than other staffing levels when exposed to a medical incident demand.

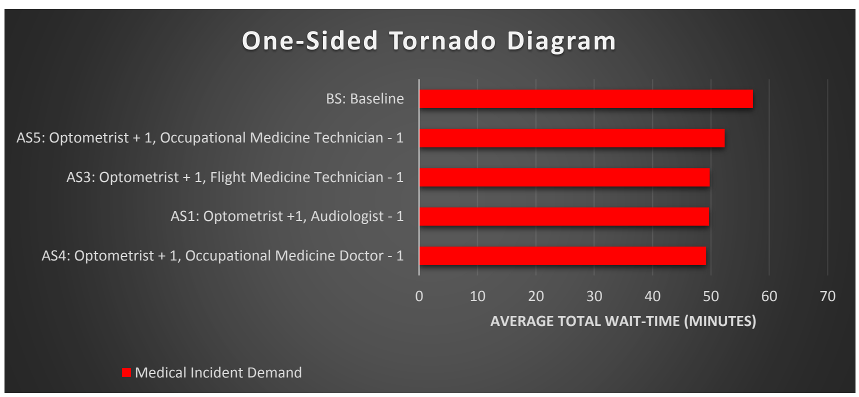
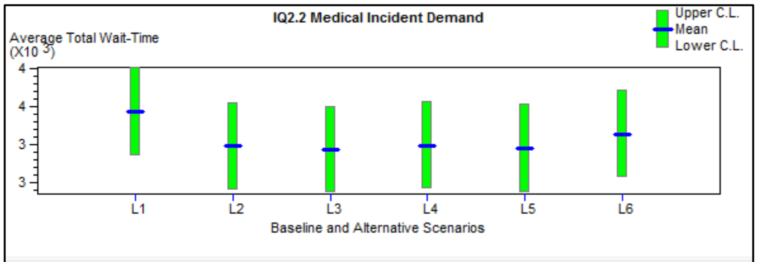


Figure 9: One-Sided Tornado Diagram of Average Total Wait-Time for Medical Incident Demand




```
One-Way ANOVA Table : IQ2.2 Medical Incident Demand

L1  - AvgTotalWaitTime Baseline 54 Patient Surge First 3Hrs
L2  - AvgTotalWaitTime AS1 54 Patient Surge First 3Hrs
L3  - AvgTotalWaitTime AS2 54 Patient Surge First 3Hrs
L4  - AvgTotalWaitTime AS3 54 Patient Surge First 3Hrs
L5  - AvgTotalWaitTime AS4 54 Patient Surge First 3Hrs
L6  - AvgTotalWaitTime AS5 54 Patient Surge First 3Hrs

SOURCE OF VARIATION   SUM SQUARES     DF  MEAN SQUARES      F-EXP
-----------------------------------------------------------------------
BETWEEN TREATMENTS     7.726e+006      5    1.545e+006      0.453
ERROR (W.TREATMENTS)   8.383e+008    246     3.41e+006
-----------------------------------------------------------------------
TOTAL                   8.46e+008    251        F-CRIT      2.251
FAIL TO REJECT  H0  => MEANS ARE EQUAL  AT  0.05 LEVEL
```

Figure 10: Statistical Analysis: One-Way ANOVA of Baseline and Alternative Scenarios Subjected to Medical Incident Demand

5.2 Cost-Benefit Analysis Results

This section provides the cost-benefit analysis results under the three demand environments already stated: baseline demand, deployment demand, and medical incident demand. The best alternatives in terms of staff reduction dollar savings and wait-time reduction dollar equivalent are presented.

For a cost-benefit analysis on baseline demand and based on the criteria of rank ordering the savings estimate from the highest to the lowest in terms of dollar amounts established in Section 3.4 Cost-Benefit Analysis Methodology, alternative scenario 4 is the highest ranked alternative when compared to the other alternative scenarios. The reason why increasing the optometrist staffing level by one and decreasing the occupational medicine doctor staffing level by one is the best alternative in terms of the highest savings incurred is because it saves the system of clinics a monthly average of $15,800, rounded to the nearest $100, for removing an occupational medicine doctor, see Table 16. Alternative system 4 is the best solution to implement when the system of clinics is subject to baseline demand. A one-way ANOVA is used to test the significance of the mean savings estimate of any of the alternative scenarios. This study finds that at least one alternative scenario has a statistically lower cost to implement than the remaining staffing levels in a baseline demand environment; p-value = 0.000, see Figure 11. In order to determine if the difference in the dependent variable (savings estimate) between the alternative scenarios is significant, a post-hoc statistical analysis (Tukey Pairwise Comparison) is conducted. Figure 12 and Figure 13 both indicate that AS4 paired with each of the other alternative scenarios all have a significant difference in the dependent variable. When AS4 is compared with other alternative scenarios, it doesn't contain the value zero in Figure 12, and AS4 is not grouped with any other alternative scenarios in Figure 13. If the medical decision maker is only looking at the analysis from purely an average wait-time reduction perspective, then AS2 and AS3 would both tie as the best solutions, see Table 16. Unfortunately, it costs money to affect a reduction in wait-time by changing staffing levels in the system of clinics.

Table 16: Cost-Benefit Analysis Table - Baseline Demand

Baseline Demand						
Alternative Scenario	**Staff Type**	**Staff Type Salary Savings (Monthly)**	**Average Wait-Time Reduced per Month in Minutes (Half-Width, 95%)**	**Wait-Time Reduced Dollar Equivalent (60 Minutes = $23.00)**	**Wait-Time Reduced Dollar Equivalent + Staff Savings (Half-Width, 95%) Rounded near $100**	**Rank**
AS1	Audiologist - 1	$8,000.00	2,946 (404)	$1,129	$9,100 ($200)	3
AS2	Flt. Med. Doctor -1	$9,000.00	3,455 (302)	$1,324	$10,300 ($100)	2
AS3	Flt. Med. Nurse/Tech -1	$4,666.67	3,455 (302)	$1,324	$6,000 ($100)	5
AS4	Occ. Med. Doctor -1	$14,500.00	3,391 (311)	$1,300	$15,800 ($100)	1
AS5	Occ. Med. Nurse/Tech -1	$5,750.00	3,451 (304)	$1,323	$7,100 ($100)	4

One-way ANOVA: AS1, AS2, AS3, AS4, AS5

```
Method

Null hypothesis         All means are equal
Alternative hypothesis  At least one mean is different
Significance level      α = 0.05

Equal variances were assumed for the analysis.


Factor Information

Factor  Levels  Values
Factor       5  AS1, AS2, AS3, AS4, AS5


Analysis of Variance

Source   DF      Adj SS     Adj MS  F-Value  P-Value
Factor    4  2460122088  615030522  3805.33    0.000
Error   205    33132838     161624
Total   209  2493254927


Model Summary

      S    R-sq  R-sq(adj)  R-sq(pred)
402.024  98.67%     98.65%      98.61%


Means

Factor   N     Mean  StDev        95% CI
AS1     42   9129.5  496.7  ( 9007.2,  9251.8)
AS2     42  10324.5  371.1  (10202.2, 10446.8)
AS3     42   5991.1  371.1  ( 5868.8,  6113.5)
AS4     42  15799.8  382.4  (15677.5, 15922.1)
AS5     42   7072.7  373.8  ( 6950.4,  7195.0)

Pooled StDev = 402.024
```

Figure 11: One-way ANOVA for AS1 through AS5 (Baseline Demand)

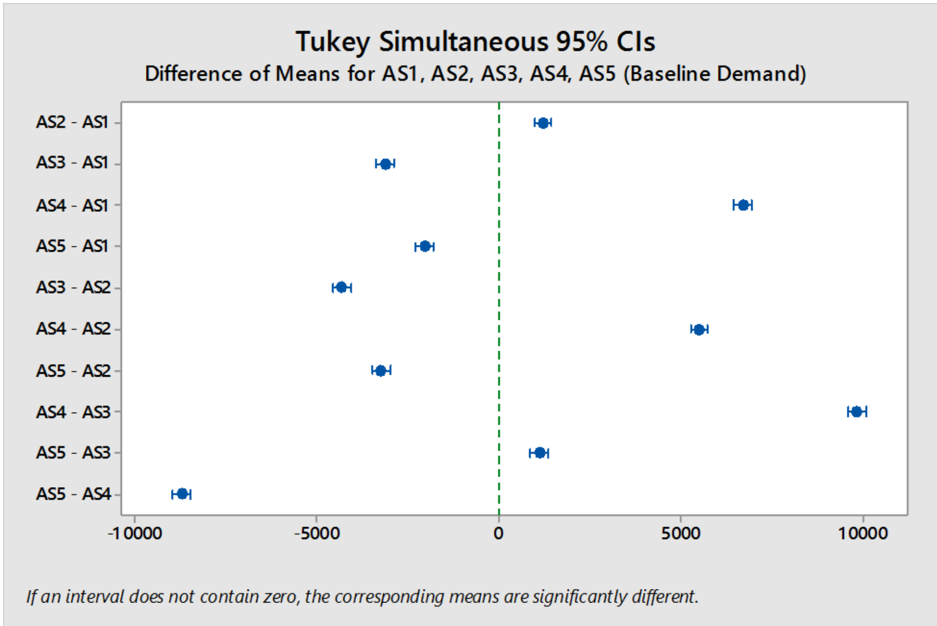


Figure 12: Tukey Simultaneous 95% Confidence Intervals (Baseline Demand)

Tukey Pairwise Comparisons

Grouping Information Using the Tukey Method and 95% Confidence

Factor	N	Mean	Grouping
AS4	42	15799.8	A
AS2	42	10324.5	B
AS1	42	9129.5	C
AS5	42	7072.7	D
AS3	42	5991.1	E

Means that do not share a letter are significantly different.

Figure 13: Tukey Pairwise Comparisons (Baseline Demand)

For a cost-benefit analysis on deployment demand and based on the criteria of rank ordering the savings estimate from the highest to the lowest in terms of dollar amounts established in Section 3.4 Cost-Benefit Analysis Methodology, alternative scenario 4 is the highest ranked alternative when compared to the other alternative scenarios. The reason why increasing the optometrist staffing level by one and decreasing the occupational medicine doctor staffing level by one is the best alternative in terms of the highest savings incurred is because it saves the system of clinics a monthly average $14,600, rounded to the nearest $100, for removing an occupational medicine doctor, see Table 17. Alternative system 4 is the best solution to implement when the system of clinics is subject to deployment demand. A one-way ANOVA is used to test the significance of the mean savings estimate of any of the alternative scenarios. It is found that at least one alternative scenario is found to have a statistically lower cost to implement than the remaining staffing levels in a deployment demand environment; p-value = 0.000, see Figure 14. In order to determine if the difference in the dependent variable (savings estimate) between the alternative scenarios is significant, a post-hoc statistical analysis (Tukey Pairwise Comparison) is conducted. Figure 15 and Figure 16 both indicate that AS4 paired with each of the other alternative scenarios all have a significant difference in the dependent variable. When AS4 is compared with other alternative scenarios, it doesn't contain the value zero in Figure 15, and AS4 is not grouped with any other alternative scenarios in Figure 16. If the medical decision maker is only looking at the analysis from purely an average wait-time reduction perspective, then AS1 is the best solution, see Table 17. Unfortunately, it costs money to affect a reduction in wait-time by changing staffing levels in the system of clinics.

Table 17: Cost-Benefit Analysis Table –Deployment Demand

Deployment Demand						
Alternative Scenario	**Staff Type**	**Staff Type Salary Savings (Monthly)**	**Average Wait-Time Reduced per Month in Minutes (Half-Width, 95%)**	**Wait-Time Reduced Dollar Equivalent (60 Minutes = $23.00)**	**Wait-Time Reduced Dollar Equivalent + Staff Savings (Half-Width, 95%) Rounded near $100**	**Rank**
AS1	Audiologist - 1	$8,000.00	988 (3,933)	$379	$8,400 ($1,500)	2
AS2	Flt. Med. Doctor -1	$9,000.00	-3,191 (3,688)	-$1,223	$7,800 ($1,400)	3
AS3	Flt. Med. Nurse/Tech -1	$4,666.67	837 (3,561)	$321	$5,000 ($1,400)	5
AS4	Occ. Med. Doctor -1	$14,500.00	281 (4,177)	$108	$14,600 ($1,600)	1
AS5	Occ. Med. Nurse/Tech -1	$5,750.00	280 (4,177)	$107	$5,900 ($1,600)	4

One-way ANOVA: AS1, AS2, AS3, AS4, AS5

```
Method

Null hypothesis         All means are equal
Alternative hypothesis  At least one mean is different
Significance level      α = 0.05

Equal variances were assumed for the analysis.


Factor Information

Factor  Levels  Values
Factor       5  AS1, AS2, AS3, AS4, AS5


Analysis of Variance

Source   DF      Adj SS     Adj MS  F-Value  P-Value
Factor    4  2394204603  598551151    25.80    0.000
Error   205  4755277135   23196474
Total   209  7149481739


Model Summary

      S    R-sq  R-sq(adj)  R-sq(pred)
4816.27  33.49%     32.19%      30.20%


Means

Factor   N   Mean  StDev      95% CI
AS1     42   8379   4838  ( 6913,  9844)
AS2     42   7777   4537  ( 6312,  9242)
AS3     42   4987   4380  ( 3522,  6453)
AS4     42  14608   5139  (13142, 16073)
AS5     42   5857   5138  ( 4392,  7323)

Pooled StDev = 4816.27
```

Figure 14: One-way ANOVA for AS1 through AS5 (Deployment Demand)

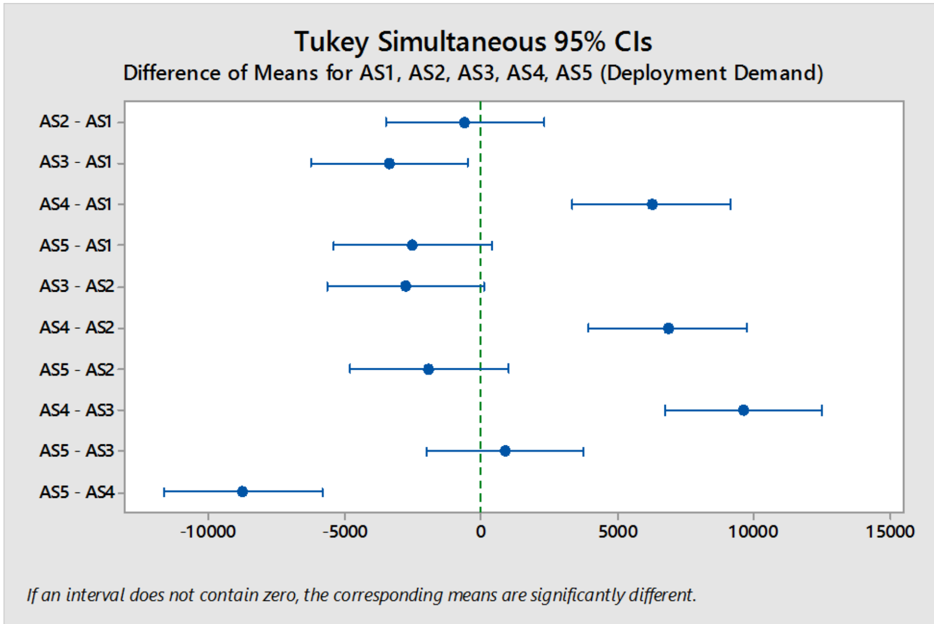


Figure 15: Tukey Simultaneous 95% Confidence Intervals (Deployment Demand)

Tukey Pairwise Comparisons

```
Grouping Information Using the Tukey Method and 95% Confidence

Factor   N   Mean  Grouping
AS4     42  14608  A
AS1     42   8379    B
AS2     42   7777    B C
AS5     42   5857    B C
AS3     42   4987      C

Means that do not share a letter are significantly different.
```

Figure 16: Tukey Pairwise Comparisons (Deployment Demand)

For a cost-benefit analysis on medical incident demand and based on the criteria of rank ordering the savings estimate from the highest to the lowest in terms of dollar amounts established in Section 3.4 Cost-Benefit Analysis Methodology, alternative scenario 4 is the highest ranked alternative when compared to the other alternative scenarios. The reason why increasing the optometrist staffing level by one and decreasing the occupational medicine doctor staffing level by one is the best alternative in terms of the highest savings incurred is because it saves the system of clinics a monthly average $16,200, rounded to the nearest $100, for removing an occupational medicine doctor, see Table 18. Alternative system 4 is the best solution to implement when the system of clinics is subject to medical incident demand. A one-way ANOVA is used to test the significance of any of the alternative scenarios. This study finds that at least one alternative scenario has a statistically lower cost to implement than the remaining staffing levels in a baseline demand environment; p-value = 0.000, see Figure 17. In order to determine if the difference in the dependent variable (savings estimate) between the alternative scenarios is significant, a post-hoc statistical analysis (Tukey Pairwise Comparison) is conducted. Figure 18 and Figure 19 both indicate that AS4 paired with each of the other alternative scenarios all have a significant difference in the dependent variable. When AS4 is compared with other alternative scenarios, it doesn't contain the value zero in Figure 18, and AS4 is not grouped with any other alternative scenarios in Figure 19. If the medical decision maker is only looking at the analysis from purely a wait-time reduction perspective, then AS2 is the best solution, see Table 18. Unfortunately, it costs money to affect a reduction in wait-time by adding an optometrist to the system of clinics. Because all three cost-benefit analysis tables for the baseline, deployment, and medical incident demands indicate that AS4 is ranked first, a combined table for all three patient demand environments is not necessary.

