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A Mathematical Modeling Framework For Phlebotomist Scheduling And Blood Draw Assignments In Laboratory Medicine

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A Mathematical Modeling Framework for Phlebotomist Scheduling and Blood Draw Assignments in Laboratory Medicine

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Biographical Sketch

Laquanda T. Leaven was born on January 26, 1987 in Portsmouth, Virginia, but grew up in a small, rural community in South Carolina. She received her high school diploma from Marlboro County High School in 2005. She went on to receive the Bachelor of Science degree in Industrial and Operations Engineering in 2009 from the University of Michigan in Ann Arbor, Michigan. After conversing with many of her professors, while at Michigan, about the opportunities afforded to those with advanced degrees she decided to go on and pursue graduate studies. In 2010, she went on to complete a Master of Science degree in Industrial and Systems Engineering with a concentration in health systems operations research from North Carolina Agricultural and Technical State University. She continued to further her studies in health systems operations research and is now a candidate for the Doctor of Philosophy degree in Industrial and Systems Engineering. Laquanda is a member of Alpha Pi Mu (the National Industrial Engineering Honor Society), the Institute for Operations Research and the Management Sciences (INFORMS), and the Institute of Industrial Engineers (IIE). Laquanda is also a Sunday School Teacher for high school students at her church.

Dedication

This dissertation is dedicated to my family and all those who will come after me with a desire to obtain a Ph.D degree. To my parents that encouraged me to allow God to order my steps, I will forever be grateful to you. To my grandmother, Gertrude Hamer whose love for God and her family goes beyond that which words can explain, I thank you. At 94 years old, she was the epitome of grace, love, and Proverbs 31. I stood by her bedside on November 29, 2012 as she took her last breath and joined our heavenly father. As difficult as this was, I know she will enjoy walking around heaven all day. In this lifetime, if I can become only half of the woman she was I will have been divinely favored. To my grandparents, Mr. and Mrs. Franklin Leaven who were married for 60 years on February 8, 2013, your love has inspired me to keep pushing, to trust God, and to maintain a humble posture. God saw fit to make my grandfather one of his angels on February 9, 2013. I'm sure he and grandmother are keeping each other company. To my brothers, Emmanuel and Sterling Leaven, thank you for introducing me to engineering! I have always tried to walk in your footsteps such that in everything I do whether it is engineering, teaching, etc. I ensure that God gets the glory. To every single person that may read this and has a desire to pursue a Ph.D, I encourage you to GO FOR IT! It is definitely a journey of ups, downs, long nights, research uncertainties, etc., but I guarantee that it will be worth it once you have completed the process. There is no greater gratitude than knowing that you have successfully finished the Ph.D program, so keep pushing! I love all of my family, supporters, and friends. I thank each and every one of you for your support and encouragement.

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As I close this chapter and begin the next, I will cherish the positive experiences that North Carolina Agricultural and Technical State University has offered. We truly produce the best and the brightest engineering scholars! No matter where we go or who we meet along the way of our own separate journeys there is something that will remain with us for the rest of our days…… **AGGIE PRIDE!**

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Key to Abbreviations

AHP	Analytic Hierarchy Process
ANP	Analytic Network Process
CAP	College of American Pathologists
FDA	Food and Drug Administration
FES	Functional Electrical Stimulation
LIS	Laboratory Information System
LP	Linear Programming
NHS	National Health Service
PDA	Personal Digital Assistants
THC	Thana Health Complex
TLA	Total Laboratory Automation
TPS	Toyota Production System
SILP	Stochastic Integer Linear Programming

Abstract

Laboratory services in healthcare delivery systems play a vital role in inpatient care. Studies have shown that laboratory data affects approximately 65% of the most critical decisions on admission, discharge, and medication. Laboratory testing accounts for approximately 10% of hospital billing. Reducing laboratory costs would contribute to reducing total healthcare cost, which is one of the major goals for the U.S. healthcare delivery system.

This research focuses on improving the performance of the hospital laboratory in a large hospital system. The intention of this study is to identify and then optimize the most critical stage to improve the entire laboratory testing process. Using analytic hierarchy process (AHP) and analytic network process (ANP) modeling, the preanalytical stage was identified as most critical. Then, a two-stage stochastic integer linear programming (SILP) model was formulated to determine better weekly phlebotomist schedules and blood collection assignments in the preanalytical stage. The objective of the two-stage SILP is to balance the workload of the phlebotomists within and between shifts, as reducing workload imbalance would result in improved patient care. Due to the size of the two-stage SILP problem, a scenario reduction model and a heuristic algorithm were proposed to solve the problem. The performance evaluation results show that for practical cases the heuristic algorithm proposed could find near-optimal solutions with a relative gap less than 3.5% within 20 minutes. The two-stage SILP model and the heuristic algorithm proposed will assist laboratory management in balancing phlebotomist workload, which could reduce the risk of poor phlebotomist performance and patient neglect caused by work overload. By implementing the recommendations of this study, hospital laboratories should see significant improvements in workload balance and resource utilization, which are both considered cost savings strategies.

CHAPTER 1

Introduction

1.1 Background

Laboratory services in healthcare delivery systems play a vital role in inpatient care. Studies have shown that laboratory data affects approximately 65% of the most critical decisions on admission, discharge, and medication (Mario, 1999). Laboratory medicine which can also be described as clinical pathology is a field where pathologists provide testing of patient samples (generally blood or urine). For example, the presence of bacteria can be detected from a patient sample, which provides information for the necessary treatment. A clinical test can be conducted on a sample to determine the level of enzymes in the blood to see if a patient has a risk of a heart attack or if the level of glucose in the blood of a patient is related to diabetes. Hospital laboratories are facilities within healthcare delivery systems where laboratory medicine is conducted.

Most hospital laboratories are divided into divisions based on the categories of tests performed. A hospital laboratory usually includes the following nine divisions:

- **Hematology**: This division conducts tests on patients' blood samples, and the most frequently conducted test is the complete blood count also called a full blood count. This type of test gives information about the cells in a patient's blood. Abnormal high or low counts could indicate the existence of many types of diseases. This is the reason this test is amongst the most frequently performed blood test in hematology, as it provides a synopsis of a patient's general health condition.
- **Urinalysis**: This division performs tests to evaluate urine samples from patients. Urinalysis is used to detect a variety of disorders, including but not limited to urinary

tract infection, diabetes, and kidney disease. Urinalysis includes analyzing the appearance, concentration, and content of urine. Results from abnormal urinalysis could indicate whether there is a disease or illness present in the patient's body. Abnormal results of a urinalysis frequently indicate that additional testing and further evaluation to discover the source of the problem will be required.

- **Chemistry**: The clinical chemistry division in laboratory medicine conducts analysis of bodily fluids. This area utilizes a broad field of analytical techniques that detect and measure chemicals in body fluids, cells, or tissues, such as enzymes, hormones, proteins, and drugs. There are a plethora of diagnostics comprising tests that detect and determine changes in the chemical composition of body fluids and tissues to diagnose or predict the course of a disease. All biochemical tests fall under chemical pathology, and these tests are performed mainly on serum or plasma.
- **Blood Bank**: This division in a hospital laboratory is comprised of blood donations, stored and preserved for later use in blood transfusions. Proper testing is performed to reduce the risk of transfusion related errors. It is imperative for blood banks to pass all the eligibility guidelines as mandated by the National Health Service (NHS) and Food and Drug Administration (FDA) in order to provide blood transfusions for inpatients.
- **Microbiology**: The microbiology division conducts tests to identify microorganisms such as, bacteria, viruses, fungi, and parasites that are of medical significance and capable of causing infectious diseases in patients. Through the advancement of vaccines, deadly and incapacitating diseases have been either eradicated or are more treatable because of the efforts of researchers in the area of medical microbiology.

- **Histology**: This division performs testing to determine the form of structures seen under the microscope. Histology focuses on the tissues of the body, including body cells. Often referred to as microscopic anatomy, histology studies the relationships of the minuscule structures of cells, tissues, and organs with their functions. For example, histological analysis of liver biopsy samples is helpful in the diagnosis of possible liver damage.
- **Cytology**: This division in laboratory medicine focuses on the medical and scientific analysis of cells. Cytology is a sub-division of pathology where examinations are performed on body fluids. A frequent example of diagnostic cytology is the evaluation of cervical smears. In order for a cytology evaluation to be conducted, the matter to be examined is placed on glass slides and then stained. A pathologist uses a microscope to analyze the individual cells in the sample.
- **Pathology**: This medical division focuses on the temperament and causes of diseases. It includes diagnostic testing and monitoring of chronic diseases. Studies have indicated that pathology is a vital component to the diagnosis of every cancer. General pathology is an extensive and complex scientific field which seeks to identify injuries to cells and tissues, and the body's method of responding to these injuries.
- **Point of Care**: This area is described as medical testing at the bed of the patient. This enhances the likelihood that the physician will obtain the results faster. Point of Care Testing includes but is not limited to: blood glucose testing, electrolytes analysis, rapid coagulation testing, drug abuse screening, pregnancy testing, food pathogens screening, hospital diagnostics, infectious disease testing, and cholesterol screening.

In the hospital laboratory process there are three core stages: Preanalytical Stage, Analytical Stage, and Postanalytical Stage. Resources needed vary among the stages. The resources for the Preanalytical stage consist of the phlebotomists, tubes, and personal digital assistants (PDAs). The phlebotomists are medically trained staff to collect blood from the patients. During the blood collection process certain tubes must be used due to the chemicals in each tube type. The type of tube to use is dependent on the test that has been ordered by the physician. The PDAs used by the phlebotomists are the hand held devices which provide the blood collection schedule they are to follow during their shift. The resources for the Analytical stage consist of the medical technicians who perform the test on the patient sample, and the instrumentation, which is the equipment required to conduct the test. Lastly, the resources needed for the Postanalytical stage consists of the Laboratory Information System (LIS), which evaluates the test results. The medical technicians then check for normal/abnormal ranges in the test results. The pathologists at that moment examine the test results and provide the diagnosis for the patient. Issues that occur in the laboratory process are often identified as bottlenecks for other departments in the hospital. In the following section, the motivation and importance of conducting this research is discussed.

1.2 Motivation

Laboratory medicine plays an imperative role in clinicians being able to reach a diagnosis for patients. Therefore, laboratory medicine is a key component in healthcare delivery systems due to the amount of spending that occurs and the medical decisions that are involved. There is a great need to reduce healthcare costs as much as possible and improve service quality. This study has addressed both of those needs.

Laboratory testing accounts for approximately 10% of hospital billing. A goal for the U.S. managed healthcare delivery system is to considerably reduce laboratory spending. There are two methods to reduce costs, which consist of the technological approach and the pathophysiology based approach (Plebani, 1999). The technological approach aims to reduce costs by consolidating laboratories, making improvements in laboratory automation, etc. The pathophysiology based approach strives to lower cost through the improvement of the diagnostic performance of tests, developing effective diagnostic strategies, and effective utilization of laboratory resources for the treatment of patients. The advantage of these cost reduction strategies is that they compel people from different areas within healthcare to come together to thoroughly understand all facets of patient care, most importantly understanding what it takes to provide patient care effectively and efficiently while still delivering high quality service. This research study has addressed balancing workload amongst phlebotomists and maximizing phlebotomist utilization in hospital laboratories that are apart of large healthcare systems. Maximizing phlebotomist utilization and balancing workload, are both considered cost reduction strategies.

If a patient-centered vision predominates in laboratory medicine, the clinical laboratory will be linked to physicians and patients, making it more tangible to the latter (Pansini, Di Serio, & Tampoia, 2003). Improving service quality is a critical part of laboratory medicine. Medical errors in healthcare delivery systems account for approximately 100,000 deaths each year, which indicate improvements in service quality are needed. Most inaccuracies in hospital laboratories occur in the preanalytical or postanalytical stages, whereas a small portion (13–32%) takes place in the analytical stage (Mario, 2009). Errors that occur in one of the core stages will affect the stages following. The preanalytical, analytical, and postanalytical stages, when conducted

properly, play a vital role in preventing laboratory errors. Yet, if any of the stages is improved, it will improve the stages following and the entire testing process. With a proper quality control system, the service quality in the entire testing process will be increased. Seven improvement recommendations for clinical laboratories have been proposed in the literature (Hollensead, Lockwood, & Elin, 2004).

- Establish a continuous quality improvement initiative, which focuses on improving laboratory medicine and pathology.
- Have user-friendly computer systems, which allows for direct physician ordering of laboratory tests.
- Incorporate a quality wristband policy that uses bar codes on both the wristband and specimen tubes to insure proper patient identification.
- Develop quality programs to continuously assess personnel competency.
- Incorporate automated systems where feasible.
- A system for error detection in patient reports should be in place for all laboratory departments.
- Policies and procedures should be laid out and properly disclosed to all laboratory personnel.

This research has addressed achieving phlebotomist workload balance, resource utilization, service quality, and patient satisfaction through optimizing the most critical stage in the laboratory process. According to the literature, optimizing scheduling in laboratory medicine has not been regarded as a necessity for laboratory management. In actuality, without optimal scheduling policies in place for laboratory medicine, there is a great risk for patients to be negatively affected due to work overload. When work overload is present, patient neglect has the

potential to be introduced due to patients not receiving the time and attention required. Also, with work overload there is a risk for the optimal performance of the phlebotomist to decrease. Phlebotomist performance is critical in laboratory medicine because in the event of an error this could result in serious and even fatal consequences for the patient. By balancing workload, phlebotomists can provide the necessary time and attention required for each patient. Balancing phlebotomist workload, resource utilization, patient satisfaction, high service quality, and accurate laboratory performance are vital necessities for healthcare delivery systems as laboratory medicine is a pivotal part of the intricate decision making process, influencing close to 70% of medical diagnosis (Da Rin, 2009).

1.3 Objectives and Boundary

In order to increase patient satisfaction and patient safety, hospital laboratories must improve their overall effectiveness. To accomplish this, there are specific objectives in place for this research study. There are three main stages in the hospital laboratory process and one of the objectives is to determine which stage is the most critical for improvement purposes. After the stage to improve is identified, a mathematical model is formulated for that stage. The boundary of the study is that a mathematical model is developed only for the stage identified to improve. This is due to the assumption that the improvement of one stage has an indirect improvement on the other two stages.

1.4 Research Questions

- **Research Question I:** Which of the three stages in the hospital laboratory: preanalytical, analytical, or postanalytical is the most critical for optimization purposes? Mathematically, how can this be determined? How can this be validated?

- **Research Question II:** How should the phlebotomists be scheduled to balance their workload considering the uncertainty associated with the number of blood collections needing to be fulfilled?
- **Research Question III:** Based on the number of blood draws required for each hour, how can blood draw collections be assigned to balance phlebotomist workload?

1.5 Dissertation Overview

The following chapters detail a mathematical modeling framework for phlebotomist scheduling and blood draw assignments in laboratory medicine. This dissertation is divided into six chapters.

Chapter 1 provided a brief overview of the background on laboratory medicine, the motivation of this study, the objective and boundaries of this research, and lastly the research questions addressed in this dissertation. Chapter 2 provides an extensive literature review on the hospital laboratory process, measures of performance, and approaches applied to improving laboratory medicine. All of these areas are addressed in rigor because this chapter serves as the drive in recognizing the research gap, while identifying notable research advancements in the area as a whole. Chapter 3 presents the AHP and ANP models that are developed to identify the laboratory stage to be selected for optimization. The AHP and ANP models are compared to one another in the stage selection process to ensure the proper stage is selected. Chapter 4 presents a two-stage stochastic integer linear programming (SILP) model for phlebotomist scheduling and blood draw collection assignments that balances workload within and between shifts in the preanalytical stage of the laboratory process. This model determines the number of phlebotomists that should be scheduled for each shift and the number of blood draw collections that should be assigned to each phlebotomist on each shift. This scheduling and assignment

model allows management to develop a weekly scheduling template that accounts for the uncertainty associated with the number of blood collections required for inpatients. Chapter 5 details the experimental study performed on the two-stage SILP model. In the experimental study, the two-stage SILP model is used to investigate three experimental questions. The first question addresses how the workload varies from hour to hour i.e. are there hours that have higher workloads than others. The second question addresses how the change in phlebotomist utilization and service time affect the number of phlebotomists to schedule during each shift. The last question addresses whether there is significant variation in the number of phlebotomists scheduled each day, i.e. are there days that seem to have a higher workload than others. The experimental study is performed to provide support in formulating conclusions for the two-stage SILP model developed. Lastly, Chapter 6 concludes this dissertation study and discusses future research to be performed.

CHAPTER 2

Literature Review

2.1 Introduction

Hospital laboratories have suffered many challenges, one being producing high quality test results in the most efficient and effective manner possible. One main target is to never decrease the overall quality of the care and service provided. A decrease in total quality and its negative effects on patient outcomes may cause economic loss (Pansini, et al., 2003). The aim is to decrease costs while still maintaining quality. The need to reduce the costs within laboratory medicine can be accomplished by possibly reducing test requests (Vegting et al., 2012). Many researchers in this area have proposed a patient-focused care strategy, with a goal to increase the time that nurses and physicians spend in patient care and decrease the number of employees who have direct contact with an individual patient (Pansini, et al., 2003). It is believed that this could decrease the amount of errors that are experienced. By implementing this strategy, improvements through reorganization, re-engineering, and laboratory automation have been seen in the analytical stage. Improvements were also seen in the preanalytical stage by evaluating the workload and error rate within this stage. It could be concluded that better communication between physicians and laboratory medicine staff should take place within the preanalytical stage in order to experience continuous improvement throughout the entire testing process.

In Section 2.2, an overview of the laboratory process is discussed. This section provides a synopsis of the entire testing process, and each of the three stages conducted in hospital laboratories. Activities in each stage, goals, and challenges faced are also discussed. Section 2.3 provides insights on the measures of performance, and how the staff members of the laboratory know if there should be improvements put in place or if they are operating at the optimum level.

Section 2.4 introduces the approaches and methodologies that have been proposed to improve laboratory medicine. Lastly, Section 2.5 discusses the research gap in the laboratory medicine area.

2.2 Overview of Laboratory Process

Once the hospital laboratory receives the test orders from the physicians, the phlebotomists are each assigned a schedule that details the samples to be collected from the patients. When they are to collect the sample is dependent upon whether the order is a STAT or regular order. When a STAT test is ordered, someone should immediately collect, process, and report the test without delay. Blood collections for regular ordered tests are performed as scheduled or as soon as work flow allows. Within hospital laboratories, there are three major stages which include: Preanalytical, Analytical, and Postanalytical. Each of these stages will be discussed in detail in the following sections.

2.2.1 Preanalytical stage. The preanalytical stage includes the physician order, patient identification, dietary and medication considerations, coordination of care and treatment, assessment of physical status (IVs, access ports, etc.), selecting tube types, and the actual blood collection process which has a multitude of conditions within itself. Most of the errors occur at this stage. Specimen processing, which is getting the sample ready for testing, is part of the preanalytical stage. This involves centrifuging and pouring off samples for processing in the lab or sending out to other labs. This may involve refrigeration or freezing for transport. Some samples are not centrifuged but still have to be prepared for testing. Figure 2.1 illustrates each step in the preanalytical stage.

The goal for many hospital laboratories is to have a more efficient laboratory overall. In order to accomplish this goal, objectives are put in place for each of the three laboratory stages.

For the Preanalytical stage, the aim is to decrease the amount of errors that occur within this stage of the laboratory process. It has been determined that over 60% of the errors that occur in the hospital laboratory take place in the preanalytical stage (Carraro & Plebani, 2007). Since most of the errors in the Total Testing Process (TTP) occur in the preanalytical stage, priority should be placed on the preanalytical part of the testing process. The attention of laboratory professionals, physicians, and nurses should also be focused on the source of the error and not just the error itself (Mario, 2009). Once the source is identified and addressed, this should reduce the occurrence of these medical errors. Instead of trying to fix the errors, the intent is to prevent them. Preanalytical errors can contribute to 32-75% of total laboratory errors and analytical errors can account for 13-32% of total laboratory errors. One of the main sources of preanalytical errors is the differences in the test ordering patterns of physicians.