Table 18: Cost-Benefit Analysis Table – Medical Incident Demand

Medical Incident Demand						
Alternative Scenario	**Staff Type**	**Staff Type Salary Savings (Monthly)**	**Average Wait-Time Reduced per Month in Minutes (Half-Width, 95%)**	**Wait-Time Reduced Dollar Equivalent (60 Minutes = $23.00)**	**Wait-Time Reduced Dollar Equivalent + Staff Savings (Half-Width, 95%) Rounded near $100**	**Rank**
AS1	Audiologist - 1	$8,000.00	4,272 (5,468)	$1,638	$9,600 ($2,100)	3
AS2	Flt. Med. Doctor -1	$9,000.00	4,705 (5,296)	$1,804	$10,800 ($2,000)	2
AS3	Flt. Med. Nurse/Tech -1	$4,666.67	4,192 (5,408)	$1,607	$6,300 ($2,100)	5
AS4	Occ. Med. Doctor -1	$14,500.00	4,555 (5,506)	$1,746	$16,200 ($2,100)	1
AS5	Occ. Med. Nurse/Tech -1	$5,750.00	2,735 (5,460)	$1,048	$6,800 ($2,100)	4

One-way ANOVA: AS1, AS2, AS3, AS4, AS5

```
Method

Null hypothesis         All means are equal
Alternative hypothesis  At least one mean is different
Significance level      α = 0.05

Equal variances were assumed for the analysis.


Factor Information

Factor  Levels  Values
Factor       5  AS1, AS2, AS3, AS4, AS5


Analysis of Variance

Source   DF       Adj SS     Adj MS  F-Value  P-Value
Factor    4   2684429268  671107317    15.05    0.000
Error   205   9139715624   44583979
Total   209  11824144892


Model Summary

      S    R-sq  R-sq(adj)  R-sq(pred)
6677.12  22.70%     21.19%      18.89%


Means

Factor   N   Mean  StDev       95% CI
AS1     42   9638   6726  ( 7606, 11669)
AS2     42  10804   6515  ( 8772, 12835)
AS3     42   6274   6652  ( 4242,  8305)
AS4     42  16246   6773  (14215, 18277)
AS5     42   6798   6717  ( 4767,  8830)

Pooled StDev = 6677.12
```

Figure 17: One-way ANOVA for AS1 through AS5 (Medical Incident Demand)

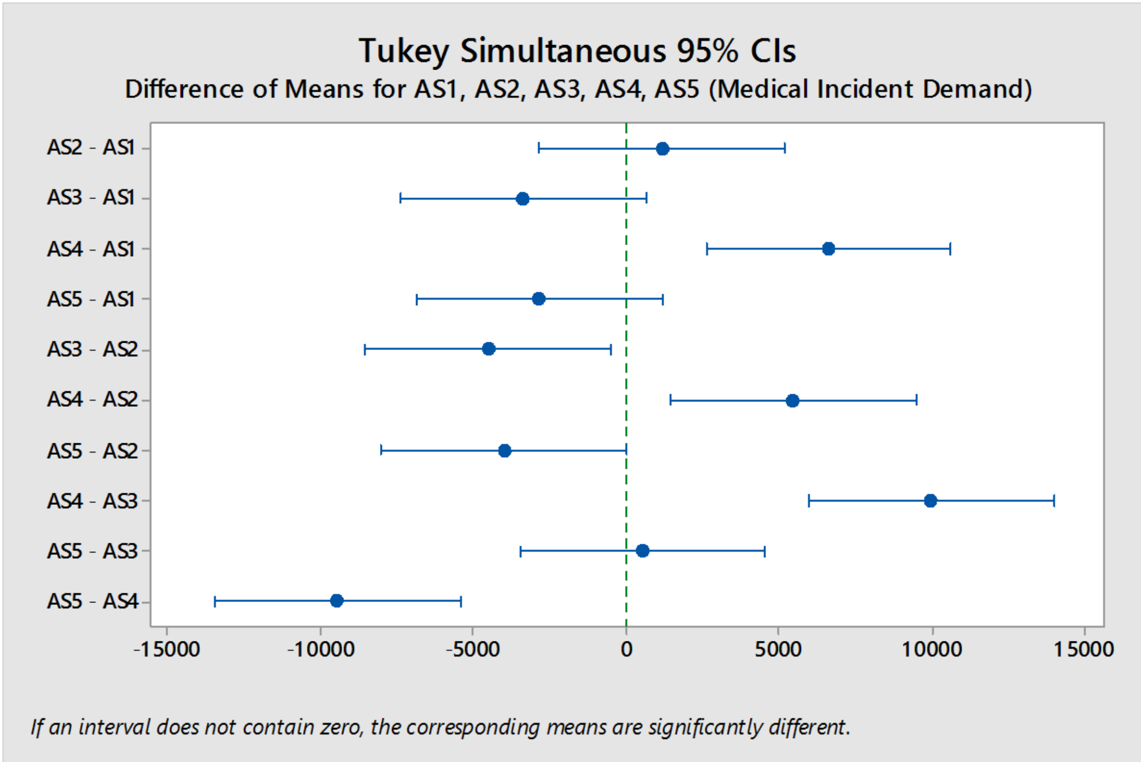


Figure 18: Tukey Simultaneous 95% Confidence Intervals (Medical Incident Demand)

Tukey Pairwise Comparisons

Grouping Information Using the Tukey Method and 95% Confidence

Factor	N	Mean	Grouping
AS4	42	16246	A
AS2	42	10804	B
AS1	42	9638	B C
AS5	42	6798	B C
AS3	42	6274	C

Means that do not share a letter are significantly different.

Figure 19: Tukey Pairwise Comparisons (Medical Incident Demand)

6. Conclusion

6.1 Sensitivity Analysis Conclusion

There are insights gained from the sensitivity and cost-benefit analyses conducted. It is shown that the average total wait-times of the baseline and alternative systems are sensitive to a deployment demand but are not statistically significant in relation to all the baseline and alternative scenarios; lack of statistical significance among the baseline and alternative scenarios indicate that the average total wait-time of one scenario is not any more sensitive than the average total wait-time of the rest of the scenarios. If the increase in demand is greater than 200%, then it is expected to see greater differences in the average total wait-time, especially if the system of clinics reduce the staffing levels of the flight medicine doctor even though the difference in average total wait-time is not considered statistically significant among the alternative scenarios at 200%. Reducing the staffing levels of the flight medicine doctor at deployment demand levels greater than 200% may make the difference in average total wait-time significant among the alternative scenarios. It is also shown that the average total wait-times of the baseline and alternative systems are sensitive to a medical incident demand but are not statistically significant in relation to all the baseline and alternative scenarios in the same medical incident demand environment; lack of statistical significance among the difference of the average total wait-time of the scenarios indicate that the average total wait-time of one scenario is not any more sensitive than the average total wait-time of the rest of the scenarios. If the number of additional patients are increased, the time length of the surge of additional patients coming in to the system of clinics is reduced (less than 3 hours), or a combination of both, then it is expected to see greater differences in the average total wait-time, regardless of which scenario is implemented.

6.2 Cost-Benefit Analysis Conclusion

The results from the cost-benefit analyses clearly show that implementing alternative scenario 4 would yield the highest return-on-investment for the lowest cost to implement in all three patient demand scenarios; the difference in mean savings estimate of alternative scenario 4 compared to each of the other alternative scenarios is statistically significant in baseline, deployment, and medical incident demand environments. This is primarily due to the high cost of keeping an occupational medicine doctor on the payroll.

6.3 Future Work

Future work includes evaluating other alternative scenarios beyond the five studied and subjecting these to an increase in patient demand. For example, reducing wait-time could be achieved if both the optometrist and flight medicine doctor increased staffing levels while reducing some of the nurse/technicians in an increased patient and environment. Additional future work includes looking into different patient demand environments. It would be interesting to determine what the deployment and medical incident demand levels are at the robustness threshold as well as evaluate other demand levels. The same analyses conduced in this research should be performed at other military installations to determine if their processes can be improved as well.

Acknowledgements

This work was supported in part by the 88th Aerospace Medicine Squadron, Wright-Patterson AFB, OH. The views expressed in this paper are those of the authors and do not reflect the official policy or position of the United States Air Force, Department of Defense, or the United States Government.

References

Chou, T.-C., & Talalay, P. (1984). Quantitative analysis of dose-effect relationships: the combined effects of multiple drugs or enzyme inhibitors. *Advances in enzyme regulation, 22*, 27-55.

de Weck, O. L., Ross, A. M., & Rhodes, D. H. (2012, June 18-20). Investigating Relationships and Semantic Sets amongst System Lifecycle Properties (Ilities). *Third International Engineering Systems Symposium*, (pp. 1-12). Delft University of Technology.

Delaney, J. A., & Seeger, J. D. (1967). Sensitivity Analysis. In *Developing an Observational CER Protocol: A User's Guide* (pp. 145-159). Retrieved from http://www.effectivehealthcare.ahrq.gov/ehc/assets/File/Ch_11-User-Guide-to-OCER_130129.pdf

Dorr, D. A., Horn, S. D., & Smout, R. J. (2005, May). Cost Analysis of Nursing Home Registered Nurse Staffing Times. *Journal of the American Geriatrics Society, 53*(5), 840-845.

Eichler, H.-G., Kong, S. X., Gerth, W. C., Mavros, P., & Jonsson, B. (2004). Use of Cost-Effectiveness Analysis in Health-Care Resource Allocation Decision-Making: How Are Cost-Effectiveness Thresholds Expected to Emerge? *Value in Health, 7*(5), 518-528.

Kelton, W. D., Sadowski, R. P., & Zupick, N. B. (2015). *Simulation with Arena* (sixth edition ed.). New York: McGraw-Hill Education.

Rothberg, M. B., Abraham, I., Lindenauer, P. K., & Rose, D. N. (2005, August). Improving Nurse-to_Patient Staffing Ratios as a Cost-Effective Safety Intervention. *Medical Care, 43*(8), 785-791.

Ryan, E. T., Jacques, D. R., & Colombi, J. M. (2013). An Ontological Framework for Clarifying Flexibility-Related Terminology via Literature Survey. *Systems Engineering, 16*(1), pp. 99-110.

Schneeweiss, S. (2006, May). Sensitivity analysis and external adjustment for unmeasured confounders in epidemiologic database studies of therapeutics. *Pharmacoepidemiology and Drug Safety, 15*(5), pp. 291-303.

Schneeweiss, S., Seeger, J. D., Landon, J., & Walker, A. M. (2008). Aprotinin during Coronary-Artery Bypass Grafting and Risk of Death. *The New England Journal of Medicine, 358*, 771-783.

Simeone, N. (2014, February 24). *Hagel Outlines Budget Reducing Troop Strength, Force Structure*. Retrieved from U.S. Department of Defense: http://www.defense.gov/news/newsarticle.aspx?id=121703

Wang, S. J., Middleton, B., Prosser, L. A., Bardon, C. G., Spurr, C. D., Carchidi, P. J., . . . Bates, D. W. (2003, April). A cost-benefit analysis of electronic medical records in primary care. *The American Journal of Medicine, 114*(5), 397-403.

V. Conclusions and Recommendations

Chapter Overview

The purpose of this chapter is to answer the investigative questions, provide insights, provide a solution recommendation, and provide recommendations for future research. Discrete-event simulation, sensitivity analysis, and cost-benefits analysis are utilized in this research to determine if different staffing levels can affect the patient's overall wait-time; which of the different staffing levels is the most robust as patient demand increases; and which of the different staffing levels has the lowest cost to implement. The results of this research provide insights into the current military healthcare system that is comparable to the system of clinics and can be used to improve the process of the current system of clinics at Wright-Patterson AFB, OH.

Investigative Question 1: How can staffing levels be adjusted to improve the patient's overall wait-time in the system of clinics?

The results of the simulation experiments indicate that adding an additional optometrist can substantially reduce the average wait-time of the optometry clinic and thus the average time in system for the system of clinics. Adding one more optometrist can reduce the patients visiting the optometry clinic in a system of clinics by as much as 16.6 minutes, on average. In a military setting, that is 16.6 minutes of time not wasted waiting to see the optometrist and using that gained time back in performing official military duties. If adding one more optometrist is not feasible when implementing the alternative system, then load sharing with other optometrists at the main hospital at

WPAFB could be a viable alternative. Evaluating the load sharing scenario is left to future work.

Due to the difficulties in increasing military unit manpower requirement this study investigated alternatives that achieved zero-sum manning for the system of clinics. Simulation of five staffing changes reveals that there are 4 viable options for significantly reducing total average wait-time in the system with insignificant impacts to the individual process average wait-times. These options are reducing a flight medicine doctor, flight medicine nurse/technician, occupational medicine doctor, or occupational medicine nurse/technician.

Investigative Question 2: Which staffing level solution is the most robust as patient demand increases?

It is shown that the average total wait-times of the baseline and alternative systems are sensitive to deployment demand but are not statistically significant in relation to the difference of average total wait-time of all the scenarios; all systems have an average total wait-time of 15 minutes or more. However, lack of statistical significance in the difference of the average total wait-time among the scenarios in a deployment demand environment indicate that the average total wait-time of one scenario is not any more sensitive than the average total wait-time of the rest of the scenarios. If the increase in deployment demand is greater than 200%, then it is expected to see greater increase in the average total wait-time, especially if you reduce the staffing levels of the flight medicine doctor. This study also finds that the average total wait-times of the baseline and alternative systems are sensitive to a medical incident demand but are not statistically significant in relation to the difference of average total wait-time in all the scenarios; lack of statistical significance of the difference of average total wait-time among the scenarios in a medical incident demand environment indicate that the average total wait-time of one scenario is not any more sensitive than the average total wait-time of the rest of the scenarios. If the number of additional patients are increased, the time length of the surge of additional patients coming in to the system of clinics is reduced (less than 3 hours), or a combination of both, then it is expected to see greater increase in the average total wait-time, regardless of which scenario is implemented. It is found that none of the scenarios are robust against the demands of deployments and medical incidents based on the sensitivity criteria established in Chapter 4.

Investigative Question 3: Which system improvement solution has the lowest cost to implement?

The results from the cost-benefit analyses clearly show that implementing alternative scenario 4 would yield the lowest cost to implement due to a high savings incurred if implemented in all three patient demand scenarios; the difference of the average savings estimate between alternative scenario 4 and each of the other alternative scenarios is statistically significant in baseline, deployment, and medical incident demand environments. This is due to the high cost of keeping an occupational medicine doctor on the payroll.

Research Question: How can the total wait-time patients experience in the military system of clinics be cost-effectively reduced during baseline demand and when patient demand increases as the clinics within the system of clinics compete for scarce resources?

After conducting analysis for the first investigative question, 4 preferable candidate solutions were produced. The sensitivity and cost-benefit analysis used to answer the second and third investigate questions helped to narrow the solution space. It is found that the alternative scenario where the optometrist staffing level is increased by one and the occupational medicine doctor staffing level is decreased by one is the best choice among the other alternative scenarios. When implemented, this alternative scenario will improve the current system in terms of reducing the average total wait-time at baseline demand as well as save the system of clinics money in all three demand environments. However, it will not be robust in terms of the average total wait-time when the alternative system is faced with a deployment demand and a medical incident demand.

Significance of Research

The 711th Human Performance Wing at Wright-Patterson AFB, OH, is sponsoring this research. The system of clinics located at Wright-Patterson AFB has never been modeled before this research was conducted. This research not only characterized the behavior of the system of clinics, it also provided insights about the behavior of the system of clinics when subjected to an increase in patient demand both from an increase in deployments perspective as well as from the perspective of a mild medical incident occurring in the local area. This research can be replicated to other healthcare systems in other military installations to provide military healthcare decision makers insights into the behavior of those systems both in the current patient demand and when patient demand changes.

Recommendation for Action

The recommended solution is to implement alternative scenario 4. Alternative scenario 4 is implemented by adding an additional optometrist to the staff while removing an occupational medicine doctor from the staff. This is the recommended solution despite alternative scenario 4 not being robust in deployment and medical incident demand environments. It is found through the cost-benefit analysis that alternative scenario 4 is still the best solution when the system is subjected to baseline, deployment, and medical incident demands; statistical analysis indicates that the difference of mean savings estimate between alternative scenario 4 and each of the other alternative scenarios is statistically significant in terms of savings in all three demand environments.

Recommendations for Future Research

Future work includes developing other alternative scenarios that can reduce the average wait-time. For example, reducing the average wait-time could be achieved by increase the number of examination rooms available, by alternating the process flow, by changing the current queuing strategy of a priority queue to a first come first served queue, or by changing the appointment scheduling process. Additional future work includes adding or removing more staff, performing the same analysis on other military installations, and doing an Air Force-wide assessment to determine if optometry has a career field shortage.

More future work includes evaluating other alternative scenarios beyond the five studied and subjecting these to an increase in patient demand. For example, reducing the patient wait-time could be achieved if both the optometrist and flight medicine doctor increased staffing levels while reducing two or more of the nurse/technicians in an increased patient and environment. Additional future work includes looking into different patient demand environments. It would be interesting to determine what the deployment and medical incident demand levels are at the robustness threshold as well as evaluate other demand levels. The same analyses conduced in this research should be performed at other military installations to determine if their processes can be improved as well.

Summary

This chapter evaluates all three investigative questions and insights are drawn from the results of the analyses to provide the significance of the research. A solution is recommended based of the results of the analyses. Recommendations for future are included to investigate other scenarios and provide additional insights to the system of clinics.

Appendix A: Detailed Method in Establishing the Baseline Model

Overview

This appendix describes the method to establish the baseline model in full detail. The first step in developing a baseline model is to formulate a conceptual model of the system in order to ensure that system tasks, resources, and work flows are accurately captured. Next, the required data are collected and fitted to probability distributions. The analysis of the input data is combined with the conceptual model of the system into a task network that forms the baseline simulation model. This baseline simulation model features the task flows, arrival rates, process probability distributions, system resources and probabilistic events. Finally, the time in system (TIS) data from the baseline simulation model are validated against the TIS data from the real world system. This method is further described in the subsections below.

Step 1: Conceptual Model

The first step in creating a usable baseline simulation model is to understand the system of clinics being studied. In order to understand the system of clinics, a conceptual model of the daily operations is developed. To develop this framework, the staff members of the system of clinics provided a general description of daily operations, graphically depicted in Figure 20. A typical daily operation starts when patients check in at the front desk upon arrival. Patients are given paperwork to fill out, if needed. Then patients visit other stations where a nurse or technician perform various tasks on them (e.g., check vitals/preparation, laboratory work, electrocardiogram (ECG), X-ray, visit other clinics, and additional visits to nurses or technicians) if they are required prior to visiting the doctor. After these preparatory tasks, patients wait until the doctor is available. When patients are waiting, the current queuing strategy of the system of clinics at WPAFB is a priority queue: Patients with a scheduled appointment have priority to see the doctor over walk-in patients. After visiting with the doctor, a follow-up appointment is scheduled if an additional visit is required. Patients then exit the system of clinics.

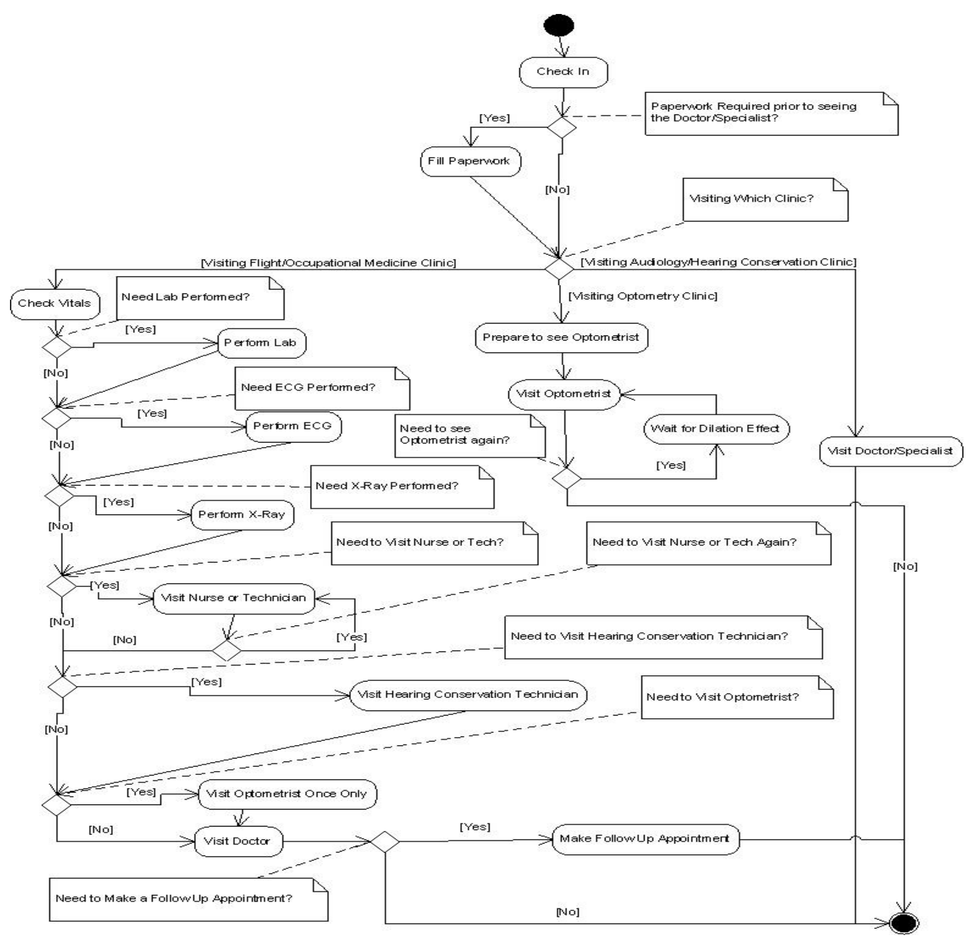


Figure 20: System of Clinics Task Network

Step 2: Data Collection

For each activity described in the conceptual model, timing and decision data are required in order to build the simulation model. These data were collected by the clinic medical staff by first performing a trial data collection effort during the month of July 2014 to become familiar with the data collection process. The official data collection effort was conducted in August 2014. Data were collected using a clipboard with a clock built into it and a data collection sheet, see Figure 21 and Figure 22. The data collection sheet records the following general information about the patient's visit: clinic type (audiology, flight medicine clinic, hearing conservation clinic, occupational medicine clinic, or optometry), patient type (military, civilian, or dependent), status (scheduled appointment or walk-in), date, appointment time (if applicable), and appointment type. The data collection sheet also records the start and end time of each process the patient undergoes which includes: patient check-in, filling out paperwork, hearing conservation visit, checking vitals/preparing patient, nurse or technician visit, laboratory tasks, X-ray examination, ECG, provider visit, additional provider visits, and scheduling a follow-up appointment. Annotating the start and end times on the sheet have negligible impact on the performance of the medical staff's duties. A few of the processes were performed infrequently, thus failing to provide an adequate number of observations during the August 2014 collection period. Thus, the data collection effort was extended to include the trial data from July 2014 and an additional collection from September 2014 for these infrequent tasks: laboratory tasks, X-ray examination, ECG, and visits to additional nurses or technicians. It is reasonable to include some data from the trial period in July 2014 for these processes because the times for these tasks were accurately collected.