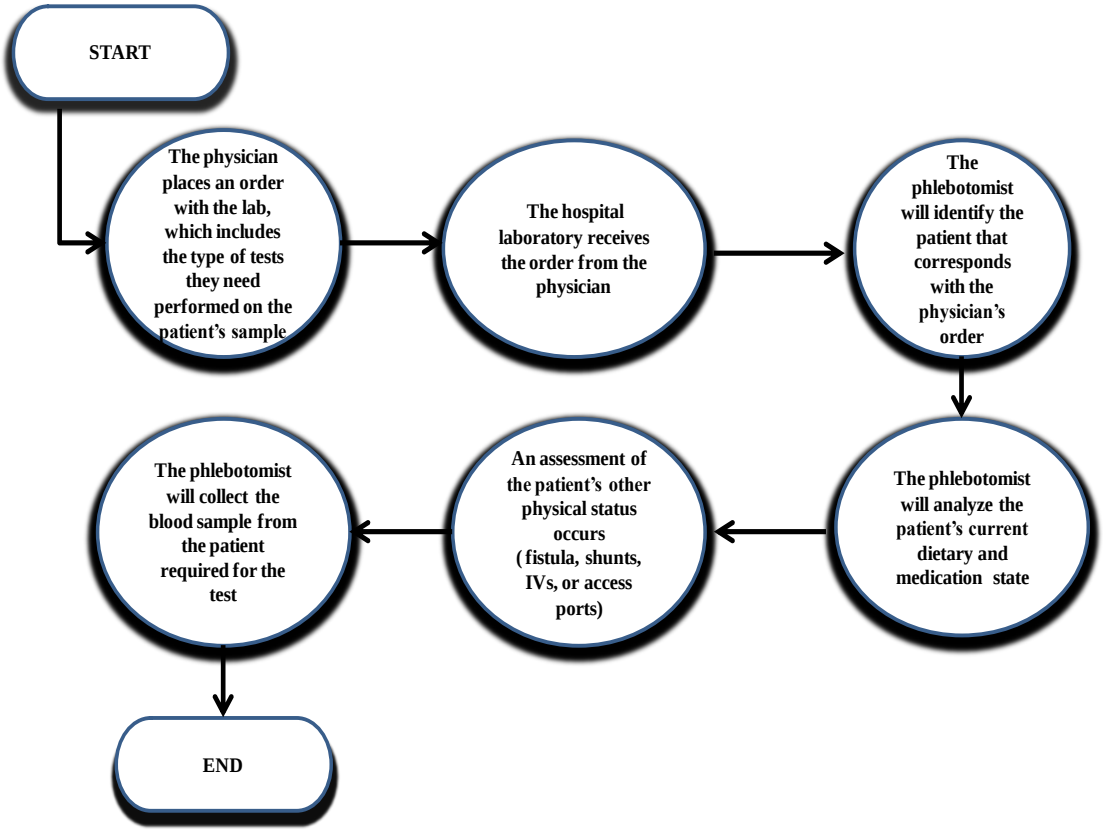

Figure 2.1. Preanalytical stage in hospital laboratory.

A reduction in errors could be achieved through improving specimen quality and standardizing the test ordering process (Vegting, et al., 2012). Essentially, proper training is needed for all phlebotomists in order to minimize errors and optimize resource utilization, as this will allow for improvement of the entire testing process. A reduction in errors could also be achieved through proper workstation design (Da Rin, 2009). Automation of the preanalytical stage is a method of preventing and reducing errors. When selecting an automated preanalytical workstation, certain performance and quality measures should be guaranteed, such as ensuring patient and specimen identification. This will increase accuracy throughout the entire testing process.

It is of great importance to understand the different types of errors that occur and how often they occur. Once this analysis is performed, clinical laboratory personnel can begin to study the root cause of these errors and address them. Many researchers have studied the frequency and types of preanalytical inaccuracies found in hospital laboratories by evaluating and monitoring specimens requested (Hollensead, et al., 2004). Most errors occur before samples are analyzed during the sampling process or during the preparation for analysis.

2.2.2 Analytical stage. The analytical stage involves the testing aspect. There are several different testing methods used depending on the test request. The main divisions within a hospital laboratory are as follows: Hematology, Urinalysis, Chemistry, Blood Bank, Microbiology, Histology, Cytology, Pathology, and Point of Care Testing. There are hundreds of different tests that could be ordered at any given time. The medical technologist or technician is responsible for tasks pertaining to the instrumentation or testing requirements, instrumentation calibrations, and on-the-spot maintenance. The analytical stage consists of running tests on the specimen and retrieving the results. Figure 2.2 illustrates each step in the analytical stage.

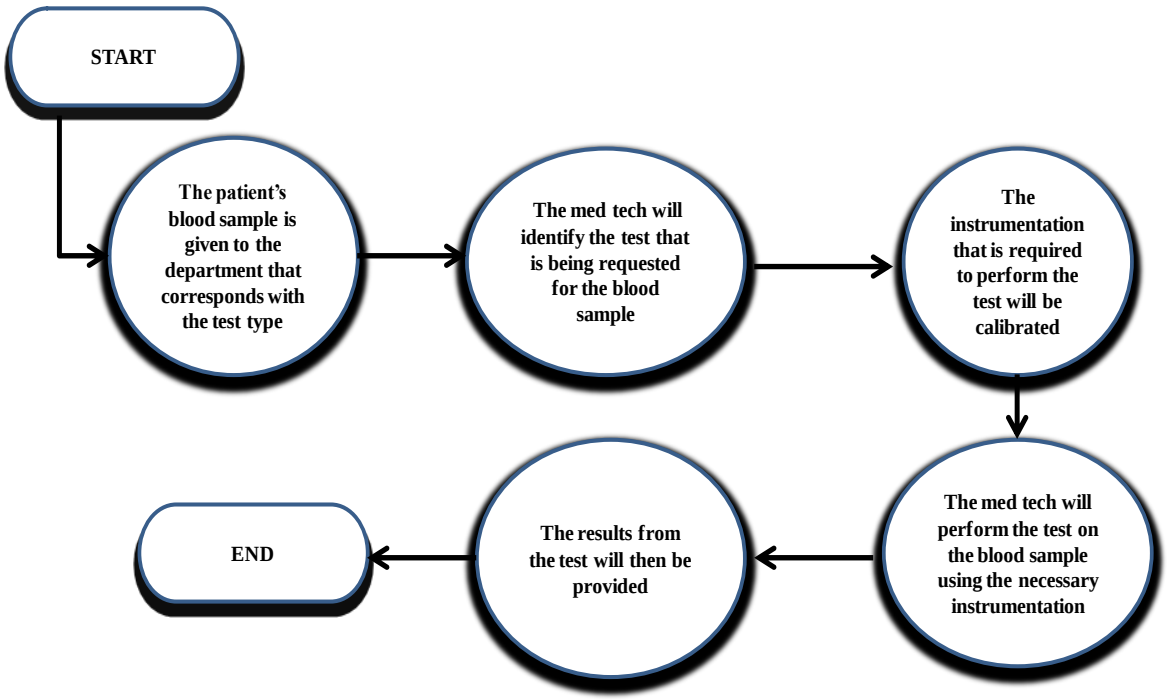

Figure 2.2. Analytical stage in hospital laboratory.

2.2.3 Postanalytical stage. The postanalytical stage involves review of the results prior to sending them out. Medical technicians are involved in this process by reviewing the lab results for normal or abnormal ranges. A pathologist review might also be required. Results are sent to the ordering or referring physician once they have been analyzed for abnormalities. There are strict guidelines on how the results can be sent or transmitted. An implementation that has been put in place in the last few years for many hospital laboratories is a process called auto verification. Rules can be written in the Laboratory Information System (LIS) to evaluate the results and if all criteria are met, the results can be sent to the patient records without a technologist review. In practice, this frees up the technicians to focus on the problem specimens. Figure 2.3 illustrates each step in the postanalytical stage.

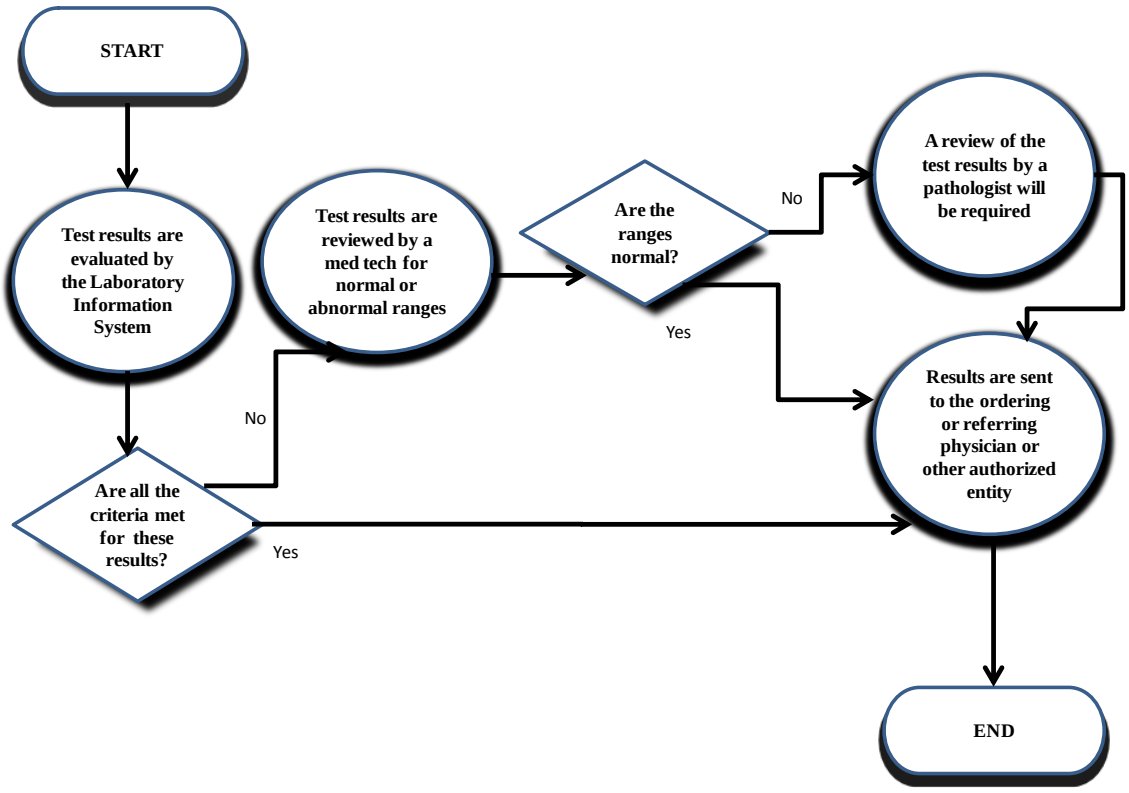

Figure 2.3. Postanalytical stage in hospital laboratory.

2.3 Measures of Performance

Performance metrics in hospital laboratories are based on cost, time, and customer satisfaction. In each of the stages it is important to consider the amount of cost saving that can be obtained, the amount of time that can be reduced, and the increase in quality of the procedures. The mean flow time is a metric that refers to the mean laboratory throughput time, which is the time to complete the entire testing process from the preanalytical stage to the postanalytical stage. Low variance of flow time is needed if the hospital laboratory management wants to ensure similar throughput times for tests in different categories. A research study was conducted, which investigated critical performance measures in laboratory medicine (Howanitz, 2005). The following eight different performance measures were identified to maximize laboratory improvement.

- Customer Satisfaction: In laboratory medicine there are two main customers, the physician and the patient. In order to ensure customer satisfaction for both parties, a critical attribute identified was the accuracy of laboratory results. The accuracy of test results emphasizes the importance of quality testing performance as a significant performance measure essential for all laboratory tests.
- Turnaround Time (TATs): Laboratory test TATs are the most imperative performance measure for many clinical laboratories. TAT is the time from when the physician places a test order for a patient to the time the results are received. It is very common for laboratory staff to hear from displeased physicians that the test TATs are not fast enough.
- Accuracy of Wristband Identification: Patients are normally identified by a wristband, and when the wristband isn't accurate, there is an increased likelihood of medical errors. When specimens are collected for laboratory testing, if patients are identified improperly the errors in identification can result in deferred diagnosis, additional laboratory testing, treatment of the wrong patient for the wrong disease, and possibly death.
- Proficiency Testing: Clinical laboratories in healthcare delivery facilities have utilized proficiency testing to document and improve the critical performance of laboratory testing. The College of American Pathologists (CAP) performs proficiency testing for hospital laboratories. This procedure allows laboratories to regularly assess their performance and improve the accuracy of the patient results they provide. This process involves CAP providing individual laboratories with unknown specimens for testing. The medical staff in the laboratory analyzes the specimens and provides the

results to the CAP for evaluation. In return, the laboratory receives a report of their performance.

- Minimal Specimen Rejection: Correct patient specimens are required for accurate laboratory results. When specimens are not correct, they have to be rejected, and another specimen must be collected. It is important to minimize the number of specimens that are rejected to avoid excessive needle sticks for patients. When excessive blood specimens are obtained from patients, this increases their chances of needing blood transfusions.
- Critical Values Reporting: Critical values, also known as panic values, have been implemented in all clinical laboratories in hospital systems. Critical values found in laboratory results indicate a life-threatening condition and require immediate action for the patient to survive. Therefore, it is imperative to communicate these results immediately to the proper physician in order to take the appropriate action for the patient. In hospital laboratories, on average 5% of the critical values found in test results are ignored because the appropriate physician cannot be located. The percentage of critical values ignored should be as close to 0 as possible.
- Blood Utilization: Blood and blood products often are the most costly items in a clinical laboratory budget. It is important to ensure that all blood and blood products sent to healthcare delivery systems are used for patients and do not go to waste.
- Blood Culture Contamination: Phlebotomists are directly related to this performance measure. If a blood sample is contaminated, it is due to the poor performance of the phlebotomist. Specimen samples associated with significantly lower contamination rates indicate the presence of dedicated phlebotomy service.

In this research, the performance measures are workload balance and patient satisfaction. Mathematical modeling is used to balance the workload for the phlebotomists in the preanalytical stage. Balanced workload will directly have a positive effect on patient satisfaction, as this will allow patients to receive the time and attention they require.

2.4 Approaches Applied in Improving Laboratory Medicine

In the literature regarding laboratory medicine, a variety of studies have been performed in order to improve laboratory medicine. The current studies utilize lean principles and quality improvement, where the focus is to eliminate waste and develop quality metrics to ensure safe, efficient, and effective processes. Additional research studies have been performed that have used simulation as an improvement technique, where the focus is to simulate and analyze different situations to determine where the most cost savings can be achieved. The automation approach has been studied, and is a technique that focuses on implementing automated preanalytical workstations in hospital laboratories to increase resource utilization and minimize laboratory errors. In the following sections, the approaches applied in improving laboratory medicine are discussed in detail. Table 2.1 provides a synopsis of the studies reviewed in this section.

Table 2.1

Synopsis of Literature Reviewed

Approach	Problem	Study
Lean	Testing process cycle time too long	(Persoon, Zaleski, & Frerichs, 2006)
Lean	Negative patient experience/long wait time	(Melanson et al., 2009)
Lean	Takes too long to receive test results	(Zito & Stewart, 2008)
Lean	Large number of blood stream infections	(Shannon et al., 2006)

Table 2.1 (*cont.)*

Approach	Problem	Study
Lean	Laboratory test defects	(Zarbo & D'Angelo, 2007)
Lean	Poor performance in the lab	(Serrano, Hegge, Sato, Richmond, & Stahnke, 2010)
Lean	Lack of processes standardization	(Raab et al., 2008)
Lean	Pap testing and diagnostic inaccuracies	(Raab et al., 2008)
Lean	Lack of validation measures for testing	(Das, 2011)
Quality	Large number of medical errors	(Raab, 2006)
Quality	Laboratory data misleading	(Nevalainen et al., 2000)
Quality	Poor laboratory test quality	(Westgard & Westgard, 2006)
Quality	Lack of laboratory information systems	(Harrison & McDowell, 2008)
Quality	Lack of understanding the role quality plays in surgical pathology	(Nakhleh, 2006)
Quality	Defects in microbiology laboratory	(Elder, 2008)
Automation	Excessive errors in preanalytical phase	(Da Rin, 2009)
Automation	Current centrifugation system runs slowly	(Yavilevich, 2002)
Automation	Excessive errors associated with specimen sorting	(Holman, Mifflin, Felder, & Demers, 2002)
Automation	Increased staff workload	(Tornel, Ayuso, & Martinez, 2005)
Automation	Staff shortage and excessive errors	(Melanson, Lindeman, & Jarolim, 2007)
Simulation	Need to reduce costs in laboratory	(De Capitani, Marocchi, & Tolio, 2002)
Simulation	Increased workload effecting staff performance time	(Goldschmidt, de Vries, van Merode, & Derks, 1998)

2.4.1 Lean and quality approach in laboratory medicine. Many clinical laboratories have incorporated the lean and quality improvement strategy to increase patient safety and improve quality and workflow (Elder, 2008; Serrano, et al., 2010). It is essential to have constant improvement in these areas. In order to track improvement, many studies have incorporated

quality measures and indicators (Nevalainen, et al., 2000). The quality of the staff's performance, as well as the quality of the testing, is essential to a patient's safety. If a phlebotomist has poor performance, this will produce poor test results (Westgard & Westgard, 2006). Quality improvement should be incorporated in every facet of hospital laboratories. This includes each stage of the entire testing process. The laboratory information system is also an important entity and tool utilized in the entire testing process. Effective laboratory information systems could support further healthcare quality improvement (Harrison & McDowell, 2008). In terms of improving quality, many staff members do not thoroughly understand the benefit or purpose of having quality control methods in place. Many researchers have stated, to alleviate this problem and have well informed healthcare professionals, training programs should be established (Nakhleh, 2006). Training programs help with the transition of making hospital laboratories continuous improvement environments. Studies have indicated, incorporating lean methods into hospital laboratories result in a decrease in turnaround time (Raab, et al., 2008) and a increase lab accuracy and efficiency (Das, 2011). Table 2.2 provides a synopsis of the lean and quality studies reviewed.

Table 2.2

Synopsis of Articles Reviewed for Lean and Quality Approach

Study	Objective	Approach	Recommendation	Results
(Nevalainen, et al., 2000)	Identify the problems with the laboratory data	Quality	Normalize data to parts-per-million defects	Significant improvements needed
(Persoon, et al., 2006)	Reduce total testing process cycle time	Lean	One piece flow/ removes batching	Cycle time reduced By 30%

Table 2.2 (*cont.*)

Study	Objective	Approach	Recommendation	Results
(Shannon, et al., 2006)	Determine cause of blood stream infections	Lean	Implement best practice policies	50% reduction in infections
(Raab, 2006)	Reduce medical errors/increase safety	Quality	Work flow process redesign	Defects decreased from 9.9% to 4.7%
(Nakhleh, 2006)	Increase the understanding of the role quality plays in surgical pathology	Quality	Provide training programs to staff	More knowledgeable, informed staff
(Westgard & Westgard, 2006)	Assess the quality of laboratory tests	Quality	Quality of laboratory tests requires improvement	More intense quality control
(Zarbo & D'Angelo, 2007)	Determine the cause of defects in tests	Lean	Implement ~100 process improvements	Defects decreased from 30% to 12.5%
(Zito & Stewart, 2008)	Reduce time to get results to physician	Lean	Single piece flow system	Reduction in turnaround time
(Harrison & McDowell, 2008)	Evaluate hospital Laboratory Information Systems (LIS)	Quality	Continue to invest in state of the art LIS	Improved healthcare quality
(Raab et al., 2008)	Measure the effect of lean on a histopathology laboratory	Lean	Convert to a lean laboratory	Turnaround time decreased from 9.7 to 9.0 hours

Table 2.2 *(cont.)*

Study	Objective	Approach	Recommendation	Results
(Raab et al., 2008)	Implement lean for pap testing and diagnostic accuracy	Lean	Create a one piece workflow and record process completion with a Lean checklist	Improved pap test quality and diagnostic accuracy
(Elder, 2008)	Investigate the importance of implementing quality/six sigma techniques	Quality	Refine the quality of the process	Reduced cost and improved quality
(Melanson, et al., 2009)	Improve patient experience with laboratory	Lean	Remove non-value added steps	Wait time decreased from 21 to 5 minutes
(Serrano, et al., 2010)	Increase patient safety and laboratory performance	Lean	Implement process redesign	Achieved the CAP ISO-15189 accreditation
(Das, 2011)	Determine how to develop validation measures for testing	Lean	Apply validation measures for all tests	Improved accuracy

In a recent research study, the lean production methodology was applied to a hospital laboratory preanalytical process (Persoon, et al., 2006). Many of the laboratory's customers (physicians) were not pleased with the turnaround time for receiving a patient's test results. The researchers believed that the overall cycle time could be reduced if the preanalytical stage was

improved. Their goal was to report 80% of laboratory tests in less than one hour and to no longer acknowledge a distinction between STAT and routine tests. In their process redesign, they incorporated the concept of single piece flow, which indicates all activities must be performed on each object undergoing the process before the work starts on the next object. This method removes the notion of batching. How the work would be accomplished in the preanalytical stage was redesigned using four rules of the Toyota Production System (TPS). The results of the preanalytical stage redesign indicated significant improvements in the laboratory test turnaround time by approximately a 30% reduction. Phlebotomy customer (physicians and patients) satisfaction and workflow are important factors to consider in any type of clinical laboratory.