DATA COLLECTION FOR PROCESS IMPROVEMENT

Patient ID:

Clinic:
Patient Type: Military / Civilian / Dependent (circle one)
Status: Walk-In / Scheduled Appointment (circle one)

Use back page for additional comments on appointment type with staff initials.

Date:
Appointment Time:
Appointment Type:

Front Desk – Patient Checking In

Time In (hour:min:sec): Out (hour:min:sec): Staff Initials:
Comments:

Patient Filling Out Paperwork? Yes / No (circle one)

Paperwork Out (hour:min:sec): Returned (hour:min:sec): Staff Initials:
Comments:

Wait Time for Hearing Conservation (If Applicable)

Wait Time Start (hour:min:sec): Staff Initials:
Comments:

Wait Time End (hour:min:sec): Staff Initials:
Comments:

Hearing Conservation? Yes / No (circle one)

Time In (hour:min:sec): Out (hour:min:sec): Staff Initials:
Comments:

Wait for Nurse/Technician – Drop Off/Pick Up Medical Chart

Dropped Off (hour:min:sec): Staff Initials:
Comments:

Picked Up (hour:min:sec): Staff Initials:
Comments:

Nurse/Technician – Checking Vitals (If multiple sessions with patient, then use reverse side for additional time recordings)

Time In (hour:min:sec): Out (hour:min:sec): Staff Initials:
Comments:

Lab? Yes / No (circle one)

Lab Time In (hour:min:sec): Out (hour:min:sec): Staff Initials:
Comments:

X-Ray? Yes / No (circle one)

X-Ray Time In (hour:min:sec): Out (hour:min:sec): Staff Initials:
Comments:

Provider – Type of Provider (fill in type): (If multiple sessions with patient, then use reverse side for additional time recordings)

Time In (hour:min:sec): Out (hour:min:sec): Staff Initials:
Comments:

Front Desk – Follow-Up Appointment? Yes / No (circle one)

Time In (hour:min:sec): Out (hour:min:sec): Staff Initials:
Comments:

(Use back page for additional comments with your initials next to it.)

Figure 21: Data Collection Sheet (Front Page)

ADDITIONAL COMMENTS:

Nurse/Technician – Additional Sessions with Patient

Session 2– Time In (hour:min:sec): Out (hour:min:sec): Staff Initials:

Session 3– Time In (hour:min:sec): Out (hour:min:sec): Staff Initials:

Session 4– Time In (hour:min:sec): Out (hour:min:sec): Staff Initials:

Comments:

Additional Provider Sessions with Patient – Type of Provider (fill in type):

Session 2– Time In (hour:min:sec): Out (hour:min:sec): Staff Initials:

Session 3– Time In (hour:min:sec): Out (hour:min:sec): Staff Initials:

Session 4– Time In (hour:min:sec): Out (hour:min:sec): Staff Initials:

Comments:

Figure 22: Data Collection Sheet (Back Page)

Step 3: Input Analysis

Upon completion of the data collection effort, input data modeling was performed on the patient arrivals and process times in order to form probability distributions. These probability distributions were tested for independence, homogeneity, and goodness-of-fit. All of the final distributions in the baseline model either successfully passed these tests or were replaced by an empirical distribution directly representing the data. Table 19 summarizes the frequency for each process and possible patient path flows within the system of clinics; this information is used to establish the decision logic for the simulation model. Table 20 summarizes the frequency counts for the clinic visited, patient type, and status of the patient; these frequencies are used to establish the decision logic for the simulation model. Table 21 summarizes the likelihood of an optometry patient seeing the optometrist twice in a single visit; this is unique from other processes in that the patient visits the optometrist again whereas the patient visits other processes only once. Table 21 is used to establish the decision logic for the simulation model. Table 22 summarizes the probability distribution for each of the datasets being fitted; these distributions are used in the simulation model to determine the interarrival time for each patient entering the system as well as process times for process visited by a patient as they go through the system.

Table 19: Flight/Occupational Medicine Clinic Process Frequency Counts

Assign Flight/Occupational Medicine Paperwork

	Paperwork Count	Total Count	Paperwork	No Paperwork
Flight Medicine	98	104	94%	6%
Occupational Medicine	95	179	53%	47%

Need to Visit Hearing Conservation? (For Flight/Occupationa Medicine Patients)

	Obs Count	Total Count	TRUE	FALSE
Flight Medicine	27	104	26%	74%
Occupational Medicine	35	179	20%	80%

Need to Visit Nurse or Tech 2nd Time? (For Flight/Occupationa Medicine Patients)

	Obs Count	Total Count	TRUE	FALSE
Flight Medicine	1	104	1%	99%
Occupational Medicine	3	179	2%	98%

Need to Visit Nurse or Tech 3rd Time? (For Flight/Occupationa Medicine Patients)

	Obs Count	Total Count	TRUE	FALSE
Flight Medicine	1	1	100%	0%
Occupational Medicine	1	3	33%	67%

Need to See Optometrist? (For Flight/Occupationa Medicine Patients)

	Obs Count	Total Count	TRUE	FALSE
See Optometrist	7	283	2%	98%

Need Follow Up Appointment? (For Flight/Occupationa Medicine Patients)

	Obs Count	Total Count	TRUE	FALSE
Schedule Follow Up	17	283	6%	94%

Need to Visit Lab or ECG or X Ray?

	Count	TRUE
Lab	18	6%
ECG	2	1%
X Ray	13	5%
No Visit Needed	250	88%

Also Need ECG or X Ray? (After Lab Assigned)

	Count	TRUE
ECG	2	11%
X Ray	1	6%
No Visit Needed	15	83%

Also Need X Ray? (After ECG Assigned)

	Count	TRUE
X Ray	1	50%
No Visit Needed	1	50%

Table 20: Patient Attribute Frequency Counts

Clinic Visited	Count	Percent
Audiology	68	13%
Flight Medicine	104	20%
Hearing Conservation	37	7%
Occupational Medicine	179	34%
Optometry	133	26%

Patient Type	Count	Percent
Civilian Employee	177	34%
Dependent	88	17%
Military	252	49%

Status	Count	Percent
Scheduled Appointment	474	91%
Walk In	45	9%

Table 21: Optometry Clinic Frequency Count

See Optometrist Twice?

	Obs Count	Total Count	TRUE	FALSE
See Optometrist Twice	18	133	14%	86%

Table 22: Probability Distribution Summary Table of Interarrival/Process Times (in seconds)

Create/Process Node	Distribution	Parameters	K-S Test p-value	Sample Mean	Sample Std. Dev.
Arrive System of Clinics	Weibull	k = 0.778 Lambda = 844	> 0.15	994	1550
Check In	Empirical	N/A	N/A	20	26
Prepare to See Optometrist with Nurse or Tech	Erlang	ExpMean = 292 k (int) = 2	0.0606	599	488
Visit Optometrist	Erlang	ExpMean = 790 k (int) = 2	0.0604	1700	1100
Dilation Effect Delay	Weibull	k = 0.616 Lambda = 1320	> 0.15	2020	2680
Visit Audiologist	Weibull	k = 1.34 Lambda = 1220	0.131	1870	833
Visit Hearing Conservation Technician (Hearing Conservation Clinic Only)	Exponential	Mean = 532	> 0.15	1080	495
Visit Hearing Conservation Technician (Non Hearing Conservation Clinics)	Beta	Alpha1 = 1.79 Alpha2 = 5.2	0.136	861	328
Fill Flight Medicine Paperwork	Weibull	k = 1.71 Lambda = 311	> 0.15	289	155
Fill Occupational Medicine Paperwork	Exponential	Mean = 454	> 0.15	463	472
Check Vitals	Gamma	Alpha = 575 Beta = 1.34	0.113	822	722
Perform Lab	Erlang	ExpMean = 261 k (int) = 2	0.119	574	321
Perform ECG	Exponential	Mean = 384	> 0.15	577	408
Perform X Ray	Beta	Alpha1 = 0.926 Alpha2 = 2.28	> 0.15	817	492
2nd Session with Flight Medicine Nurse or Tech	N/A	Constant = 377	N/A	N/A	N/A
2nd Session with Occupational Medicine Nurse or Tech	Exponential	Mean = 68.8	> 0.15	548	90.6
3rd Session with Flight Medicine Nurse or Tech	N/A	Constant = 634	N/A	N/A	N/A
3rd Session with Occupational Medicine Nurse or Tech	N/A	Constant = 818	N/A	N/A	N/A
See Flight Medicine Physician	Weibull	k = 1.19 Lambda = 1170	> 0.15	1260	917
See Occupational Medicine Physician	Weibull	k = 1.49 Lambda = 801	> 0.15	984	480
Make Follow Up Appointment	Weibull	k = 0.595 Lambda = 130	> 0.15	171	188

Test for Independence

The data is tested for independence. This is done to ensure that one event does not affect another. To do this, the data is tested for autocorrelation. Figure 23 to Figure 39 show the autocorrelation plots for all the input data. They all indicate having no issues with autocorrelation; the values are close to 0.0, not greater than 0.5 and not less than -0.5.

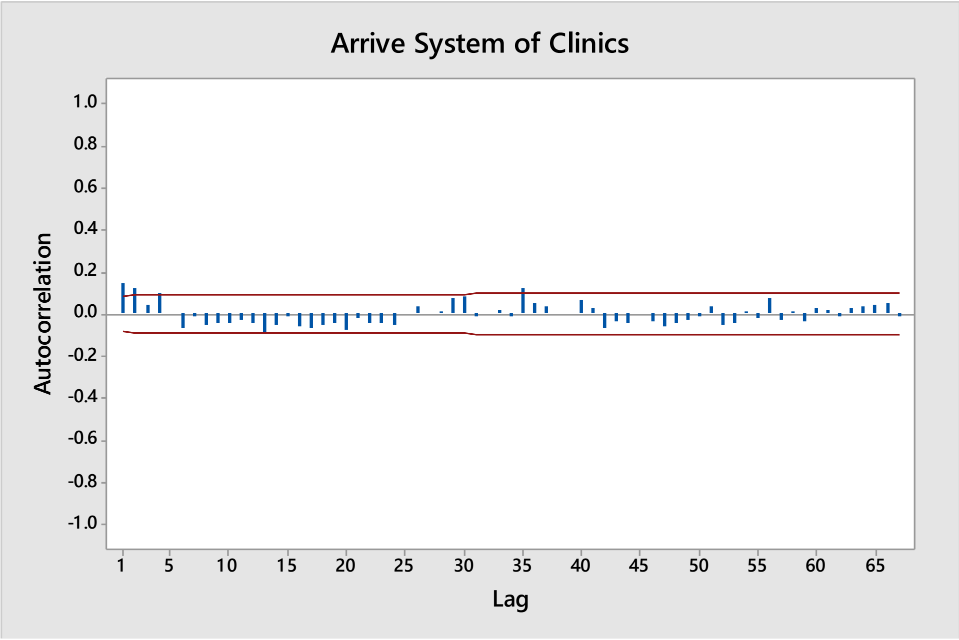


Figure 23: Autocorrelation Plot – Arrive System of Clinics

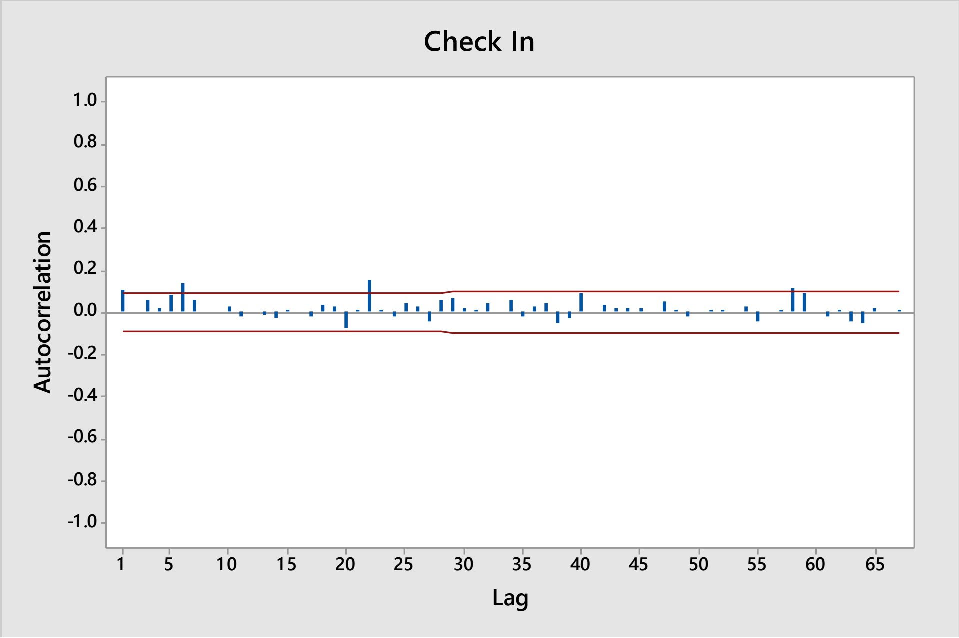


Figure 24: Autocorrelation Plot – Check In

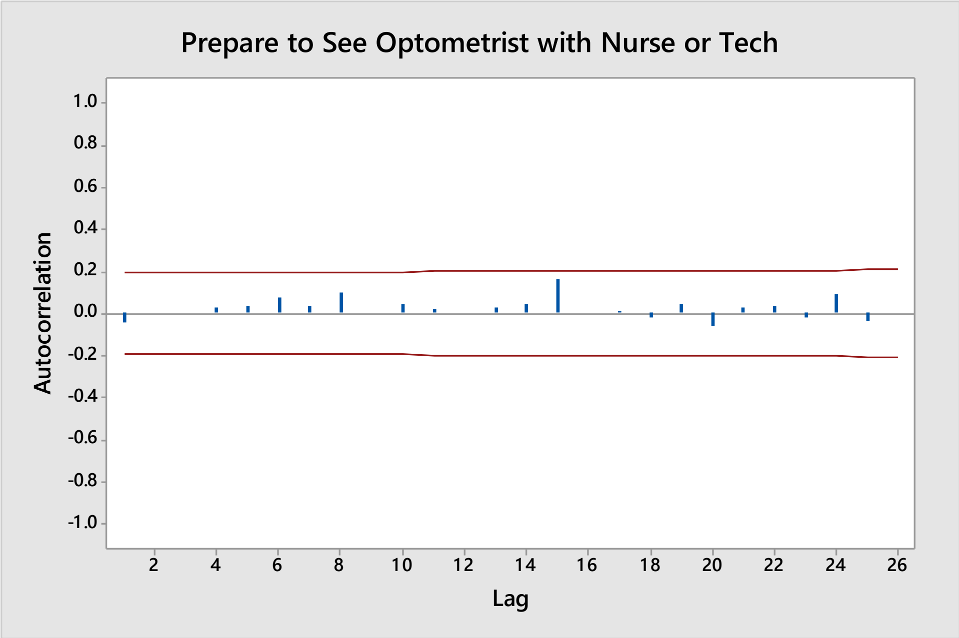


Figure 25: Autocorrelation Plot – Prepare to See Optometrist with Nurse or Tech

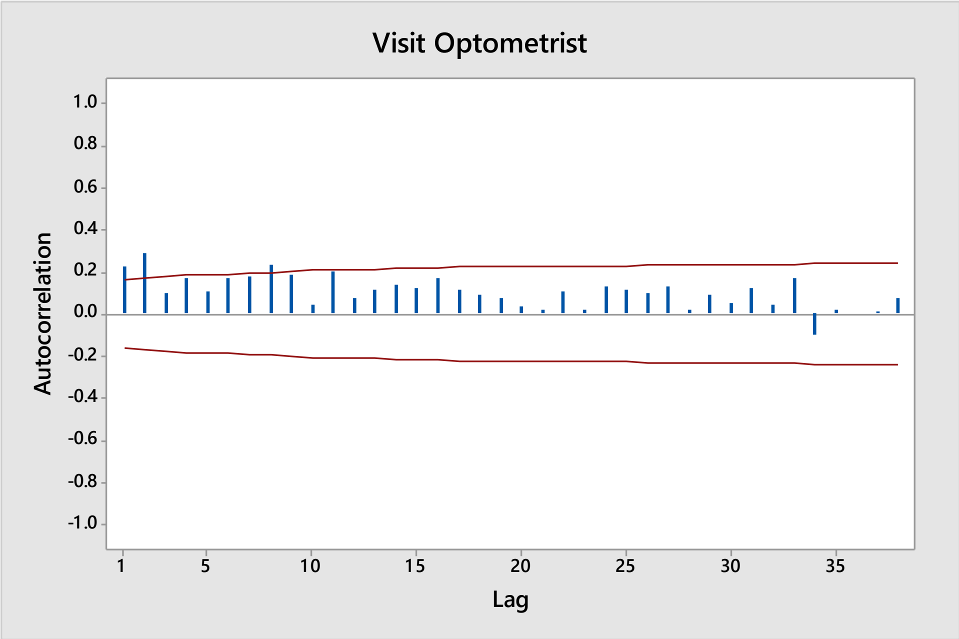


Figure 26: Autocorrelation Plot – Visit Optometrist

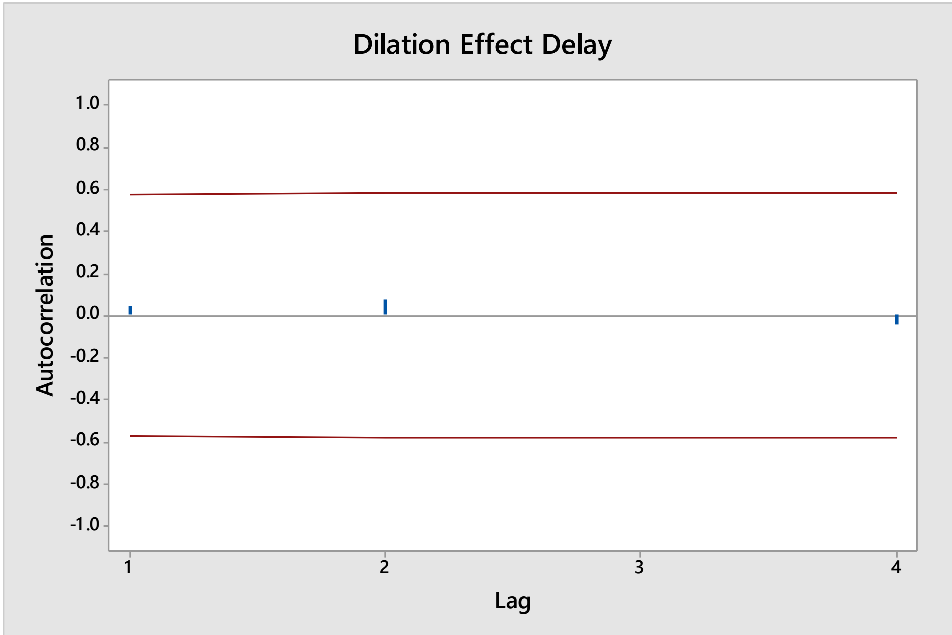


Figure 27: Autocorrelation Plot – Dilation Effect Delay

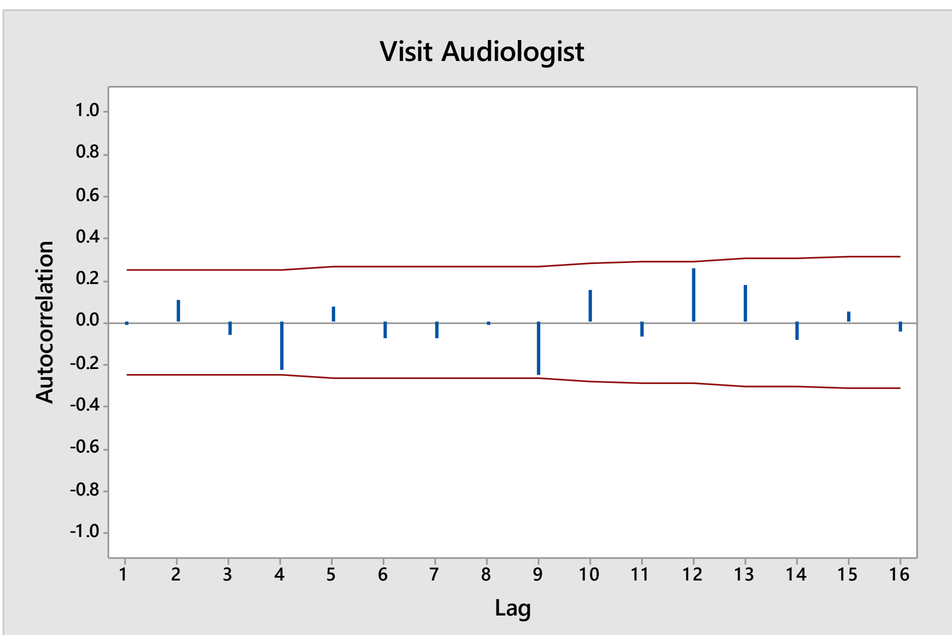


Figure 28: Autocorrelation Plot – Visit Audiologist

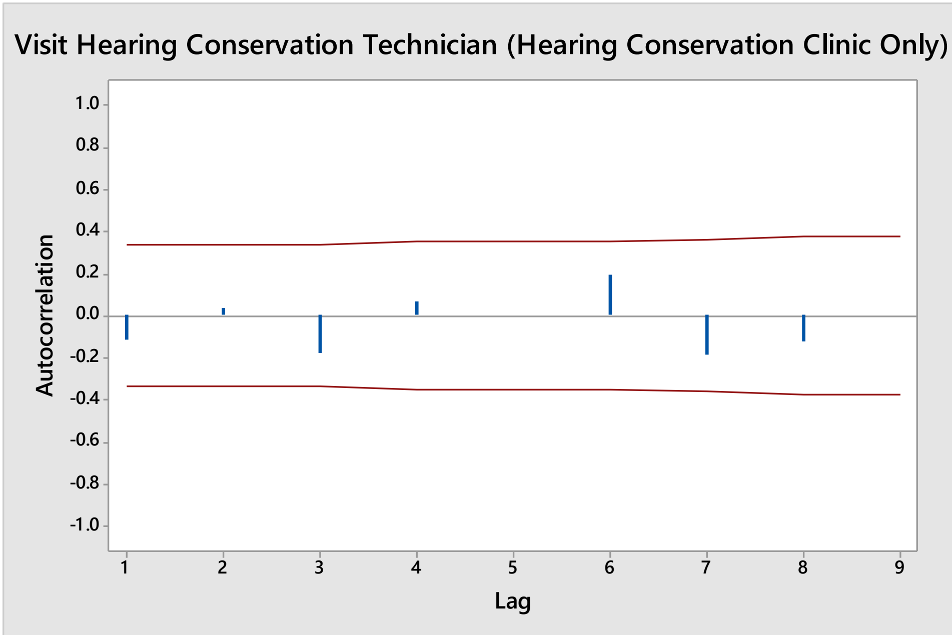


Figure 29: Autocorrelation Plot – Visit Hearing Conservation Technician (Hearing Conservation Clinic Only)

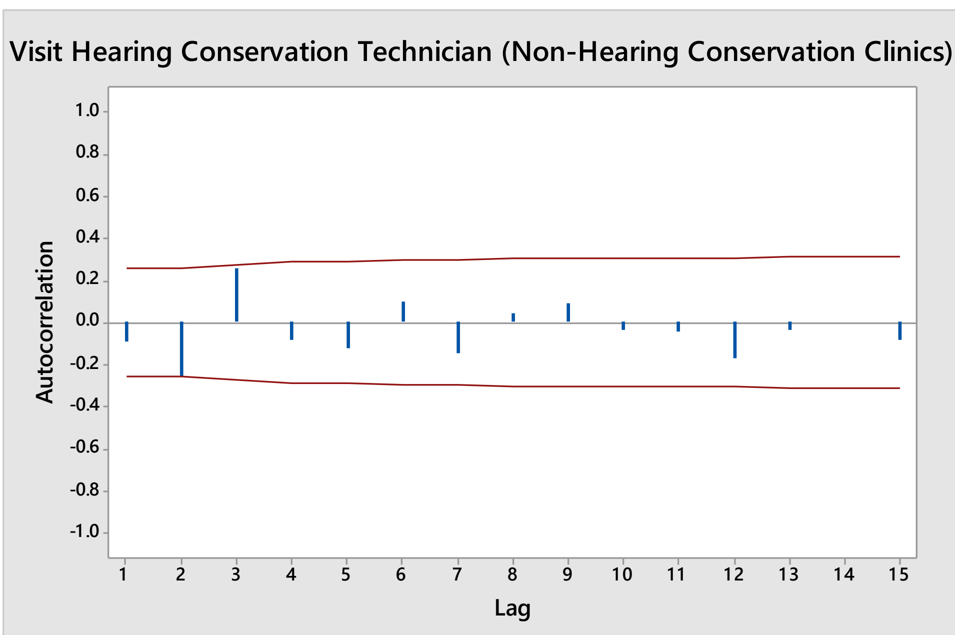


Figure 30: Autocorrelation Plot – Visit Hearing Conservation Technician (Non-Hearing Conservation Clinics)