In the study of (Melanson, et al., 2009), they focused on how to improve the overall patient experience and methods to optimize the blood collection process in outpatient phlebotomy using lean techniques. The main problem faced at the Brigham and Women's Hospital, teaching affiliate of the Harvard Medical School, was the excessive wait time patients had to experience before being served by a phlebotomist. There were also other problems that had to be addressed such as nonessential work functions, inefficiency of non-blood drawing activities, and reordering process steps. In order to address these problems, a lean expert team implemented a Kaizen Event (continuous improvement) in the outpatient department of this facility. They removed many non-value added work steps in this process and were able to conclude by implementing these improvements, patient wait times decreased from 21 minutes to 5 minutes.

A study was performed that focused on how to incorporate lean practices in a clinical laboratory (Zito & Stewart, 2008). The problem under study was how to reduce the turnaround time when sending patient test results back to physicians. The facility was using a batching

mechanism for test orders, which adds a delay to receiving the test results for certain orders. The authors proposed that a single piece flow system be adopted in this clinical laboratory. The single piece flow system would allow each order to be handled and processed separately rather than having to wait for all other elements in a batch to be processed. When orders are performed in batch, multiple possibilities exist for errors to occur, which would require rework for the phlebotomists. The researchers of this study were able to implement the single piece flow system for many of the floors of the hospital, which allowed the batch sizes to be kept to a minimum. From the process redesign, the lean team saw a significant improvement and reduction in the turnaround time for sending test results to physicians.

Approximately 200,000 patients contract bloodstream infections from catheters each year. These infections have caused a mortality rate of approximately 18%. Researchers applied the TPS strategy to the central line placement and maintenance (Shannon, et al., 2006). Through an in depth analysis, the root cause of the bloodstream infections many patients were suffering from was determined. Best practices were developed to eliminate or at the very least reduce the number of infections that occur. Within a year, healthcare facilities saw a 50% reduction in infections by implementing the best practice techniques.

Another study (Raab, 2006) addresses the problem of reducing medical errors and increasing patient safety in anatomic pathology laboratories using quality tools and techniques. The researcher defines patient safety as freedom from accident or injury resulting from the delivery of health care. Medical error is described as the failure of a planned action to be carried out as intended or the use of the wrong process/plan to achieve a goal. One challenge in decreasing medical errors noticed by the author was the lack of standardization of quality assurance procedures across laboratories. In order to overcome this challenge, a process

improvement team developed a plan to incorporate TPS principles into the laboratory practices. The goal was to obtain a defect free test result for each patient. A one-by-one work flow process was created so that the test specimen was immediately accessioned, processed, and finally screened. After implementing this process redesign, the number of defects decreased from 9.9% to 4.7%. This data indicated that the TPS process improvements resulted in higher quality testing and a decrease in medical errors.

In the study of (Zarbo & D'Angelo, 2007), the authors determined there was approximately a 30% defect rate in the pathology department. Each process and procedure was thoroughly investigated to determine the cause of such defects. The researchers took the Henry Ford Production System strategies and applied them to the pathology department in order to reduce the amount of waste and rework encountered. After the implementation of nearly 100 process improvements, the number of defects reduced from 30% to 12.5%.

2.4.2 Automation approach in laboratory medicine. Many research studies have discussed the importance of automating certain stages of hospital laboratories (Holman, et al., 2002). Automation provides an opportunity to experience a decrease in errors faced in laboratory medicine. Research has shown with automation implemented in laboratory facilities, the total turnaround time and errors experienced could be greatly reduced (Tornel et al., 2005; Melanson et al., 2007). Table 2.3 below provides a synopsis of the automation studies reviewed.

Table 2.3

Synopsis of Articles Reviewed for Automation Approach

Study	Objective	Recommendation	Results
(Yavilevich, 2002)	Increase speed of centrifugation system	Implement fast spin lab module	Implemented in preanalytical stage

Table 2.3 *(cont.)*

Study	Objective	Recommendation	Results
(Holman, et al., 2002)	Decrease laboratory errors that occur in the preanalytical stage	Implement automated preanalytical processing unit	Reduction in laboratory errors
(Tornel, et al., 2005)	Decrease workload in laboratory	Implement automated system	Staff workload was decreased
(Melanson, et.al. 2007)	Select proper automation systems for hospital laboratories	Decide on chemistry automation tool	Decrease in laboratory errors
(Da Rin, 2009)	Reduce errors through workstation design	Incorporate preanalytical workstations	Improved accuracy

Laboratory services in healthcare delivery systems play a vital role in inpatient care. Studies have shown that laboratory data affects approximately 65% of the most critical decisions on admission, discharge, and medication. In a recent research study (Da Rin, 2009), it was discussed how a reduction in errors could be obtained through proper workstation design. As in many studies, it was concluded most of the errors in the entire testing process occur in the preanalytical stage. Therefore, of the three stages (preanalytical, analytical, and postanalytical) priority should be placed on the preanalytical stage in the testing process. The author stated that automation of the preanalytical stage is a method of preventing and reducing errors. When selecting an automated preanalytical workstation, there should be certain performance and quality measures established, such as ensuring patient and specimen identification, etc. The authors proposed 13 components of a preanalytical workstation: specimen input area, sample identification, tube selection, transport system, sorting routing device, automated centrifuge,

level detection and evaluation of specimen adequacy, decapping station, aliquotter station, automated analyzer, specimen delivery, recapping station, and take out station. Strict adherence to blood collection procedures is the most effective way to guarantee quality during specimen collection and specimen processing. The automated preanalytical workstation the author proposed in this study was implemented at San Bassiano hospital. As a result, this hospital experienced improved accuracy and clinical efficiency in their laboratory processes.

The preanalytical stage is the most labor-intensive part of the overall testing process. In the study of (Yavilevich, 2002), the significant advances in blood testing accomplished in the last 30 years were discussed. Many of these advances have been through laboratory automation, but the bottleneck of the process remains to be the low speed of the centrifugation system. Centrifugation allows for plasma to be separated from the red and white blood cells. Current automation systems allow for, on average, 500 tubes to be centrifuged per hour. The author has proposed an even powerful laboratory automation system, Fast Spin technology, which will allow for 2,500 tubes to be centrifuged per hour through combining several parts of the preanalytical process into one unit. There are three parts to the Fast-Spin Module. The first part allows for separation, then the centrifugal force rotates the holders and tubes so they are in a horizontal position, and lastly once the centrifugation has stopped the holders and tubes return to their initial position. There are several advantages to the Fast-Spin preanalytical module, which include: decreased processing time and significant cost savings for hospital laboratories. Increased attention to automate hospital laboratories is due to the need to reduce healthcare costs, specifically laboratory costs. Automation is believed to greatly reduce the errors that are experienced in each of the laboratory stages. Converting a hospital laboratory to a Total

Laboratory Automation (TLA) facility is a gradual process and should begin with preanalytical automation.

2.4.3 Simulation approach in laboratory medicine. In the study of (De Capitani, et al., 2002), a simulation approach is investigated to analyze different scenarios considering personnel, preanalytical devices, and management policies. The goal of developing a simulation model is to understand how the future system will work and to provide a performance and economic assessment, prior to implementation. The first component of the study focuses on data collection and workflow analysis. The second component of the study consists of scenario design and the development of the simulation model. The final component is the simulation model validation and performance evaluation. The objective of the laboratory is to minimize the total cost associated with the preanalytical stage. Three scenarios were designed and the chosen scenario was the one with the lowest cost, while still meeting all constraints. The authors concluded that the optimal scenario was Scenario B with one operator for the loading/unloading of the tubes and three operators for inputting requests. If this scenario is implemented for the automation of the preanalytical stage in hospital laboratories, there would be cost savings of approximately 40%.

Management tools such as work flow analysis, workflow simulation, and scenario analysis are proving their effectiveness in laboratory medicine. Several studies have been conducted and show the usefulness of implementing such management tools in hospital laboratories. The goal of workflow analysis and design includes the adjustment of capacity and services, such that services are provided in the most efficient manner. High quality indicates that the level of work performed is done accurately, errors are minimized, and patients are satisfied. In a simulation study (Goldschmidt, et al., 1998), it was determined that workflow analysis could be applied in clinical laboratories using discrete event simulation. The purpose of the simulation

was to analyze how a growing workload affects the service times of the staff. The results from the study proved to be very beneficial as it allowed for proper resource allocation within hospital laboratories.

2.5 Research Gap

There have been many studies that have focused on how to improve laboratory medicine. Most of these studies have provided improvements using lean manufacturing strategies, quality improvement methods, automation, and simulation. Yet in the literature, no study has applied mathematical modeling methods to improve laboratory processes and scheduling. Mathematical modeling has proven to be beneficial in many different areas of healthcare. These areas include: surgery scheduling, outpatient appointment scheduling, and cancer screening. Since laboratory medicine is such a major part of the healthcare delivery system, it is imperative to close this gap.

The approaches utilized in this dissertation research include the development of an analytic hierarchy process (AHP) model, which was used to determine the ranking of the stages in the hospital laboratory. The stage with the highest rank was the stage selected to be optimized. An analytic network process (ANP) model was then developed to compare the results with the AHP model to ensure the proper stage was selected for improvement purposes. Next, a two-stage stochastic integer linear programming (SILP) model was formulated to optimize the selected stage from the AHP and ANP models. The two-stage SILP model determines a weekly scheduling policy and blood collection assignments that balance workload amongst the phlebotomists.

My research contribution to the literature is to improve laboratory medicine by developing an efficient heuristic algorithm to find a near-optimal solution to a two-stage SILP problem, which is a phlebotomist scheduling problem to determine a weekly shift schedule of

phlebotomists in a hospital laboratory in order to balance their workload between and within shifts. For the cases in the hospital laboratory motivating this research, the heuristic algorithm proposed could find near-optimal solutions (with a relative gap less than 3.5%) within 20 minutes. The two-stage SILP model and the heuristic algorithm will assist laboratory management in balancing phlebotomist workload in hospital laboratories, which could reduce the risk of poor phlebotomist performance and patient neglect caused by work overload. The near optimal solutions to the two-stage SILP problem also provide insights to hourly blood collections assigned to the phlebotomists working during each hour. These insights generated the blood collection assignment rules, which could be easily implemented using any spreadsheet software such as Microsoft Excel. The results of this research, when implemented, will prove to be beneficial for improving phlebotomist workload, patient safety, and the effectiveness and efficiency of hospital laboratories overall.

CHAPTER 3

AHP and ANP Modeling for Optimal Stage Selection in Hospital Laboratories

The first research question to be addressed in this dissertation study consists of three sub-questions: (1) Which of the three stages in the hospital laboratory (preanalytical, analytical, or postanalytical) is the most critical for optimization purposes? (2) Mathematically how can this be determined? (3) How can this be validated? The approach used to address these sub-questions includes the development of an AHP model, which will rank each of the stages from most critical to least critical. An ANP model is then developed to compare results with the AHP model to ensure the proper stage has been selected for optimization. In Chapter 3, the AHP and ANP models for optimal stage selection in hospital laboratories are discussed. A brief background on the AHP and ANP methodology is provided along with a review of literature for AHP and ANP modeling in medical decision making. These models for the hospital laboratory case are presented along with the stage selection results. Lastly, a brief conclusion for this chapter is provided.

3.1 Background

The Analytic Hierarchy Process (AHP) model is a structured technique analyzing complex decisions. This model is based on a mathematical structure and was developed by Thomas L. Saaty; it has been extensively studied and refined since its establishment. Rather than identifying a "correct" decision, the AHP helps decision makers find one that best suits their goal and their understanding of the problem. It provides a comprehensive and rational framework for structuring a decision problem, representing and quantifying its elements, then relating those elements to overall goals, and evaluating alternatives. The Analytic Network Process (ANP) is a theory that extends the AHP to occurrences of dependence. It permits interactions within clusters

identified and between clusters as well. The ANP provides a thorough framework to include clusters of factors connected in any way to examine the process of obtaining ratio priorities from the distribution of influence among elements and among clusters. In AHP Modeling, every factor in the hierarchy is considered to be independent of the other factors, the decision criteria are considered to be independent of each other, and the alternatives are independent of the decision criteria and of each other. The concern with the AHP modeling technique is that with many real-world and practical cases, interdependence is present among the items and the alternatives. ANP does not require independence among factors. Therefore, it is utilized as an effectual technique in these cases.

The expert feedback needed for the AHP and ANP models was provided by the hospital laboratory manager. These models have determined how four different methodologies can be utilized to improve the stages in hospital laboratories. The model results indicate the hierarchy of the stages from most critical to least critical. The results from the ANP model will be compared to the results from the AHP model to ensure proper stage selection for optimization purposes.

In the next section, a literature review on AHP and ANP modeling in medical decision making has been provided. From a review of the literature, it has been determined that AHP and ANP modeling has not been used in studies concerning laboratory medicine. Lastly, the AHP and ANP model developments for the hospital laboratory case and the corresponding results are presented.

3.2 AHP and ANP Modeling in Medical Decision Making: Review of Literature

Statistics published by the U.S. government indicate that healthcare spending is projected to reach $4.5 trillion by the year 2017. Improvements in healthcare decision making are needed in order to solidify benefits for patients and health care professionals. There are a variety of

popular tools that assist with the process of medical decision making, but the literature review in this section will focus on AHP and ANP modeling. This technique allows the decision maker to organize problems/decisions in the form of a hierarchy. There are a variety of researchers that have utilized the AHP modeling approach in respected studies in the healthcare field (Liberatore & Nydick, 2008). These studies include: therapy and treatment, healthcare evaluation, patient involvement, and project selection.

From a review of the literature, it was determined that certain problems do not always indicate a hierarchical structure; therefore the problem should be modeled as a network. There are not many studies that utilize ANP modeling in medical decision making, although this approach has been used in determining the proper treatment for cancer (Carter et al., 1999) and the proper tests for certain symptoms (Saaty & Vargas, 1998). There are studies that have indicated decision problems are best investigated through both ANP and AHP (Saaty & Vargas, 1998) . This allows for a thorough analysis and comparison to be conducted to determine if the same results are obtained from both models. If the same result is obtained, this will provide additional confirmation for the decision to be selected.

There have been a variety of models developed for assessment of quality management. While using these models, healthcare delivery systems recognized a large number of areas for improvement, in which they developed improvement projects and strategies to implement in their facilities. It is not feasible to implement all projects simultaneously, and therefore AHP and ANP modeling would prove to be beneficial in the effort of prioritization. Table 3.1 provides a synopsis of the AHP and ANP studies reviewed.

Table 3.1

Synopsis of Articles Reviewed: AHP/ANP for Medical Decision Making

Study	Objective	Approach	Recommendation	Results
(Dolan & Bordley, 1994)	Determine if isoniazid prophylaxis should be used as a treatment for patients	AHP	Use different treatment strategies	Specific treatment was prescribed per patient
(Saaty & Vargas, 1998)	Determine what tests to perform given certain symptoms	AHP/ANP	Use expert judgment to decide appropriate tests	Approach supported physicians
(Carter, et al., 1999)	Evaluate treatments for a patient with breast cancer	AHP/ANP	Choose the treatment with the highest ranking	Radiation and tamoxifen was selected as the best treatment
(Hummel, Rossum, Verkerke, & Rakhorst, 2000)	Compare a variety of catheter pumps	AHP	Base assessment on medical, economic, and patient factors	Selected the pump with the best safety and ease of use
(Chatburn & Primiano, 2001)	Decide the best method to buy a ventilator at a hospital	AHP	Utilize AHP aids in the decision making process	Budget proposal developed at university hospital
(Rossetti & Selandari, 2001)	Decide if robots can replace humans in hospital pharmacies	AHP	Implement the use of robots in hospital pharmacies	Analysis indicated the robots were preferred to humans
(Longo & Masella, 2002)	Examine processes adopted in different operating blocks	AHP	Importance of tasks in process should be measured	Best practices identified

Table 3.1*(cont.)*

Study	Objective	Approach	Recommendation	Results
(Cho & Kim, 2003)	Select proper medical devices	AHP	Purchase only the highest ranked products	The top 15 products were funded
(Chang, Cheng, & Su, 2004)	Determine the best patient discharge planning approach	AHP	Redesign the discharge planning process	Improvement in discharge planning management
(Dey, Hariharan, Kumar, & Moseley, 2004)	Measure the performance of ICU service reliability	AHP	AHP is a valuable tool to quantify the performance of an ICU division	Successfully identified ICU performance
(Ahsan & Bartlema, 2004)	Evaluate the performance of healthcare complexes	AHP	Improvements in certain areas of the complexes are required	Decision making process improved
(Hariharan, Dey, Chen, Moseley, & Kumar, 2005)	Develop a model for the performance measurement of three intensive care units	AHP	Improve the poor performance areas in each ICU	AHP is a useful model to measure performance in the ICU
(Hummel, Snoek, van Til, van Rossum, & Ijzerman, 2005)	Evaluate two alternatives for people with tetraplegia	AHP	Obtain feedback from patients with tetraplegia for both alternatives	Conventional surgery was preferred
(Richman et al., 2005)	Evaluate prostate cancer treatment selection	AHP	Enhance the treatment selection by making this decision evidence based	Validated the use of AHP for prostate cancer treatment selection
(Liberatore & Nydick, 2008)	Determine screening vs. not screening effects for prostate cancer patients	AHP	Appropriate decision-counseling protocols should be administered	Increase in awareness of the benefit of screening

3.2.1 Therapy and treatment selection. AHP and ANP modeling has been used for the selection of the best and most appropriate medical treatments and therapies for healthcare patients. The AHP has been utilized to help decide on the preferred treatment for adults afflicted with a sore throat (Singh, Dolan, & Centor, 2006). The criteria considered were reducing symptom duration, preventing infectious complications, minimizing antibiotic side effects, and avoiding under and over treatment of a patient. The alternatives included no test, no treatment; rapid strep test and treat if positive; throat culture and treat if positive; rapid strep test and treat if positive, and if negative, throat culture and treat if positive. Data that had been published was used to estimate how each alternative fulfilled the evaluative criteria, and was the basis for the required pairwise comparisons. It was determined that the preferred treatment strategy depended on the patient. Many studies have utilized the AHP model to determine the best treatment for a variety of health conditions from tuberculosis (Dolan & Bordley, 1994) to breast cancer (Carter, et al., 1999). The application of the AHP was also used as part of a case-based reasoning technique regarding discharge planning for patients in Taiwan healthcare facilities (Chang, et al., 2004). The categories of long-term resources available were senior welfare institutions, community care resources, and home care resources. Using information obtained from experts, seven evaluation dimensions were chosen: functional conditions, physical conditions, caregivers, support systems, nursing care, basic information, and medical care awareness. The AHP model was used to establish the weights of each of the seven evaluators. In order to substantiate the feasibility of the recommended approach, it was applied to the discharge cases in the neurology and pulmonary division at the healthcare delivery system in Taiwan. Increased accuracy was achieved regarding the discharge planning for five sample cases.