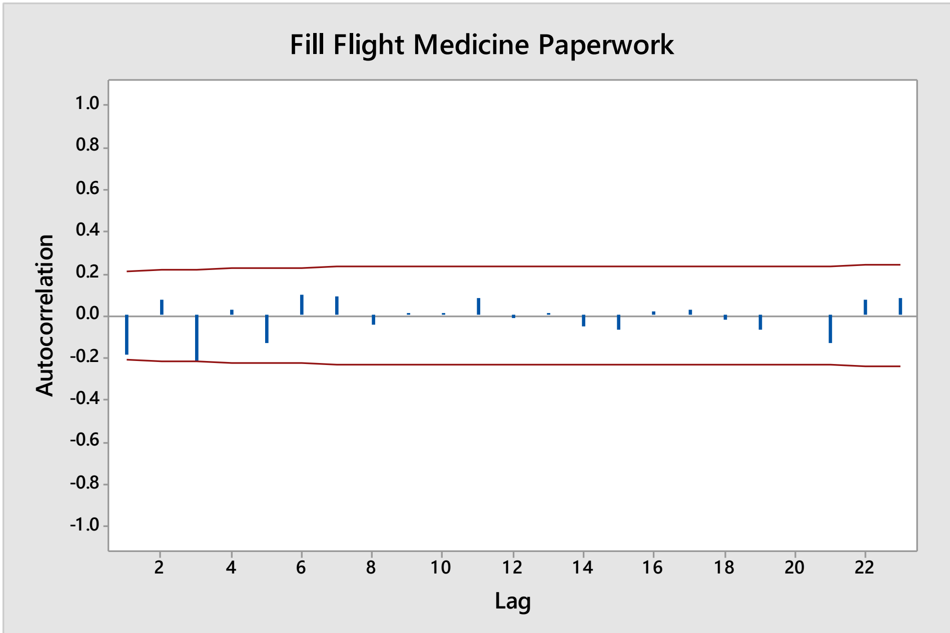


Figure 31: Autocorrelation Plot – Fill Flight Medicine Paperwork

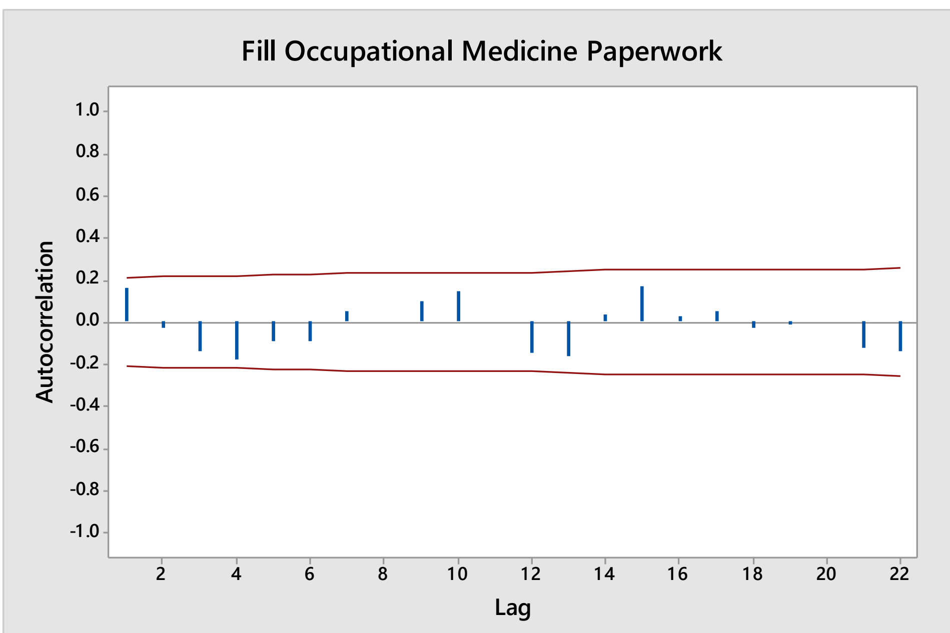


Figure 32: Autocorrelation Plot – Fill Occupational Medicine Paperwork

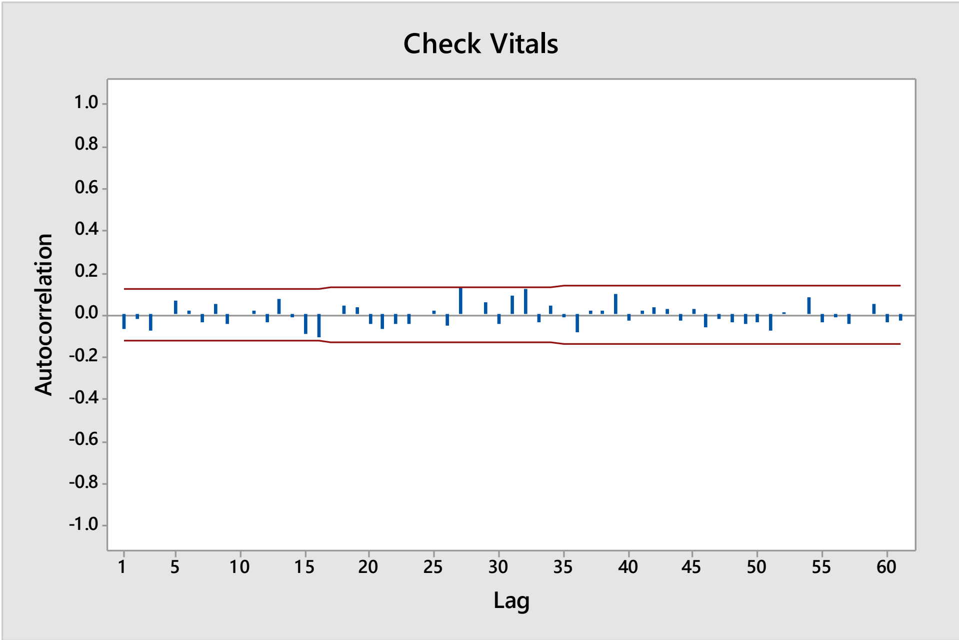


Figure 33: Autocorrelation Plot – Check Vitals

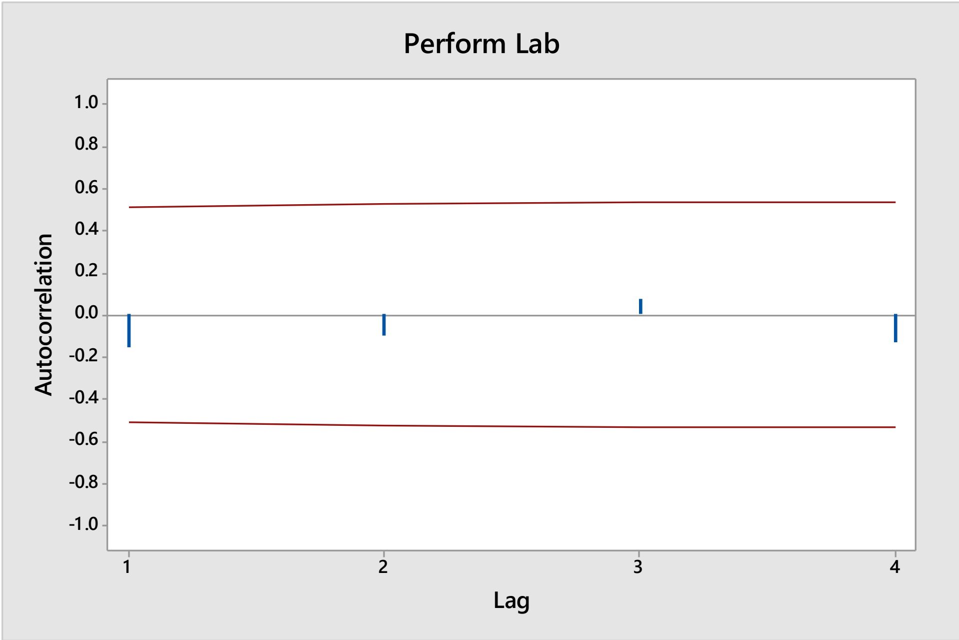


Figure 34: Autocorrelation Plot – Perform Lab

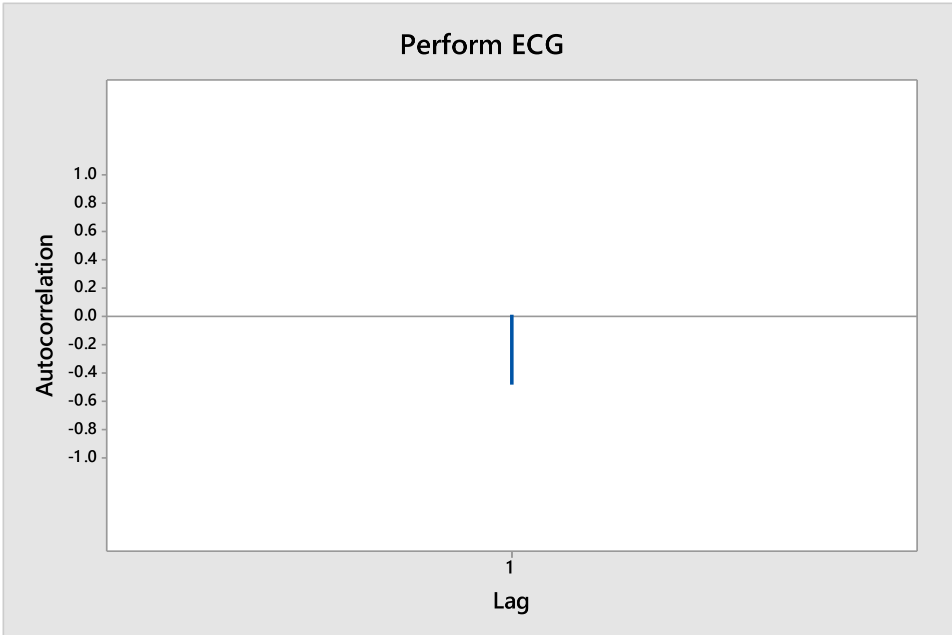


Figure 35: Autocorrelation Plot – Perform ECG

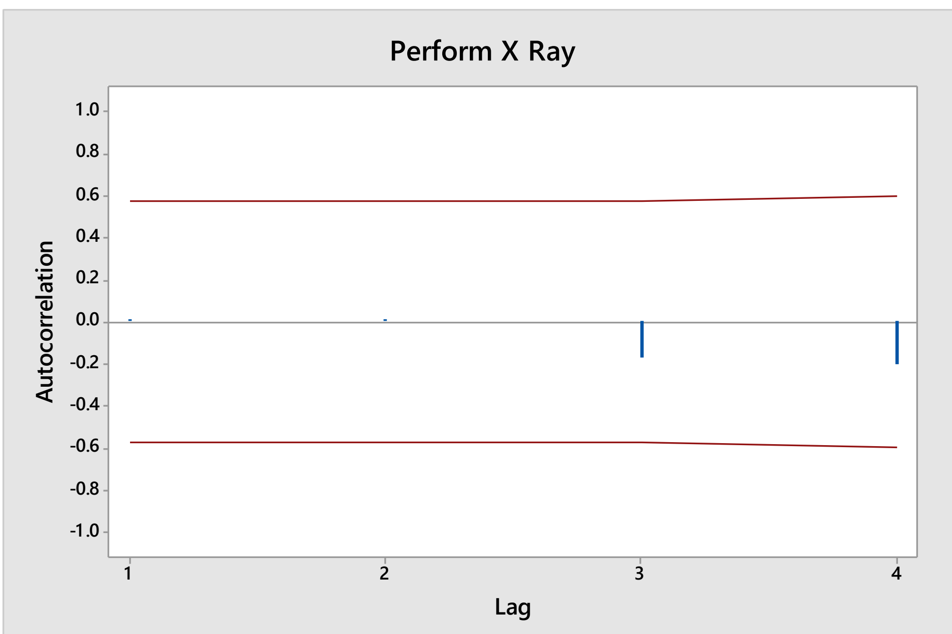


Figure 36: Autocorrelation Plot – Perform X Ray

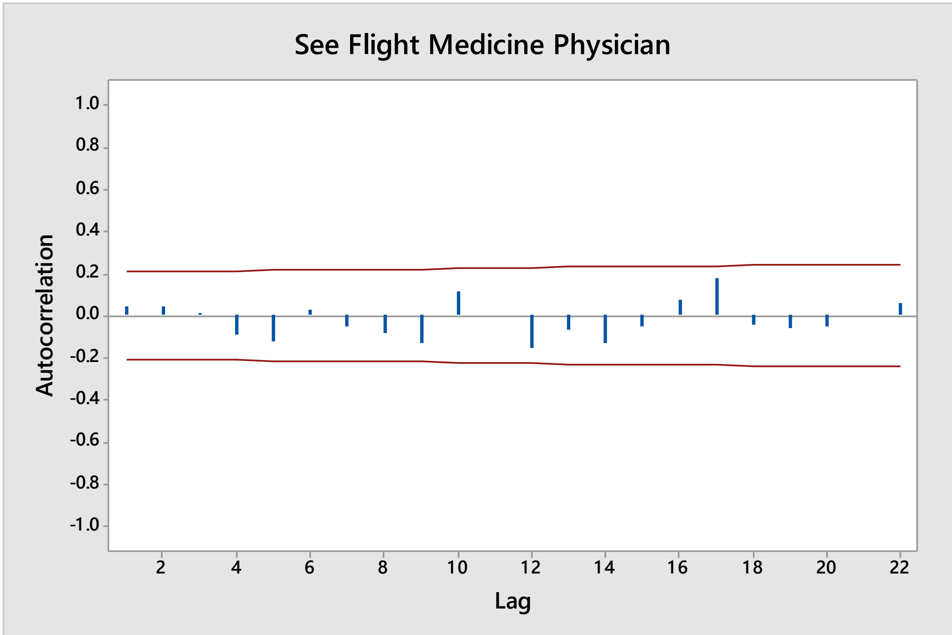


Figure 37: Autocorrelation Plot – See Flight Medicine Physician

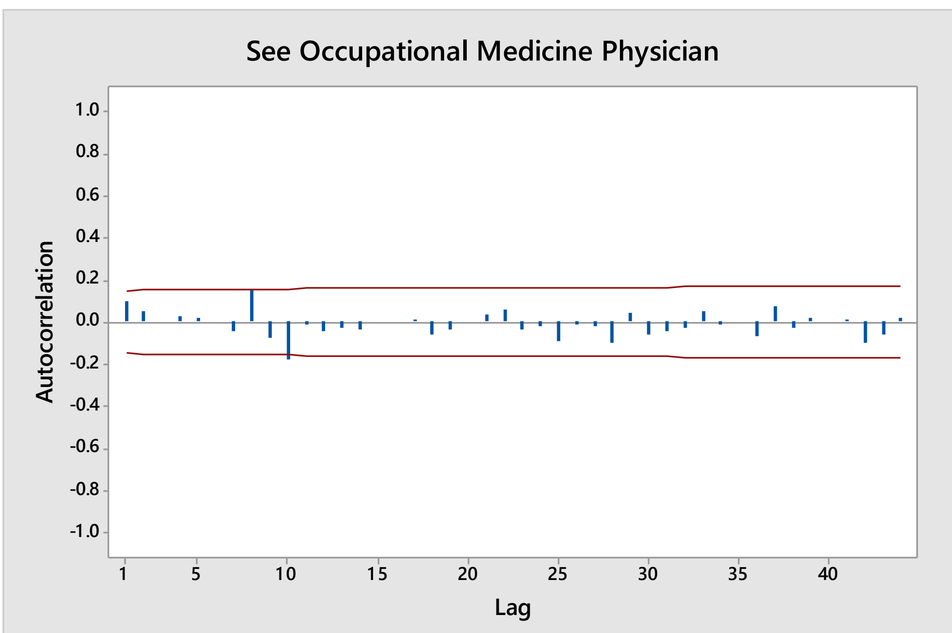


Figure 38: Autocorrelation Plot – See Occupational Medicine Physician

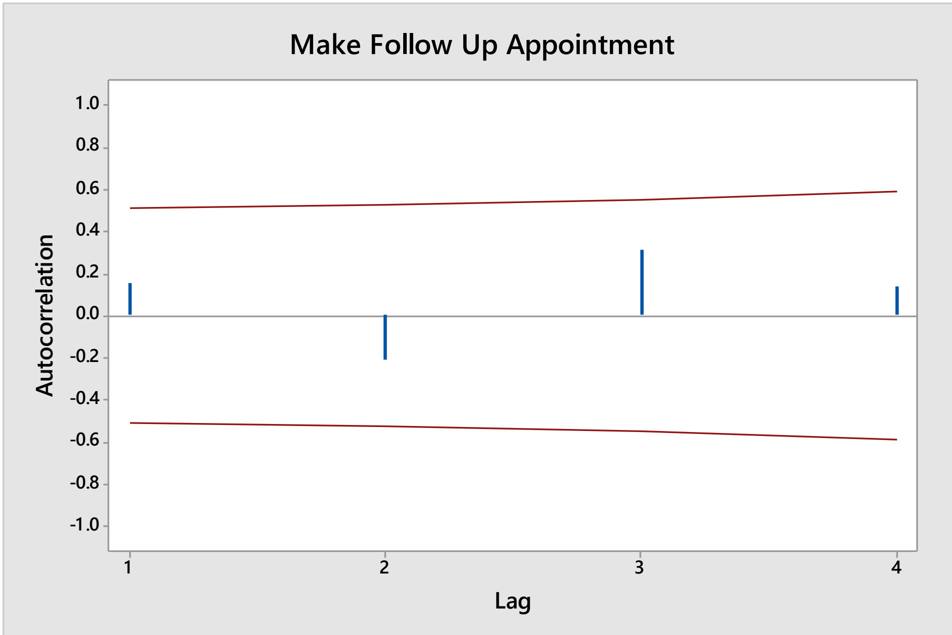


Figure 39: Autocorrelation Plot – Make Follow Up Appointment

Test for Homogeneity

Homogeneity is a mathematical term used to describe data that are identically distributed. To test for this, a visual inspection of the histogram is performed to ensure that the distribution being fitted is unimodal. This indicates that the observations from the data collected come from the same probability distribution. The histograms are shown in each of the input data theoretical distribution sections.

Goodness-of-Fit Test

A goodness-of-fit test is used to determine if the data collected from the system of clinics can be represented by a theoretical distribution once the data is tested for independence and homogeneity. This is done by conducting a hypothesis test. The null hypothesis states that the fitted theoretical distribution is statistically similar to the empirical data. The alternative hypothesis states that the fitted theoretical distribution is not statistically similar to the empirical data. The objective outcome of this test is to find a theoretical distribution that fails to reject the null hypothesis at the confidence level of alpha being 0.05 ($\alpha = 0.05$). The Kolmogorov-Smirnov test is the type of goodness-of-fit test that is used for this study. Since $\alpha = 0.05$, the null hypothesis is rejected if the p-value of the Kolmogorov-Smirnov test is less than 0.05. This concludes that the theoretical distribution being fitted is not statistically similar to what is observed in the data collected. If the p-value of the Kolmogorov-Smirnov test is greater than or equal to 0.05, then the null hypothesis is not rejected. This concludes that the theoretical distribution being fitted is statistically similar to what is observed in the data collected. For our purposes, this latter outcome is desired.

Theoretical Distribution - Interarrival Time

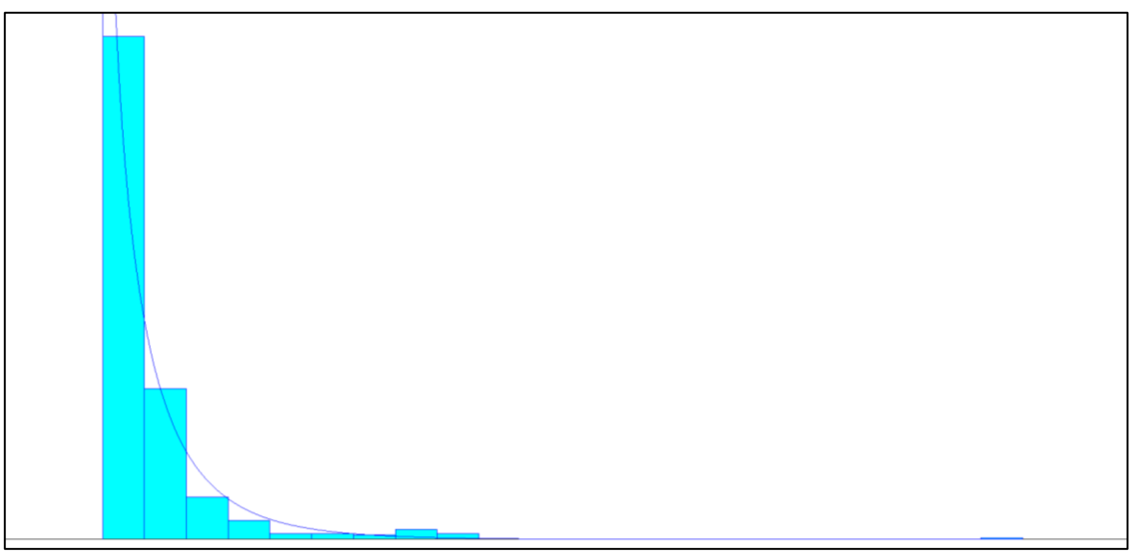


Figure 40: Interarrival Time – Histogram

```
Function        Sq Error
------------------------
Weibull        0.00181
Lognormal      0.00383
Beta           0.00767
Erlang         0.00926
Exponential    0.00926
Gamma          0.00951
Normal         0.226
Triangular     0.412
Uniform        0.452
```

Figure 41: Interarrival Time - Fit All Summary

```
        Distribution Summary

Distribution:   Weibull
Expression:     -0.001 + WEIB(844, 0.778)
Square Error:   0.001761

Chi Square Test
  Number of intervals   = 6
  Degrees of freedom    = 3
  Test Statistic        = 15.4
  Corresponding p-value < 0.005

Kolmogorov-Smirnov Test
  Test Statistic        = 0.0413
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points   = 516
Min Data Value          = 0
Max Data Value          = 1.99e+004
Sample Mean             = 994
Sample Std Dev          = 1.55e+003

        Histogram Summary

Histogram Range         = -0.001 to 1.99e+004
Number of Intervals     = 22
```

Figure 42: Interarrival Time – Weibull Distribution Summary

Theoretical Distribution - Check In Time

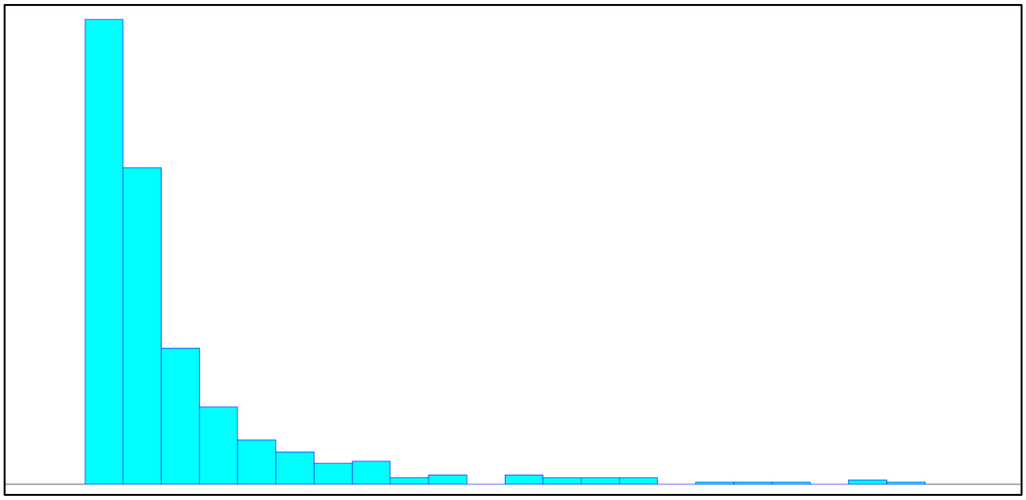


Figure 43: Check In Time – Histogram

Table 23: Check In Time – Empirical Distribution Summary

Full ARENA Expression
CONT (0, 0, 0.0119521912350598, 1, 0.0318725099601594, 3, 0.099601593625498, 4, 0.187250996015936, 5, 0.250996015936255, 6, 0.332669322709163, 7, 0.394422310756972, 8, 0.448207171314741, 9, 0.48804780876494, 10, 0.543824701195219, 11, 0.579681274900398, 12, 0.603585657370518, 13, 0.635458167330677, 14, 0.649402390438247, 15, 0.663346613545817, 16, 0.689243027888446, 17, 0.703187250996016, 18, 0.719123505976096, 19, 0.743027888446215, 20, 0.754980079681275, 21, 0.764940239043825, 22, 0.772908366533865, 23, 0.778884462151394, 24, 0.788844621513944, 25, 0.798804780876494, 26, 0.808764940239044, 27, 0.812749003984064, 28, 0.816733067729084, 29, 0.830677290836653, 30, 0.834661354581673, 31, 0.844621513944223, 32, 0.846613545816733, 34, 0.852589641434263, 36, 0.860557768924303, 37, 0.866533864541833, 38, 0.876494023904382, 39, 0.882470119521912, 40, 0.888446215139442, 41, 0.896414342629482, 42, 0.904382470119522, 43, 0.906374501992032, 44, 0.910358565737052, 49, 0.912350597609562, 50, 0.914342629482072, 51, 0.918326693227092, 53, 0.924302788844621, 54, 0.926294820717131, 55, 0.928286852589641, 56, 0.930278884462151, 58, 0.932270916334661, 59, 0.940239043824701, 60, 0.942231075697211, 61, 0.944223107569721, 62, 0.946215139442231, 64, 0.948207171314741, 65, 0.950199203187251, 67, 0.952191235059761, 68, 0.954183266932271, 72, 0.958167330677291, 76, 0.962151394422311, 81, 0.964143426294821, 90, 0.966135458167331, 93, 0.968127490039841, 94, 0.970119521912351, 95, 0.972111553784861, 100, 0.97609561752988, 102, 0.97808764940239, 107, 0.9800796812749, 113, 0.98207171314741, 114, 0.98605577689243, 118, 0.98804780876494, 120, 0.99003984063745, 134, 0.99203187250996, 144, 0.99402390438247, 154, 0.99601593625498, 167, 0.99800796812749, 170, 1, 180)

mean = 20
std. dev. = 26

Theoretical Distribution - Prepare to See Optometrist with Nurse or Tech Time

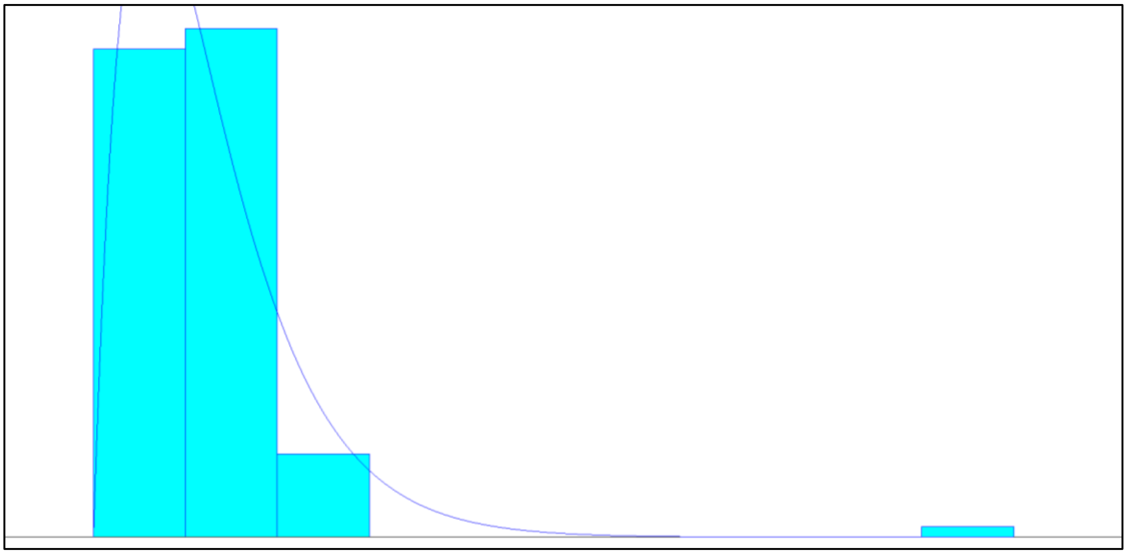


Figure 44: Prepare to See Optometrist with Nurse or Tech Time – Histogram

Function	Sq Error
Erlang	0.0175
Weibull	0.0229
Gamma	0.0232
Beta	0.0428
Normal	0.0477
Exponential	0.064
Lognormal	0.0913
Triangular	0.3
Uniform	0.324

Figure 45: Prepare to See Optometrist with Nurse or Tech Time - Fit All Summary

```
        Distribution Summary

Distribution:   Erlang
Expression:     15 + ERLA(292, 2)
Square Error:   0.017503

Chi Square Test
  Number of intervals   = 3
  Degrees of freedom    = 0
  Test Statistic        = 9.93
  Corresponding p-value < 0.005

Kolmogorov-Smirnov Test
  Test Statistic        = 0.128
  Corresponding p-value = 0.0606

        Data Summary

Number of Data Points   = 105
Min Data Value          = 15
Max Data Value          = 4.75e+003
Sample Mean             = 599
Sample Std Dev          = 488

        Histogram Summary

Histogram Range         = 15 to 4.75e+003
Number of Intervals     = 10
```

Figure 46: Prepare to See Optometrist with Nurse or Tech Time – Erlang Distribution Summary

Theoretical Distribution - Visit Optometrist Time

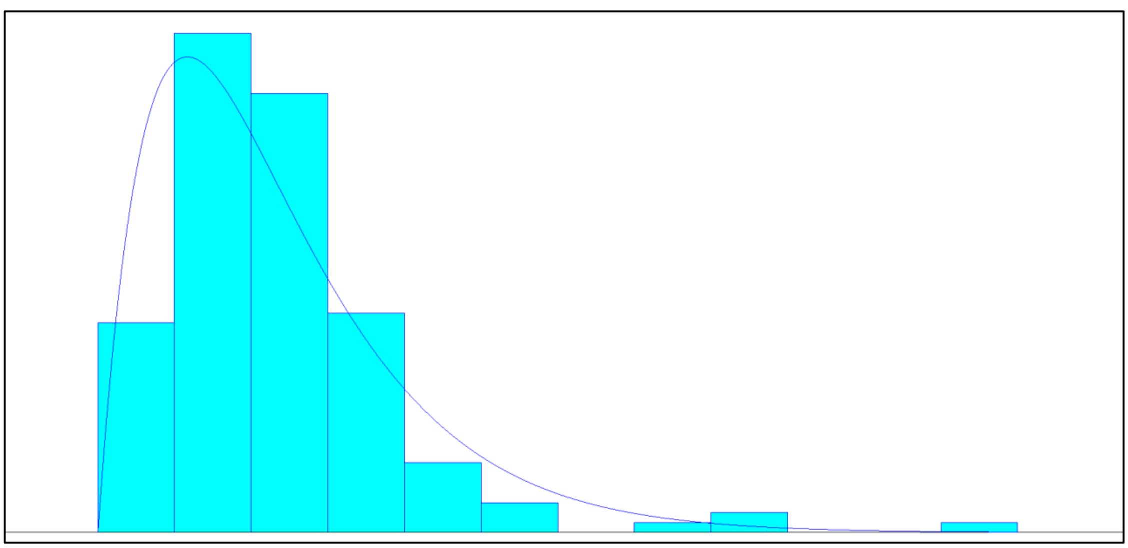


Figure 47: Visit Optometrist Time – Histogram

Function	Sq Error
Erlang	0.0137
Weibull	0.017
Gamma	0.0191
Normal	0.0218
Beta	0.0228
Exponential	0.0795
Triangular	0.0874
Lognormal	0.0948
Uniform	0.155

Figure 48: Visit Optometrist Time - Fit All Summary

```
        Distribution Summary

Distribution:   Erlang
Expression:     120 + ERLA(790, 2)
Square Error:   0.013685

Chi Square Test
  Number of intervals   = 6
  Degrees of freedom    = 3
  Test Statistic        = 13.1
  Corresponding p-value < 0.005

Kolmogorov-Smirnov Test
  Test Statistic        = 0.107
  Corresponding p-value = 0.0604

        Data Summary

Number of Data Points   = 151
Min Data Value          = 120
Max Data Value          = 8.26e+003
Sample Mean             = 1.7e+003
Sample Std Dev          = 1.1e+003

        Histogram Summary

Histogram Range         = 120 to 8.26e+003
Number of Intervals     = 12
```