3.2.2 Healthcare evaluation. Many studies have investigated the use of AHP modeling for the evaluation of health care facilities and health care policy analysis. In a particular study, the researchers studied how the AHP can be used to analyze the performance of healthcare delivery systems (Hariharan et al., 2004; Dey et al., 2004). The main criteria included: patient care, establishment, and administration. This modeling approach provided useful details regarding the performance of hospitals.

There were two tertiary care hospitals evaluated in Barbados and India. Dey et al. (2004) recognized areas where each hospital did not perform well and recommendations for improvement were provided using the AHP methodology. A similar AHP approach, to evaluate the performance of an intensive care unit, in a Barbados hospital was also conducted (Hariharan, et al., 2005). Using the AHP, Longo and Masella (2002) evaluated the performance of different organizational processes in a variety of operating blocks in eight different Italian hospitals. The analysis was based on cost, quality, and income. The judgments that were required for the study were provided by nurses and the clinician staff. The results provided insights and the areas that should be improved within each facility.

A research study was performed that utilized the AHP model to analyze the performance of Thana Health Complexes (THC) which are comprised of healthcare facilities (Ahsan & Bartlema, 2004). The five criteria included: THC activities, maternal care, child health, family planning, and management. Experts participated in the study and determined all criteria and subcriteria. Seven Thanas were analyzed based on collected data from a public health department. The results of the study were used to decide the Thanas that require improvements in certain areas.

3.2.3 Patient involvement. Patient involvement in the healthcare decision making process has been addressed in several studies. Liberatore & Nydick (2008) discuss how the AHP model is used to aid in a decision counseling practice for African American males deciding to take part in a prostate cancer screening examination. Studies have indicated that the risk of dying from prostate cancer is much higher among African American males.

Hummel et al. (2005) investigates how the AHP model can help a rehabilitation team analyze the performance of two options, functional electrical stimulation (FES) and conventional surgery to progress the arm–hand functionalities of people with sixth cervical vertebra level Motor Group 2 tetraplegia. The criteria considered in this study included: ease of use, social acceptance, arm–hand function, minimal risks, and minimal load of treatment. The authors concluded that conventional surgery was preferred over FES.

Richman et al. (2005) applied the AHP model to aid in selecting the most appropriate prostate cancer treatment. The criteria included: chance for cancer cure, risk of cancer progression, long-term survival, quality of life, limiting acute complications of treatment, risk from blood transfusion, and cost to patient. The expert physician panel provided weighted judgments connecting the different treatment options with each sub-objective. The results provided a prioritized list of the alternative treatments for the patients.

3.2.4 Project selection. The AHP model for selection and evaluation of projects and technology in health care settings has been utilized in many research studies. Hummel et al. (2000) utilized the AHP model to conduct a practical medical technology assessment of a blood pump called a pulsatile catheter pump. The assessment was based on criteria that included medical, economic, and social factors. The results provided a helpful and useful assessment of this blood pump for the healthcare management staff.

Chatburn and Primiano (2001) utilized a decision-making tool identified as a multi-attribute utility model to help determine how to buy a ventilator for a healthcare facility. The authors evaluated neonatal ventilators for a women's health hospital utilizing the AHP modeling technique. The model was based on pairwise comparisons provided by the hospital's director of respiratory therapy and clinical engineering. The categories of criteria included: safety, clinical factors, biomedical engineering factors, and cost. The alternatives included: the existing ventilator, an updated version, and a state-of-the-art unit. The contributors believed the AHP model to be easy to use and supported the decision to purchase the ventilator.

Cho and Kim (2003) indicated how the AHP would be used for the selection of medical devices and materials for grants by the Korean Ministry of Health and Welfare. The three criteria included: marketability, technology applicability, and public benefits. Within the hierarchy, 88 alternatives were organized. Funding priorities for the 88 alternatives were identified, and the top 15 products were funded based on the results. Rossetti and Selandari (2001) focus on the application of the AHP model to determine if a fleet of mobile robots could be put in place to substitute an established human-based delivery system in hospital pharmacies. The proposed AHP model included economic and technical performance elements, social, human, and environmental factors. The results indicated that a fleet of mobile robots can be put in place to substitute the human-based transportation system.

3.3 AHP Model for Hospital Laboratory Case

The AHP model for this study has been used to demonstrate how the best features from four different improvement strategies: Theory of Constraints, Lean, Critical Business Process, and Six Sigma, could be used to develop an approach for prioritizing and selecting the stage for optimization in a hospital laboratory. The AHP model is provide below in Figure 3.1.

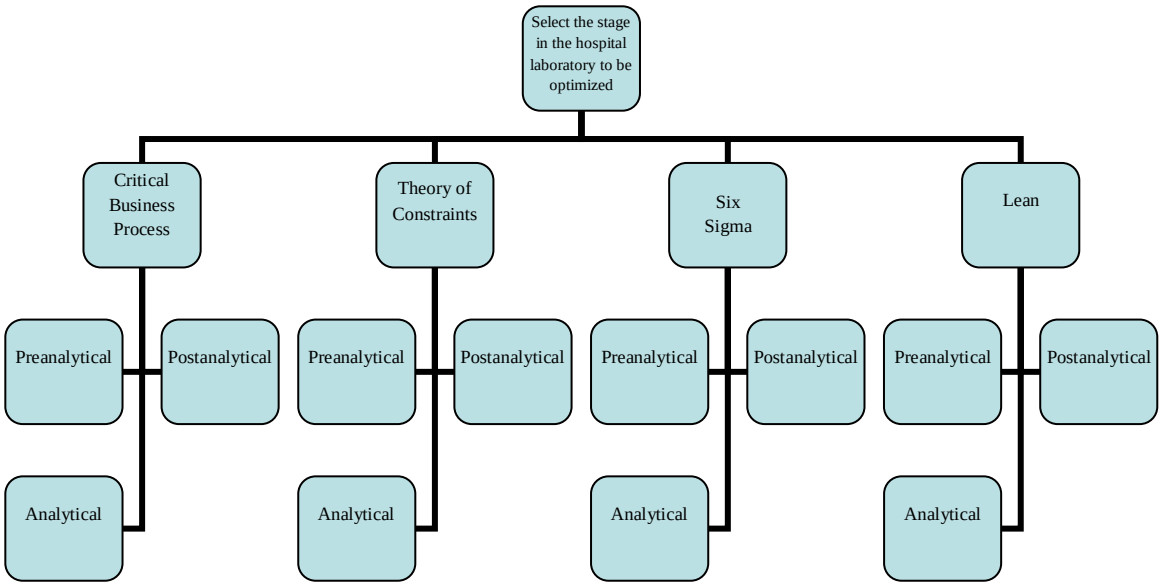

Figure 3.1. AHP model for the hospital laboratory case.

In the AHP model, i is the index for methodology and j is the index for stages in the laboratory process. w_i denotes the weight for methodology i and w_{ij} denotes the weight for methodology i and stage j. Weight w_i and w_{ij} are determined using pairwise comparisons. These weights are presented in Table 3.2 and Table 3.3. Based on the weights, the overall score of each stage (W_j) is determined by $W_j = \sum_{i=1}^{I} w_i w_{ij}$.

Table 3.2

Weights for Each Methodology

Methodology	**Weight**
Lean= w_1	0.3027
Six Sigma=w_2	0.4792
Theory of Constraints=w_3	0.1368
Critical Business Process=w_4	0.0813

Table 3.3

Weights for Each Methodology i and Stage j

	Preanalytical Stage *j*=1	**Analytical Stage *j*=2**	**Postanalytical Stage *j*=3**
Lean *i*=1	0.5492	0.3312	0.1196
Six Sigma *i*=2	0.5515	0.2767	0.1718
Theory of Constraints *i*=3	0.5389	0.2972	0.1637
Critical Business Process *i*=4	0.4670	0.3763	0.1567

Once the weights were determined, a consistency check of the comparisons was completed. The consistency check involved calculating the ratio of the consistency index to the random index. For the AHP model, the consistency index and random index are 0.067 and 0.90 respectively. Thomas Saaty, founder of the AHP model, has proven that if the ratio is greater than 0.1, serious inconsistencies may exist and the AHP model may not yield meaningful results. If the ratio is less than 0.1, the degree of consistency is satisfactory. According to the ratio of 0.0744, it can be concluded that the results provided from the AHP model in this study are meaningful.

3.4 AHP Model Results

Based on the results from the model, a hierarchy is determined for the three stages in the laboratory process. The results indicate the order of importance/criticality of the stages in the hospital laboratory. The results from the AHP model developed, state that the Preanalytical Stage should be selected first to optimize since it has the highest score (0.5422), then the Analytical Stage with the next highest score (0.3139), and lastly the Postanalytical Stage with the lowest score (0.1539). The results of the AHP model align with the conclusions from many studies, which is that the preanalytical stage is the most critical stage in the entire testing process. Since

the other two stages follow the first stage, it is presumed that improvements in the preanalytical stage will benefit the overall process similar to that of the "domino effect" concept. The results from the AHP model for the hospital laboratory case are provided in Table 3.4 below. For additional details regarding the AHP analysis reference *Appendix A.*

Table 3.4

Score for Each Laboratory Stage

Laboratory Stage	AHP Score
Preanalytical	0.5422
Analytical	0.3139
Postanalytical	0.1539

3.5 ANP Model for Hospital Laboratory Case

The ANP model for this study was developed as a method of validation for the results from the AHP model discussed previously. It was formulated to demonstrate how the best features from four different improvement strategies: Theory of Constraints, Lean, Critical Business Process, and Six Sigma, could be used together to develop an approach for prioritizing and selecting the stage for improvement in a hospital laboratory. The modeling software used for the ANP model for the hospital laboratory case, was Super Decisions. The Super Decisions software is used for decision-making with dependence and feedback. This software uses an essential prioritization method based on deriving priorities through judgments on pairs of factors or from direct measurements. The authentication and success of the ANP has been seen in applications where the results produced corresponded with identified answers in the real world or from predicted outcomes. Therefore, this technique is a trustworthy and objective methodology for making decisions based on priorities and significance. Figure 3.2 illustrates the initial step of the ANP model, which is the development of the control network. In the control network, the

user determines the overall goal for the model, which in this case is to select the best stage to optimize in the hospital laboratory. Then, the user must develop the sub-networks of the model and indicate the relationship between the control network and the sub-networks. The four improvement techniques: Lean, Six Sigma, Theory of Constraints, and Critical Business Process each represent a sub-network for the model. Once the control network and sub-networks have been developed, the next step involves developing the clusters within each sub-network. There will be two clusters in each sub-network. The two clusters include the alternatives in one and the attributes of the methodology in the other. The alternatives for all of the sub-networks include: Preanalytical Stage, Analytical Stage, and Postanalytical Stage. Figures 3.3-3.6 illustrate each of the sub-networks for the ANP model.