Figure 49: Visit Optometrist Time – Erlang Distribution Summary

Theoretical Distribution - Dilation Effect Delay Time

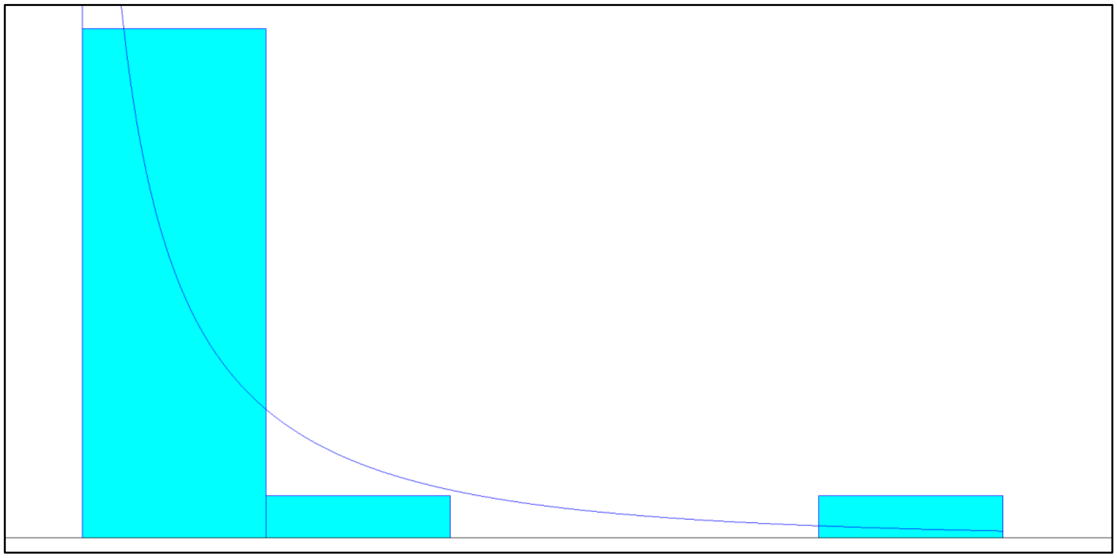


Figure 50: Dilation Effect Delay Time – Histogram

Function	Sq Error
Weibull	0.025
Exponential	0.0489
Erlang	0.0489
Gamma	0.0845
Beta	0.107
Lognormal	0.217
Normal	0.364
Triangular	0.448
Uniform	0.545

Figure 51: Dilation Effect Delay Time - Fit All Summary

```
        Distribution Summary

Distribution:   Weibull
Expression:     300 + WEIB(1.32e+003, 0.616)
Square Error:   0.025049


Kolmogorov-Smirnov Test
  Test Statistic          = 0.26
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points   = 14
Min Data Value          = 300
Max Data Value          = 1.09e+004
Sample Mean             = 2.02e+003
Sample Std Dev          = 2.68e+003

        Histogram Summary

Histogram Range         = 300 to 1.09e+004
Number of Intervals     = 5
```

Figure 52: Dilation Effect Delay Time – Weibull Distribution Summary

Theoretical Distribution - Visit Audiologist Time

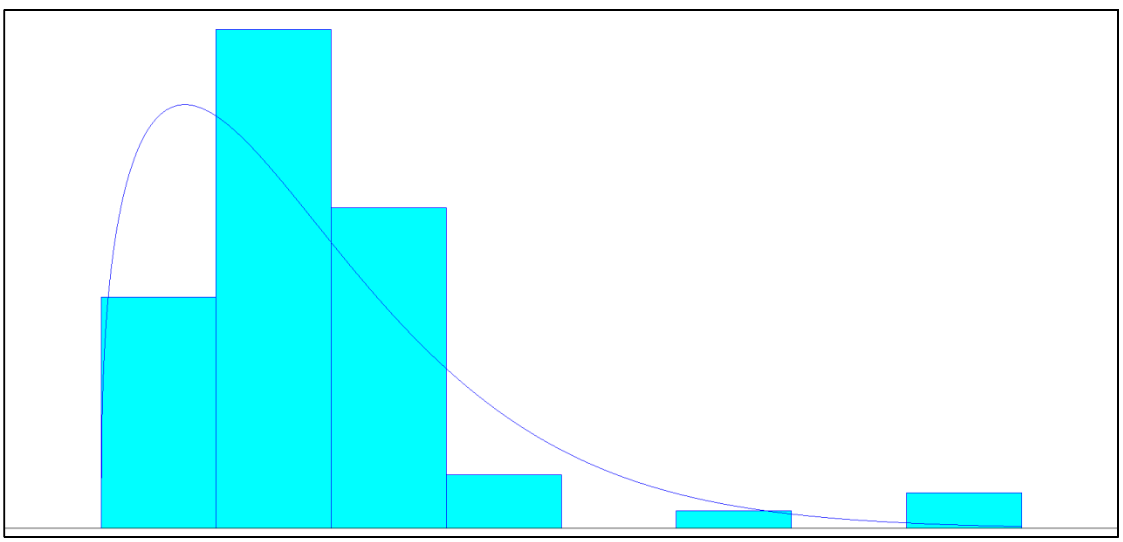


Figure 53: Visit Audiologist Time – Histogram

```
Function       Sq Error
-----------------------
Normal        0.037
Weibull       0.0447
Beta          0.0549
Gamma         0.0583
Exponential   0.104
Erlang        0.104
Triangular    0.105
Lognormal     0.176
Uniform       0.181
```

Figure 54: Visit Audiologist Time - Fit All Summary

```
        Distribution Summary

Distribution:   Weibull
Expression:     736 + WEIB(1.22e+003, 1.34)
Square Error:   0.044677

Chi Square Test
  Number of intervals   = 4
  Degrees of freedom    = 1
  Test Statistic        = 16.2
  Corresponding p-value < 0.005

Kolmogorov-Smirnov Test
  Test Statistic        = 0.143
  Corresponding p-value = 0.131

        Data Summary

Number of Data Points   = 65
Min Data Value          = 736
Max Data Value          = 5.61e+003
Sample Mean             = 1.87e+003
Sample Std Dev          = 833

        Histogram Summary

Histogram Range         = 736 to 5.61e+003
Number of Intervals     = 8
```

Figure 55: Visit Audiologist Time – Weibull Distribution Summary

Theoretical Distribution - Visit Hearing Conservation Technician (Hearing Conservation Clinic Only) Time

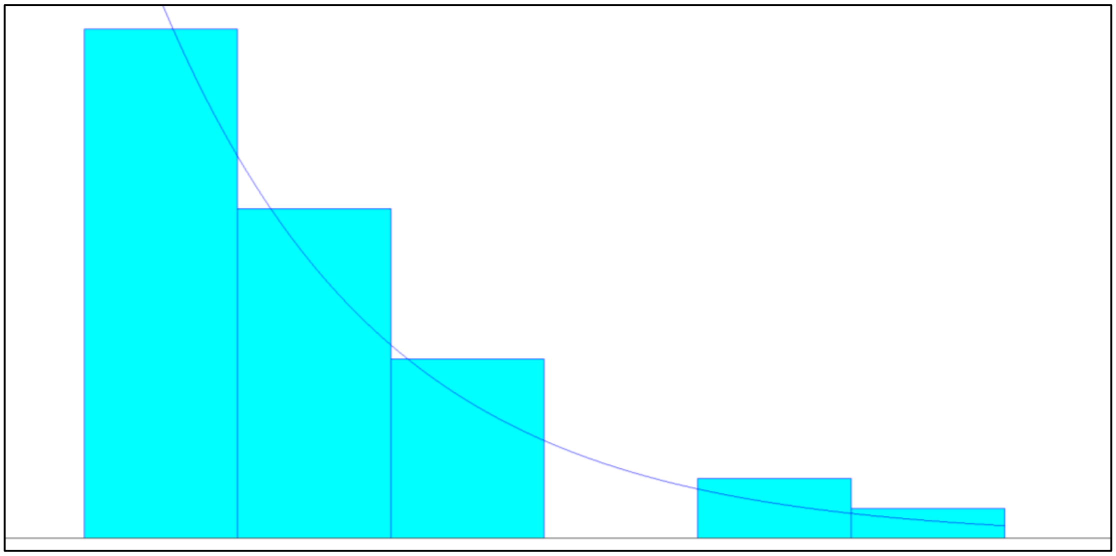


Figure 56: Visit Hearing Conservation Technician (Hearing Conservation Clinic Only) Time – Histogram

Function	Sq Error
Erlang	0.00943
Exponential	0.00943
Weibull	0.0113
Gamma	0.0127
Beta	0.0207
Lognormal	0.0469
Normal	0.0682
Triangular	0.0745
Uniform	0.163

Figure 57: Visit Hearing Conservation Technician (Hearing Conservation Clinic Only) Time - Fit All Summary

```
        Distribution Summary

Distribution:   Exponential
Expression:     547 + EXPO(532)
Square Error:   0.009430

Chi Square Test
  Number of intervals   = 3
  Degrees of freedom    = 1
  Test Statistic        = 0.58
  Corresponding p-value = 0.464

Kolmogorov-Smirnov Test
  Test Statistic        = 0.0851
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points   = 37
Min Data Value          = 547
Max Data Value          = 2.73e+003
Sample Mean             = 1.08e+003
Sample Std Dev          = 495

        Histogram Summary

Histogram Range         = 547 to 2.73e+003
Number of Intervals     = 6
```

Figure 58: Visit Hearing Conservation Technician (Hearing Conservation Clinic Only)

Time – Exponential Distribution Summary

Theoretical Distribution - Visit Hearing Conservation Technician (Non Hearing Conservation Clinics) Time

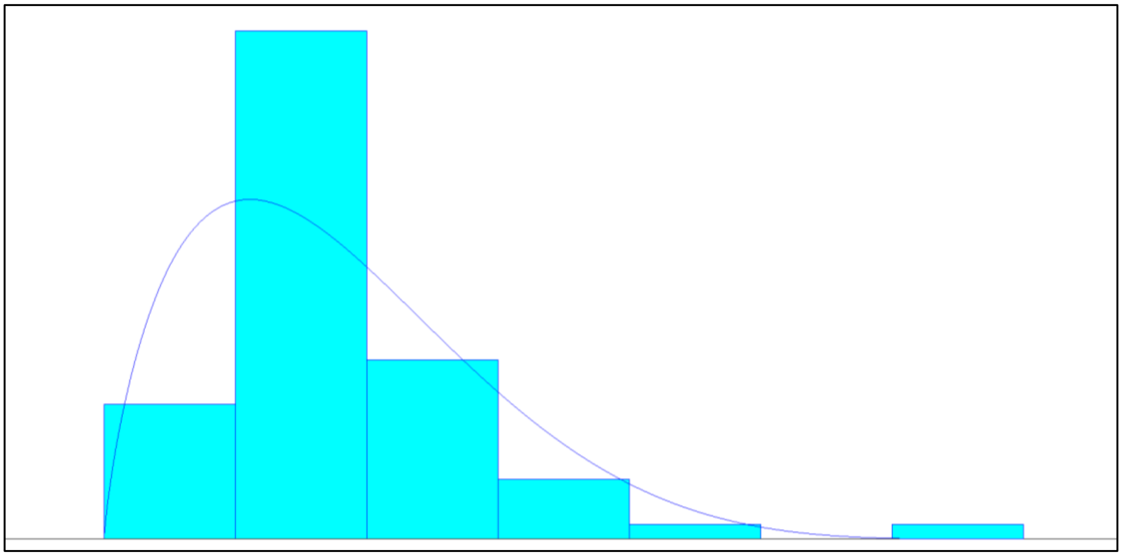


Figure 59: Visit Hearing Conservation Technician (Non Hearing Conservation Clinics) Time – Histogram

Function	Sq Error
Normal	0.0572
Beta	0.0613
Weibull	0.0699
Erlang	0.0713
Gamma	0.0974
Triangular	0.128
Exponential	0.181
Uniform	0.233
Lognormal	0.258

Figure 60: Visit Hearing Conservation Technician (Non Hearing Conservation Clinics) Time - Fit All Summary

```
        Distribution Summary

Distribution:   Beta
Expression:     317 + 2.12e+003 * BETA(1.79, 5.2)
Square Error:   0.061334

Chi Square Test
  Number of intervals   = 4
  Degrees of freedom    = 1
  Test Statistic        = 13
  Corresponding p-value < 0.005

Kolmogorov-Smirnov Test
  Test Statistic        = 0.146
  Corresponding p-value = 0.136

        Data Summary

Number of Data Points   = 61
Min Data Value          = 317
Max Data Value          = 2.44e+003
Sample Mean             = 861
Sample Std Dev          = 328

        Histogram Summary

Histogram Range         = 317 to 2.44e+003
Number of Intervals     = 7
```

Figure 61: Visit Hearing Conservation Technician (Non Hearing Conservation Clinics)

Time – Beta Distribution Summary

Theoretical Distribution - Fill Flight Medicine Paperwork Time

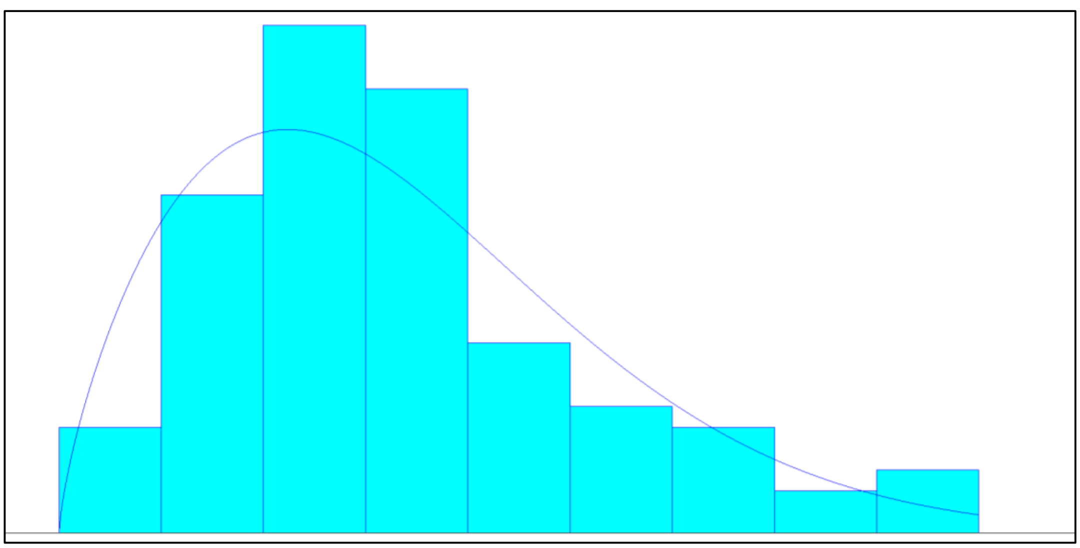


Figure 62: Fill Flight Medicine Paperwork Time – Histogram

Function	Sq Error
Weibull	0.0103
Beta	0.0149
Triangular	0.0149
Erlang	0.0159
Gamma	0.0167
Normal	0.0176
Uniform	0.0644
Exponential	0.0717
Lognormal	0.0872

Figure 63: Fill Flight Medicine Paperwork Time - Fit All Summary

```
        Distribution Summary

Distribution:   Weibull
Expression:     7 + WEIB(311, 1.71)
Square Error:   0.010305

Chi Square Test
  Number of intervals   = 5
  Degrees of freedom    = 2
  Test Statistic        = 5.02
  Corresponding p-value = 0.0852

Kolmogorov-Smirnov Test
  Test Statistic        = 0.0866
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points   = 91
Min Data Value          = 7
Max Data Value          = 756
Sample Mean             = 289
Sample Std Dev          = 155

        Histogram Summary

Histogram Range         = 7 to 756
Number of Intervals     = 9
```

Figure 64: Fill Flight Medicine Paperwork Time – Weibull Distribution Summary

Theoretical Distribution - Fill Occupational Medicine Paperwork Time

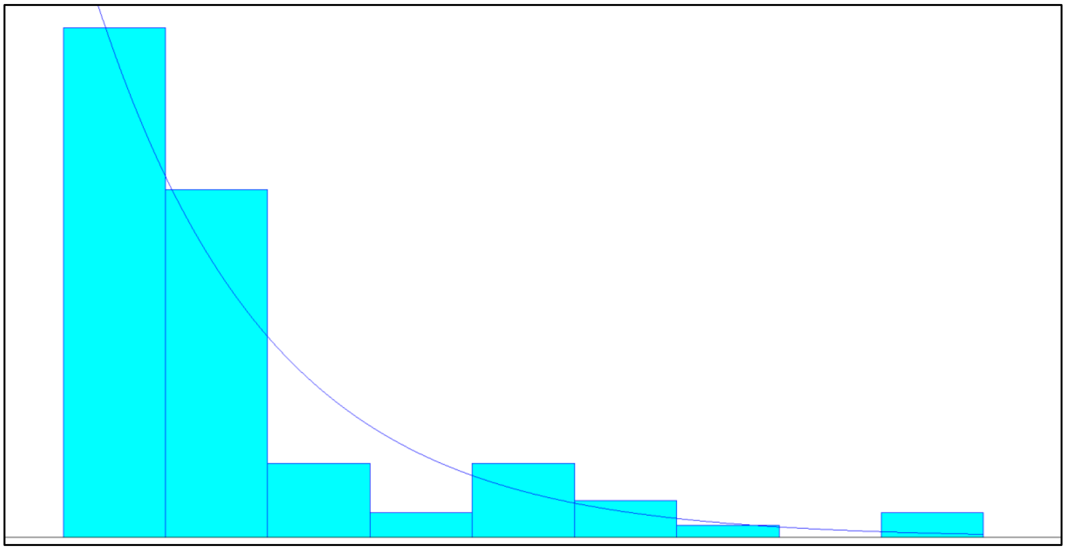


Figure 65: Fill Occupational Medicine Paperwork Time – Histogram

Function	Sq Error
Erlang	0.0138
Exponential	0.0138
Weibull	0.014
Gamma	0.0148
Lognormal	0.0265
Beta	0.0275
Normal	0.12
Triangular	0.138
Uniform	0.211

Figure 66: Fill Occupational Medicine Paperwork Time - Fit All Summary

```
        Distribution Summary

Distribution:   Exponential
Expression:     9 + EXPO(454)
Square Error:   0.013758

Chi Square Test
  Number of intervals   = 4
  Degrees of freedom    = 2
  Test Statistic        = 5.54
  Corresponding p-value = 0.0662

Kolmogorov-Smirnov Test
  Test Statistic        = 0.116
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points   = 89
Min Data Value          = 9
Max Data Value          = 2.41e+003
Sample Mean             = 463
Sample Std Dev          = 472

        Histogram Summary

Histogram Range         = 9 to 2.41e+003
Number of Intervals     = 9
```

Figure 67: Fill Occupational Medicine Paperwork Time – Exponential Distribution Summary

Theoretical Distribution - Check Vitals Time

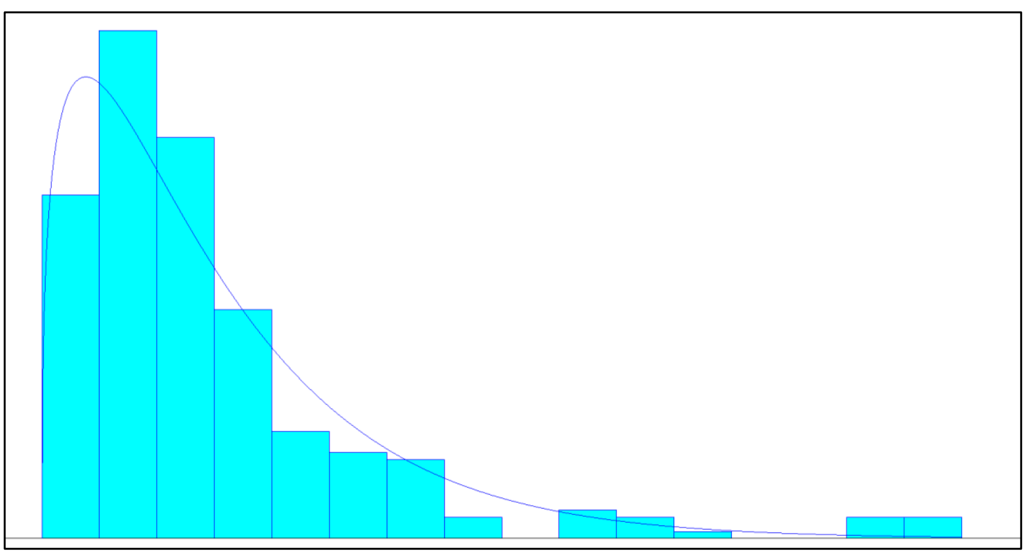


Figure 68: Check Vitals Time – Histogram

Function	Sq Error
Gamma	0.00745
Weibull	0.00975
Erlang	0.0209
Exponential	0.0209
Lognormal	0.0243
Beta	0.0291
Normal	0.0443
Triangular	0.0735
Uniform	0.113

Figure 69: Check Vitals Time - Fit All Summary

```
        Distribution Summary

Distribution:   Gamma
Expression:     51 + GAMM(575, 1.34)
Square Error:   0.007450

Chi Square Test
  Number of intervals   = 8
  Degrees of freedom    = 5
  Test Statistic        = 17.4
  Corresponding p-value < 0.005

Kolmogorov-Smirnov Test
  Test Statistic        = 0.0737
  Corresponding p-value = 0.113

        Data Summary

Number of Data Points   = 262
Min Data Value          = 51
Max Data Value          = 4.17e+003
Sample Mean             = 822
Sample Std Dev          = 722

        Histogram Summary

Histogram Range         = 51 to 4.17e+003
Number of Intervals     = 16
```

Figure 70: Check Vitals Time – Distribution Summary

Theoretical Distribution - Perform Lab Time

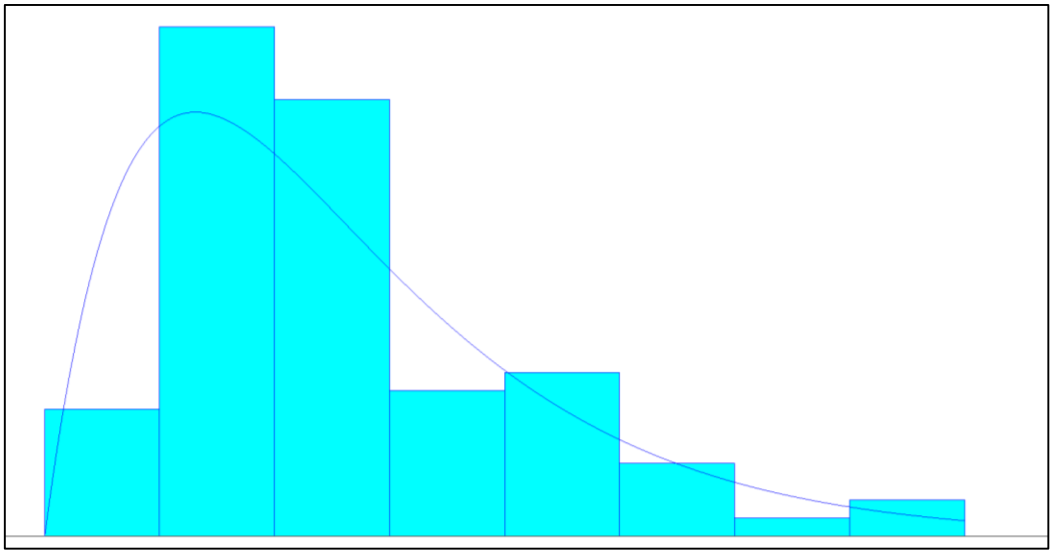


Figure 71: Perform Lab Time – Histogram

Function	Sq Error
Normal	0.184
Weibull	0.353
Beta	0.402
Triangular	0.431
Uniform	0.521
Gamma	0.523
Erlang	0.523
Exponential	0.595
Lognormal	0.619

Figure 72: Perform Lab Time - Fit All Summary

```
        Distribution Summary

Distribution:   Erlang
Expression:     52 + ERLA(261, 2)
Square Error:   0.021242

Chi Square Test
  Number of intervals   = 5
  Degrees of freedom    = 2
  Test Statistic        = 9.1
  Corresponding p-value = 0.0109

Kolmogorov-Smirnov Test
  Test Statistic        = 0.129
  Corresponding p-value = 0.119

        Data Summary

Number of Data Points   = 83
Min Data Value          = 52
Max Data Value          = 1.65e+003
Sample Mean             = 574
Sample Std Dev          = 321

        Histogram Summary

Histogram Range         = 52 to 1.65e+003
Number of Intervals     = 8
```

Figure 73: Perform Lab Time – Erlang Distribution Summary

Theoretical Distribution - Perform ECG Time

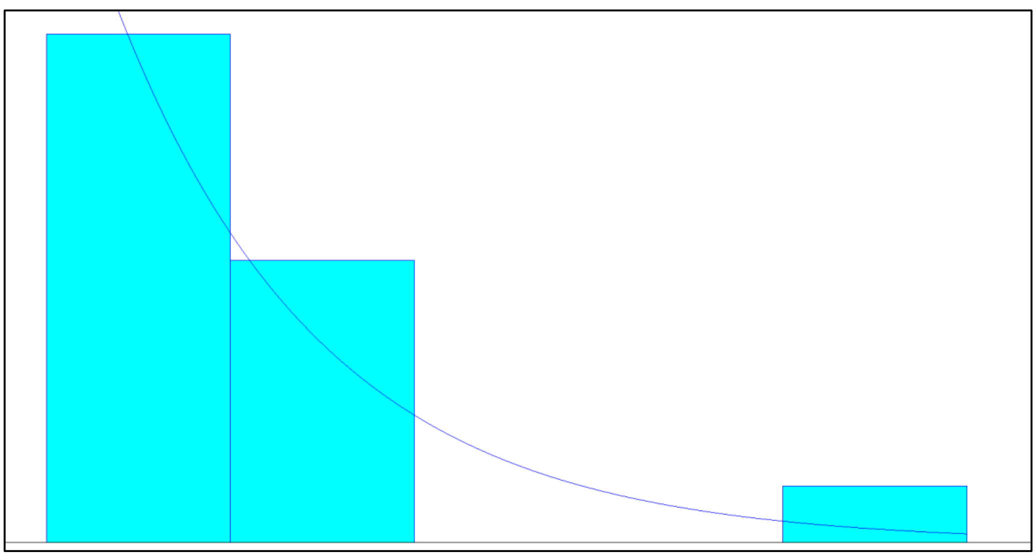


Figure 74: Perform ECG Time – Histogram

Function	Sq Error
Erlang	0.0225
Exponential	0.0225
Weibull	0.0358
Gamma	0.038
Beta	0.0768
Lognormal	0.0989
Normal	0.131
Triangular	0.165
Uniform	0.276

Figure 75: Perform ECG Time - Fit All Summary

```
        Distribution Summary

Distribution:   Exponential
Expression:     193 + EXPO(384)
Square Error:   0.022540


Kolmogorov-Smirnov Test
  Test Statistic         = 0.229
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points   = 15
Min Data Value          = 193
Max Data Value          = 1.9e+003
Sample Mean             = 577
Sample Std Dev          = 408

        Histogram Summary

Histogram Range         = 193 to 1.9e+003
Number of Intervals     = 5
```

Figure 76: Perform ECG Time – Exponential Distribution Summary

Theoretical Distribution - Perform X Ray Time

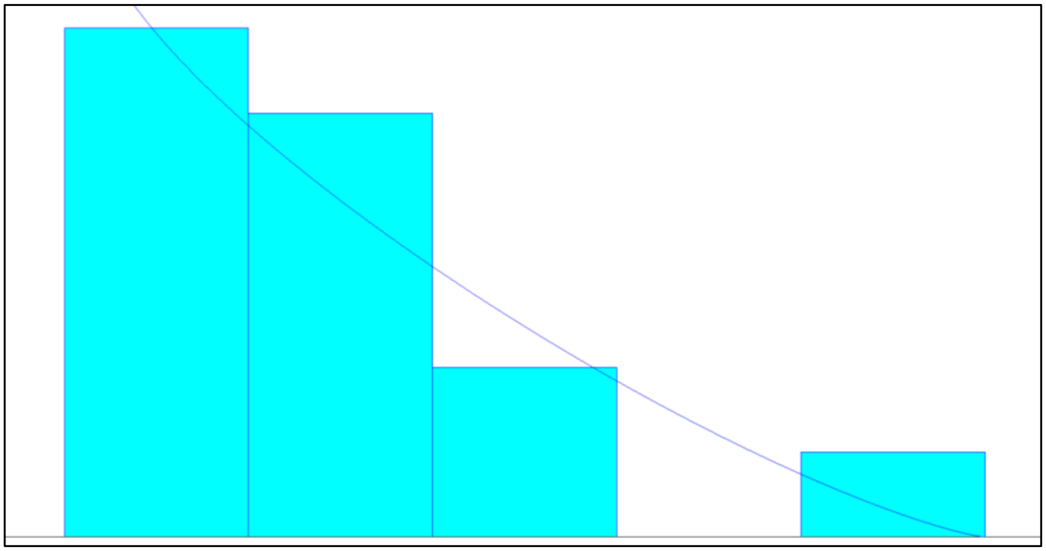


Figure 77: Perform X Ray Time – Histogram

Function	Sq Error
Beta	0.0172
Weibull	0.0176
Exponential	0.0224
Erlang	0.0224
Gamma	0.0262
Triangular	0.0464
Normal	0.0477
Lognormal	0.0759
Uniform	0.137

Figure 78: Perform X Ray Time - Fit All Summary

```
        Distribution Summary

Distribution:   Beta
Expression:     175 + 2.23e+003 * BETA(0.926, 2.28)
Square Error:   0.017191

Chi Square Test
  Number of intervals   = 3
  Degrees of freedom    = 0
  Test Statistic        = 2.75
  Corresponding p-value < 0.005

Kolmogorov-Smirnov Test
  Test Statistic        = 0.161
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points   = 28
Min Data Value          = 175
Max Data Value          = 2.4e+003
Sample Mean             = 817
Sample Std Dev          = 492

        Histogram Summary

Histogram Range         = 175 to 2.4e+003
Number of Intervals     = 5
```

Figure 79: Perform X Ray Time – Beta Distribution Summary

Theoretical Distribution - 2nd Session with Occupational Medicine Nurse or Tech Time

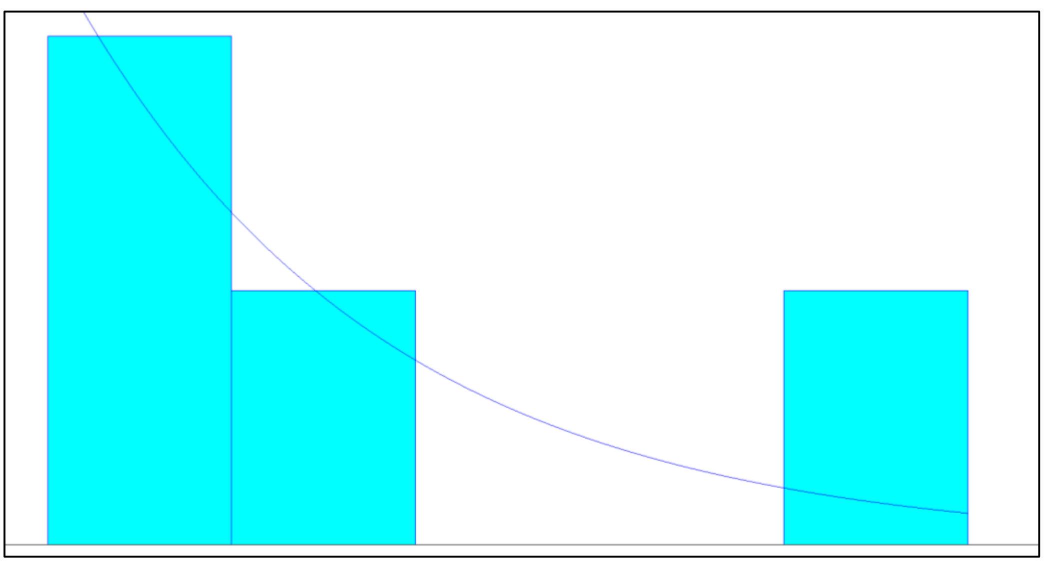


Figure 80: 2nd Session with Occupational Medicine Nurse or Tech Time – Histogram

Function	Sq Error
Erlang	0.0709
Exponential	0.0709
Gamma	0.0855
Weibull	0.108
Triangular	0.125
Lognormal	0.135
Beta	0.153
Uniform	0.175
Normal	0.196

Figure 81: 2nd Session with Occupational Medicine Nurse or Tech Time - Fit All Summary

```
        Distribution Summary

Distribution:   Exponential
Expression:     479 + EXPO(68.8)
Square Error:   0.070854


Kolmogorov-Smirnov Test
  Test Statistic         = 0.301
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points   = 4
Min Data Value          = 479
Max Data Value          = 681
Sample Mean             = 548
Sample Std Dev          = 90.6

        Histogram Summary

Histogram Range         = 479 to 681
Number of Intervals     = 5
```

Figure 82: 2nd Session with Occupational Medicine Nurse or Tech Time – Exponential Distribution Summary

Theoretical Distribution - See Flight Medicine Physician Time

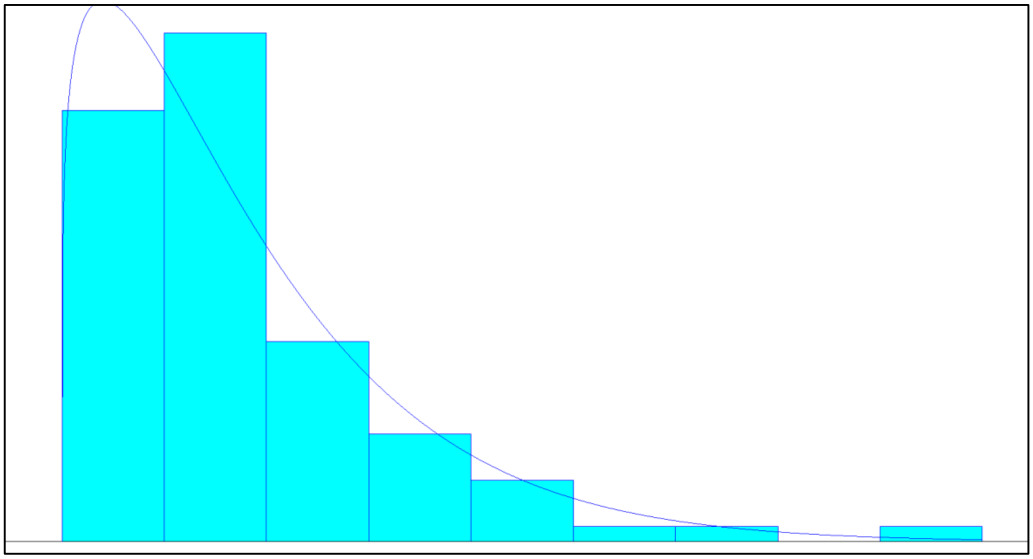
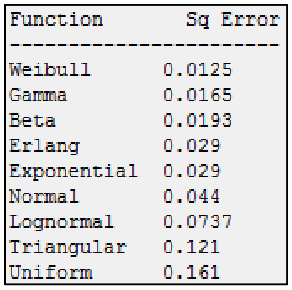


Figure 83: See Flight Medicine Physician Time – Histogram



Function	Sq Error
Weibull	0.0125
Gamma	0.0165
Beta	0.0193
Erlang	0.029
Exponential	0.029
Normal	0.044
Lognormal	0.0737
Triangular	0.121
Uniform	0.161

Figure 84: See Flight Medicine Physician Time - Fit All Summary

```
        Distribution Summary

Distribution:   Weibull
Expression:     146 + WEIB(1.17e+003, 1.19)
Square Error:   0.012487

Chi Square Test
  Number of intervals   = 4
  Degrees of freedom    = 1
  Test Statistic        = 3.89
  Corresponding p-value = 0.049

Kolmogorov-Smirnov Test
  Test Statistic        = 0.105
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points   = 88
Min Data Value          = 146
Max Data Value          = 5.71e+003
Sample Mean             = 1.26e+003
Sample Std Dev          = 917

        Histogram Summary

Histogram Range         = 146 to 5.71e+003
Number of Intervals     = 9
```

Figure 85: See Flight Medicine Physician Time – Distribution Summary

Theoretical Distribution - See Occupational Medicine Physician Time

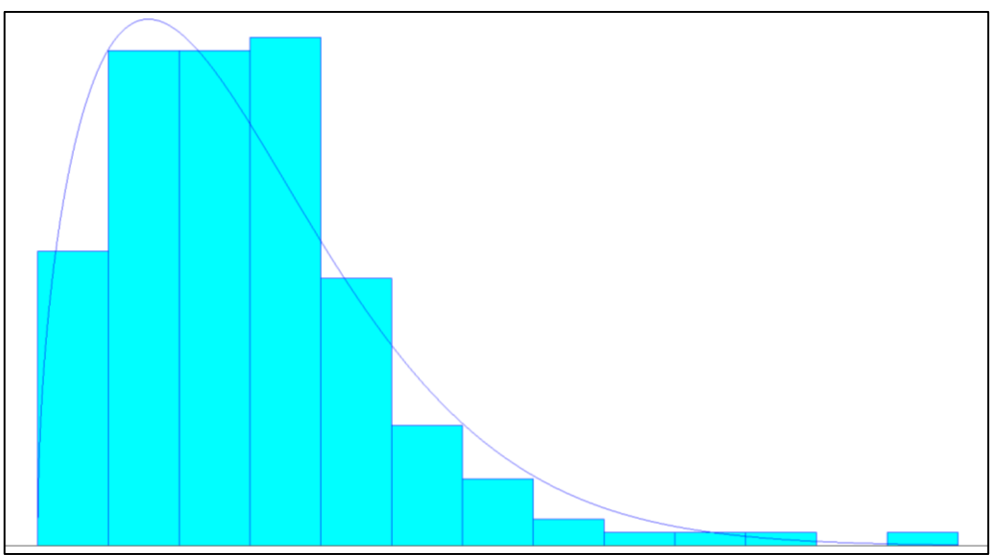


Figure 86: See Occupational Medicine Physician Time – Histogram

Function	Sq Error
Weibull	0.0056
Beta	0.00613
Erlang	0.00627
Normal	0.00912
Gamma	0.00961
Exponential	0.0446
Lognormal	0.0504
Triangular	0.0743
Uniform	0.0942

Figure 87: See Occupational Medicine Physician Time - Fit All Summary

```
        Distribution Summary

Distribution:   Weibull
Expression:     253 + WEIB(801, 1.49)
Square Error:   0.005601

Chi Square Test
  Number of intervals   = 7
  Degrees of freedom    = 4
  Test Statistic        = 8.73
  Corresponding p-value = 0.0722

Kolmogorov-Smirnov Test
  Test Statistic        = 0.0554
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points   = 174
Min Data Value          = 253
Max Data Value          = 3.42e+003
Sample Mean             = 984
Sample Std Dev          = 480

        Histogram Summary

Histogram Range         = 253 to 3.42e+003
Number of Intervals     = 13
```

Figure 88: See Occupational Medicine Physician Time – Weibull Distribution Summary

Theoretical Distribution - Make Follow Up Appointment Time

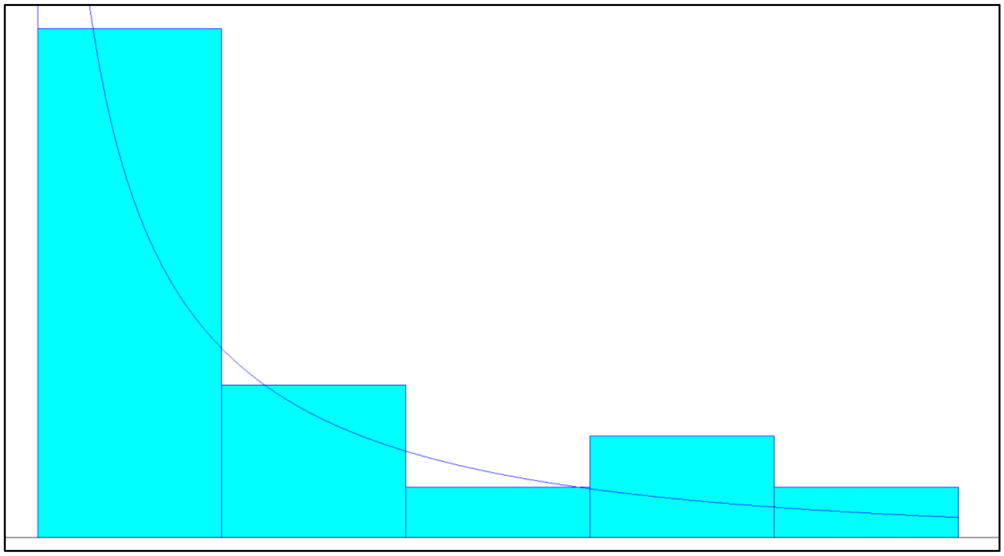


Figure 89: Make Follow Up Appointment Time – Histogram

Function	Sq Error
Weibull	0.00861
Gamma	0.0137
Erlang	0.0184
Exponential	0.0184
Lognormal	0.0373
Beta	0.109
Triangular	0.135
Normal	0.16
Uniform	0.198

Figure 90: Make Follow Up Appointment Time - Fit All Summary

```
        Distribution Summary

Distribution:   Weibull
Expression:     -0.001 + WEIB(130, 0.595)
Square Error:   0.008613


Kolmogorov-Smirnov Test
  Test Statistic         = 0.265
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points    = 17
Min Data Value           = 0
Max Data Value           = 628
Sample Mean              = 171
Sample Std Dev           = 188

        Histogram Summary

Histogram Range          = -0.001 to 628
Number of Intervals      = 5
```

Figure 91: Make Follow Up Appointment Time – Distribution Summary

Step 4: Arena Model

The input data described above are combined with the process flows to form a task network. Figure 20 in Step 1 provides a task network which is a visual representation of the conceptual model. The conceptual model is translated into a task network by representing decision logic as decision nodes, processes as task nodes, and the order of these tasks and decisions as directional arcs. When a patient goes through the system, the individual will process through the various nodes established in the task network and will follow the decision logic throughout the model. For example, all patients go through the check-in node, followed by decision logic to determine (1) if the patient needs to fill out paperwork and (2) which clinic the patient will visit:

Audiology/Hearing Conservation Clinics, Optometry Clinic, or Flight/Occupational Medicine Clinics.

If the assigned clinic is Audiology or Hearing Conservation, the task flow is simple in that the patient will go to the respective node of Visit Doctor/Specialist to process through a visit with the audiologist or hearing conservation technician. Once completed, the patient exits the system.

If the assigned clinic is Optometry, then the optometry nurse or technician prepares the patient to see the optometrist. The patient then visits the optometrist. Decision logic is used to determine if the patient needs to see the optometrist again. If the patient needs to see the optometrist again, it is because their eyes need to be dilated for examination. The patient waits for the dilation drug to take effect before visiting the optometrist a second time; the patient waiting for the dilation drug to take effect is counted as value-added time and not attributed to wait-time because this is a necessary process. Once completed, the patient exits the system.

If the assigned clinic is Flight Medicine or Occupational Medicine, the nurse or technician of their respective clinic checks the vitals of the patient. A series of decision nodes is created to determine if the patient needs to perform various tasks. If the patient needs to perform a laboratory task, ECG, X-ray, see a nurse or technician numerous times, visit hearing conservation technician, and/or visit the optometrist once, then the patient will go to the needed process nodes in any order based upon availability: if the process node is using up all the resources to perform the task, then the patient proceeds to the next task and returns to the previous node when it becomes available. When completed, the patient will visit the doctor of the respective clinic. A decision node determines if the patient makes a follow up appointment. Once completed, the patient exits the system.

In addition to capturing the process flows, decision logic, and timing data, the clinic staff also annotated the type and quantity of resources used. Table 24 summarizes the resources used in the system of clinics. There are unique characteristics associated with a few of the resources. These characteristics are listed here:

- There is a front desk station at the entrance of the building that can only be manned by one administration technician.
- The Hearing Conservation technician is being treated as a provider for this clinic.
- The Flight Medicine and Occupational Medicine clinics share 6 examination rooms.
- The laboratory and ECG rooms are operated by the nurse or technicians of either the Flight Medicine or Occupational Medicine clinic, depending on which clinic the patient belongs to.
- The ECG room is co-located with one of the optometry examination rooms.
- The X-Ray room is manned by an X-Ray technician.

Once the resources were incorporated into the model, it was then validated.

Table 24: System of Clinic Resources

	Rooms	**Providers**	**Nurse/Tech**
Front Desk Station	1	Not Applicable	1
Audiology	3	2	0
Flight Medicine	shared 6 with occupational medicine	4	shared 8 with Lab and ECG
Hearing Conservation	1	1	Not Applicable
Occupational Medicine	shared 6 with flight medicine	4	shared 4 with Lab and ECG
Optometry	1 dedicated to optometry with 1 shared with ECG	1	1
Lab	2	Not Applicable	performed by respective clinic's nurse/tech
ECG	1 shared with optometry	Not Applicable	performed by respective clinic's nurse/tech
X Ray	1	Not Applicable	1

Step 5: Validation

Validation is an important step in creating a baseline simulation model. It provides statistical evidence that the model adequately reflects the real world system. For satisfactory validation, a confidence interval of 10% within the mean is desired. For this system, the average time in system is 54.13 minutes, thus a half-width of 5.4 min or less is required. A 99% confidence interval for this system produced a half-width of 3.16 minutes, thus a 99% confidence interval level was deemed sufficient for use in validation. The tradeoff in using a 99% confidence interval level is that it provides a higher level of confidence at the risk of an unacceptably large half-width. Because the 99% confidence interval level has a half-width that is considerably less than the desired ±10% of the mean, the 99% confidence interval's half-width is deemed to be acceptably narrow.

Upon establishing a confidence interval level, real world data is compared to simulation data using a 99% confidence interval. In order to determine the number of replications needed to run the model, an approximation equation is used [11]:

$$n \cong n_0 \frac{h_0^2}{h^2} \tag{2}$$

Where n is the number of replications needed, n_0 is the number of replications in the initial production run, h_0 is the half-width of the initial production run, and h is the desired half-width. An initial run on the model is conducted with n_0=10 as an arbitrary initial number of replications. It produces an initial half-width of h_0 = 6.03 min. Based on the desired half-width of $h = 3.16$ min (taken from the real world half-width of 3.16

minutes), an estimate on the number of replications needed, *n*, is evaluated; first iteration: $n=10(6.03^2/3.16^2) = 36.49$. This process is repeated three more times to determine a reasonable number of replications; second iteration: $37(3.31^2/3.16^2) = 40.68$; third iteration: $41(3.21^2/3.16^2) = 42.39$; fourth iteration: $43(3.09^2/3.16^2) = 41.20$. It is determined that at least 41.20, rounded up (to be conservative) to 42 replications, is required to achieve the desired half-width. The confidence intervals of the real world data and simulation data reveal that there is no statistical difference between the model and the real world system, see Figure 92. This is demonstrated by the overlap of both confidence intervals, thus validating the baseline model. Note that the average time in system of the simulation is 49.29 minutes. This indicates that the simulation is, on average, 4.84 minutes faster than reality. To account for this difference, it is hypothesized that the exclusion of transit time in the model is what is causing a slightly faster time in system. This is of negligible concern for the purpose of this study as the patient wait-time is the focus of this investigation, not the total time in system, and transit time is not expected to impact wait-time.

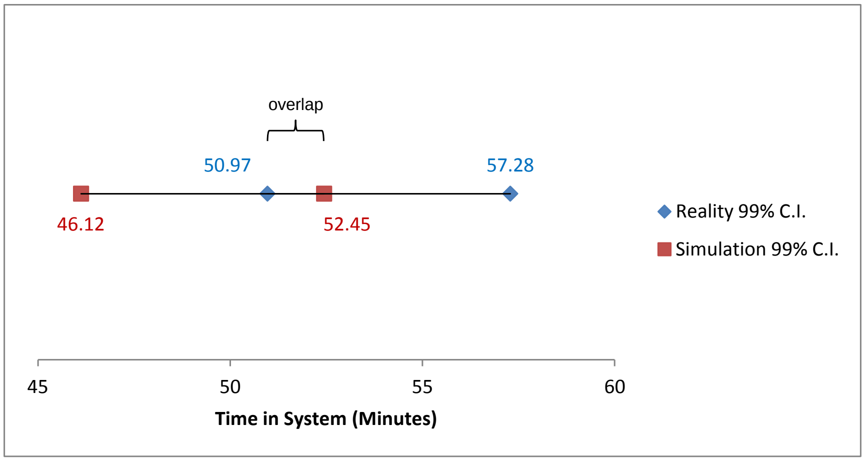


Figure 92: Real-World versus Simulation TIS with a 99% Confidence Interval

Model Limitations and Assumptions

Table 25: Model Limitations and Assumptions

Model Limitations/Assumptions	Reasoning
Miscellaneous activities are excluded	During the data collecting activity, mail delivery personnel is observed to interact with the administration technician but are not included in the model for two reasons: 1.) They are not considered a patient in the system. 2.) It only took them a few seconds to process their delivery with the administration technician and then they left the clinic.
Patients who don't qualify as a walk-in status are excluded from the model	They are excluded from the model because patients who do not qualify to "walk-in" are told to make a future appointment. It is assumed that there infrequent situations like this and that these situations do not take much of the administrative technician's time.
Paperwork completed prior to vitals checked	The patient is assumed to have completed their paperwork prior to having the nurse/technician check their vitals.
Prioritized Queue	It is assumed that patients with an appointment are given priority to those who are in "walk-in" status.
No Balking	It is assumed that patients entering the system of clinics are committed to stay in the clinic upon completion and not leave early.
No Transit Time	For the purposes of this study, transit time is not included in the model because analyzing wait-time does not take into account transit time.
Order of Availability	The model assumes that when one process node is unavailable, the patient moves to the next available process node. Upon completion of that process node, it then move on to the next needed process node and cycles back to the missed process node when it becomes available. Order: Hearing Conservation, Check Vitals, Lab, ECG, X-ray, 2nd Visit to Nurse/Technician, 3rd Visit to Nurse/Technician
Stationary Interrivals	The patient interarrival distribution is assumed stationary throughout the day; this implies no peak hours.
Process Limited to Patient Interactions	It is assumed that process times are all accounted with patient interaction only.
No Batching	The medical staff members see the patient one at a time.
Follow-Up Appointment in Person	If the patient needs a follow-up appointment after seeing the doctor, then it is assumed that the patient schedules it at the front desk before leaving and not over the phone.

Bibliography

Aktas, E., Ulengin, F., & Sahin, S. O. (2007). A decision support system to imporve the efficiency of resource allocation in healthcare management. *Socio-Economic Planning Sciences, 41*, 130-146.

Angus, D. C., Kelley, M. A., Schmitz, W. A., White, A., & Popovich, J. (2000). Current and Projected Workforce Requirements for Care of the Critically Ill and Patients With Pulmonary Disease. *Joumal of the American Medical Association, 284*(21), 2762-2770.

Associated Press. (2012, September 6). *Report: Health care system wastes $750B a year*. Retrieved May 25, 2014, from CBSNEWS: http://www.cbsnews.com/news/report-health-care-system-wastes-750b-a-year/

Banks, J., Carson II, J. S., Nelson, B. L., & Nicol, D. M. (2010). *Discrete-Event System Simulation* (5 ed.). New Jersey: Prentice Hall.

Brown, M. M., Brown, G. C., Sharma, S., & Landy, J. (2003, April). Health Care Economic Analyses and Value-Based Medicine. *Survey of Ophthalmology, 48*(2), 204-222.

careerbliss.com. (2015). *United States Air Force Employee Salaries*. Retrieved FEB 27, 2015, from Career Bliss: http://www.careerbliss.com/usaf/salaries/

Connelly, L. G., & Bair, A. E. (2004, November). Discrete Event Simulation of Emergency Department Activity: A Platform for System-level Operations Research. *Academic Emergency Medicine, 11*(11), 1177-1185.

Cote, M. J. (1999). Patient flow and resource utilization in an outpatient clinic. *Socio-Economic Planning Sciences, 33*(3), 231-245.

de Weck, O. L., Ross, A. M., & Rhodes, D. H. (2012, June 18-20). Investigating Relationships and Semantic Sets amongst System Lifecycle Properties (Ilities). *Third International Engineering Systems Symposium*, (pp. 1-12). Delft University of Technology.

Dorr, D. A., Horn, S. D., & Smout, R. J. (2005, May). Cost Analysis of Nursing Home Registered Nurse Staffing Times. *Journal of the American Geriatrics Society, 53*(5), 840-845.

Doubilet, P., Begg, C. B., Weinstein, M. C., Braun, P., & McNeil, B. J. (1985). Probabilistic Sensitivity Analysis Using Monte Carlo Simulation: A Practical Approach. *Medical Decision Making*, *5*(2), 157-177.

Eichler, H.-G., Kong, S. X., Gerth, W. C., Mavros, P., & Jonsson, B. (2004). Use of Cost-Effectiveness Analysis in Health-Care Resource Allocation Decision-Making: How Are Cost-Effectiveness Thresholds Expected to Emerge? *Value in Health, 7*(5), 518-528.

Giachetti, R. E. (2008). A simulation study of interventions to reduce appointment lead-time and patient no-show rate. *Winter Simulation Conference* (pp. 1463-1468). IEEE.

Hashimoto, F., & Bell, S. (1996). Improving Outpatient Clinic Staffing and Scheduling with Computer Simulation. *Journal of General Internal Medicine, 11*(3), 182-184.

Huschka, T. R., Narr, B. J., Denton, B. T., & Thompson, A. C. (2008). Using simulation in the implementation of an outpatient procedure center. *Proceedings of the 40th Conference on Winter Simulation* (pp. 1547-1552). Winter Simulation Conference.

Jacobson, S. H., Hall, S. N., & Swisher, J. R. (2006). Discrete-event simulation of health care systems. In *Patient flow: Reducing delay in healthcare delivery* (pp. 211-252). Springer US.

Kelton, W. D., Sadowski, R. P., & Zupick, N. B. (2015). *Simulation with Arena* (sixth edition ed.). New York: McGraw-Hill Education.

Kim, B., Elstein, Y., Shiner, B., Konrad, R., Pomerantz, A. S., & Watts, B. V. (2013). Use of discrete event simulation to improve a mental health clinic. *General Hospital Psychiatry, 35*(6), 668-670.

Kudyba, S., & Temple, R. (2010). An Introduction to the U.S. Healthcare Industry, Information Technology, and Informatics. In S. P. Kudyba (Ed.), *Healthcare Informatics: Improving Efficiency and Productivity* (pp. 1-18). Boca Raton, FL: Taylor & Francis Group.

Nord, E. (1993). The trade-off between severity of illness and treatment effect in cost-value analysis of health care. *Health Policy*, *24*, 227-238.

Obama, B. (2014, May 21). *President Obama Speaks on Veterans Health Care*. Retrieved from whitehouse.gov: http://www.whitehouse.gov/photos-and-video/video/2014/05/21/president-obama-speaks-veterans-health-care

Peninsula Children's Clinic. (2015). Retrieved 2 19, 2015, from Before Your First Visit: Peninsula Children's Clinic: http://peninsulachildrensclinic.com/beforefirstvisit.

Ryan, E. T., Jacques, D. R., & Colombi, J. M. (2013). An Ontological Framework for Clarifying Flexibility-Related Terminology via Literature Survey. *Systems Engineering, 16*(1), pp. 99-110.

Simeone, N. (2014, February 24). *Hagel Outlines Budget Reducing Troop Strength, Force Structure*. Retrieved from U.S. Department of Defense: http://www.defense.gov/news/newsarticle.aspx?id=121703

St. Michael's Emergency Room Commercials. (2015). Retrieved 2 19, 2015, from St. Michael's Emergency Rooms: http://www.24hrer.com/tvCommercials.php

Swisher, J. R., Jacobson, S. H., Jun, J. B., & Balci, O. (2001). Modeling and Analyzing a Physician Clinic Environment Using Discrete-Event (Visual) Simulation. *Computers & Operations Research, 28*, 105-125.

van den Bemt, P. M., Postma, M. J., van Roon, E. N., Chow, M.-C. C., Fijn, R., & Brouwers, J. R. (2002). Cost-Benefit Analysis of he Detection of Prescribing Errors by Hospital Pharmacy Staff. *Drug Safety, 25*(2), 135-143.

REPORT DOCUMENTATION PAGE	*Form Approved* *OMB No. 074-0188*

The public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of the collection of information, including suggestions for reducing this burden to Department of Defense, Washington Headquarters Services, Directorate for Information Operations and Reports (0704-0188), 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302. Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to a penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number.
PLEASE DO NOT RETURN YOUR FORM TO THE ABOVE ADDRESS.

1. REPORT DATE *(DD-MM-YYYY)*	**2. REPORT TYPE**	**3. DATES COVERED** *(From – To)*
12-03-2015	Master's Thesis	September 2013 – March 2015

TITLE AND SUBTITLE A Process Improvement Study on a Military System of Clinics to Manage Patient Demand and Resource Utilization Using Discrete-Event Simulation, Sensitivity Analysis, and Cost-Benefit Analysis	**5a. CONTRACT NUMBER** **5b. GRANT NUMBER** **5c. PROGRAM ELEMENT NUMBER**
6. AUTHOR(S) Corpuz, Michael Q., Captain, USAF	**5d. PROJECT NUMBER** **5e. TASK NUMBER** **5f. WORK UNIT NUMBER**
7. PERFORMING ORGANIZATION NAMES(S) AND ADDRESS(S) Air Force Institute of Technology Graduate School of Engineering and Management (AFIT/ENV) 2950 Hobson Way, Building 640 WPAFB OH 45433-8865	**8. PERFORMING ORGANIZATION REPORT NUMBER** AFIT-ENV-15-M-199
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) AFRL/711th Human Performance Wing 2510 Fifth Street, Building 840 Wright-Patterson AFB, OH 45433-7913 Phone: (937) 938-3253, E-Mail: anthony.tvaryanas@wpafb.af.mil ATTN: Colonel Anthony Tvaryanas, USAF	**10. SPONSOR/MONITOR'S ACRONYM(S)** **AFRL/RHIQ (example)** **11. SPONSOR/MONITOR'S REPORT NUMBER(S)**

12. DISTRIBUTION/AVAILABILITY STATEMENT
DISTRUBTION STATEMENT A. APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.

13. SUPPLEMENTARY NOTES

14. ABSTRACT
Inefficiencies in the healthcare system are a growing concern. Long wait-times are a concern at military clinics because it takes servicemembers away from performing their duties. Managing wait-times are particularly challenging due to frequent relocations of servicemembers and variable patient demands that are less likely to be experienced by civilian clinics. Military clinics must be capable to meet increasing demand when servicemembers require a Deployment Health Assessment; it also needs to be capable of handling an instantaneous surge of walk-ins when a medical incident occurs in the local area. It must be able to meet these demands in a fiscally austere environment.

Existing research primarily focuses on stand-alone clinics, whereas this research takes a novel approach of examining a system of clinics, in which some resources are shared. This research evaluates the impacts of variable staffing levels on total wait-time for the system of clinics at baseline demand and when demand increases, using discrete-event simulation, sensitivity analysis, and cost-benefit analysis. This research finds misallocated resources; the wait-time of alternative systems are sensitive to deployment and medical incident demands; and hiring an optometrist while removing an occupational medicine doctor provides the highest savings in baseline, deployment, and medical incident demand environments.

15. SUBJECT TERMS
military healthcare; system of clinics; discrete event simulation; sensitivity analysis; cost benefit analysis

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON**
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**			Christina F. Rusnock, MAJ, USAF, PhD, AFIT/ENV
U	U	U	UU	151	**19b. TELEPHONE NUMBER** *(Include area code)* (937) 255-3636, ext. 4611 (Christina.rusnock@afit.edu)

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std. Z39-18