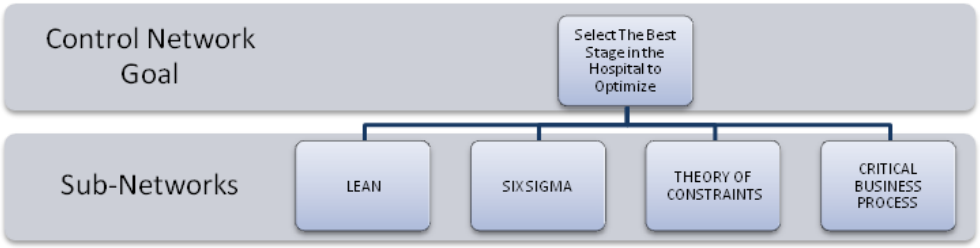

Figure 3.2. Control network for the ANP model.

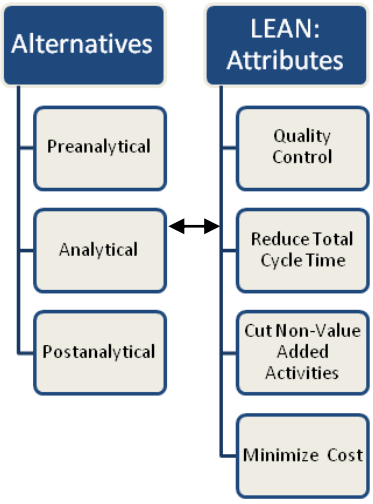

Figure 3.3. Sub-network for lean.

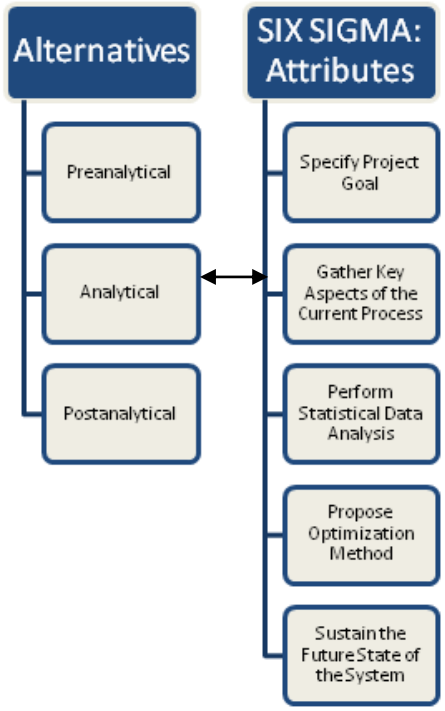

Figure 3.4. Sub-network for six sigma.

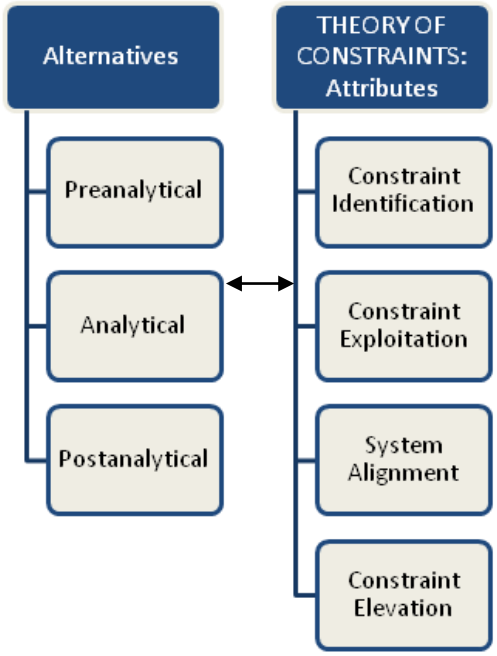

Figure 3.5. Sub-network for theory of constraints.

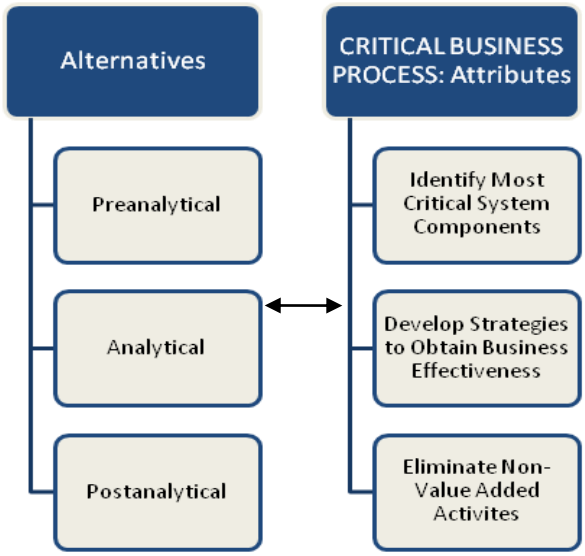

Figure 3.6. Sub-network for critical business process.

3.6 ANP Model Results

From the results of the ANP model, a priority has been determined for the three stages in the entire testing process. The results indicate the order of criticality for the stages in the hospital laboratory. The results from the ANP model consist of the unweighted matrix, the priorities, and the sensitivity graph for each sub-network. The final result will indicate the priorities for the control network, which consists of the stages of the hospital laboratory. The results are provided and discussed below for each sub-network and control network.

Figure 3.7 represents the unweighted supermatrix for the lean sub-network. The unweighted supermatrix contains the local priorities derived from the pairwise comparisons throughout the lean sub-network. The attributes, elimination of non-value added activities, minimization of cost, quality control, and reduction of total cycle time, have the following priorities with respect to the analytical stage: 0.390525, 0.276142, 0.195262, and 0.138071, respectively. These priorities are shown in the four bottom cells of the first column. This may be interpreted with the following statement, "The elimination of non-value added activities in the

analytical stage is the more dominant attribute when compared to the other attributes in the lean sub-network." This dominant attribute is the most critical when utilizing the lean technique to obtain improvements in the analytical stage. The same results were obtained in the unweighted matrix for both the preanalytical and postanalytical stages. With respect to the elimination of non-value added activities, the priorities of the three alternatives (analytical stage, postanalytical stage, and preanalytical stage) are shown in the three top cells of the fourth column, which are 0.126007, 0.416117, and 0.457875, respectively. This could be interpreted with the following statement, "The preanalytical stage, when incorporating the elimination of non-value added activities, will benefit the most when compared to the other alternatives."

Subnet under 1.Lean: Unweighted Super Matrix

Cluster Node Labels		Alternatives			Lean: Attributes			
		Analytical Stage	Postanalytical Stage	Preanalytical Stage	Elimination of Non-Value Added Activities	Minimization of Cost	Quality Control	Reduction of Total Cycle Time
Alternatives	Analytical Stage	0.000000	0.000000	0.000000	0.126007	0.209804	0.139636	0.139636
	Postanalytical Stage	0.000000	0.000000	0.000000	0.416117	0.240268	0.332520	0.332520
	Preanalytical Stage	0.000000	0.000000	0.000000	0.457875	0.549927	0.527844	0.527844
Lean: Attributes	Elimination of Non-Value Added Activities	0.390525	0.390525	0.390525	0.000000	0.000000	0.000000	0.000000
	Minimization of Cost	0.276142	0.276142	0.276142	0.000000	0.000000	0.000000	0.000000
	Quality Control	0.195262	0.195262	0.195262	0.000000	0.000000	0.000000	0.000000
	Reduction of Total Cycle Time	0.138071	0.138071	0.138071	0.000000	0.000000	0.000000	0.000000

Figure 3.7. The unweighted supermatrix for the lean sub-network.

The priorities of the three alternatives (analytical, postanalytical, and preanalytical) with respect to the lean sub-network are shown in Figure 3.8. These priorities, as the result of doing pairwise comparisons, are referred to as local priorities. The preanalytical stage has the highest priority with a value of 0.506618.

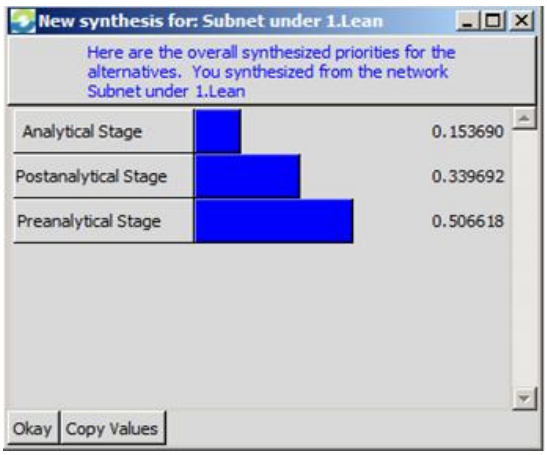

Figure 3.8. The priorities for the alternatives with respect to lean sub-network.

Figure 3.9 illustrates the sensitivity graph for the lean sub-network. The sensitivity analysis for the Lean sub-network indicates how the priorities of the three alternatives, which are the stages in the entire testing process of the hospital laboratory, change as the priority of the Lean independent variable changes. The results indicate that the change in the priority of Lean does not affect the priorities of the alternatives. The preanalytical stage has the highest priority, followed by the postanalytical and analytical stages respectively.

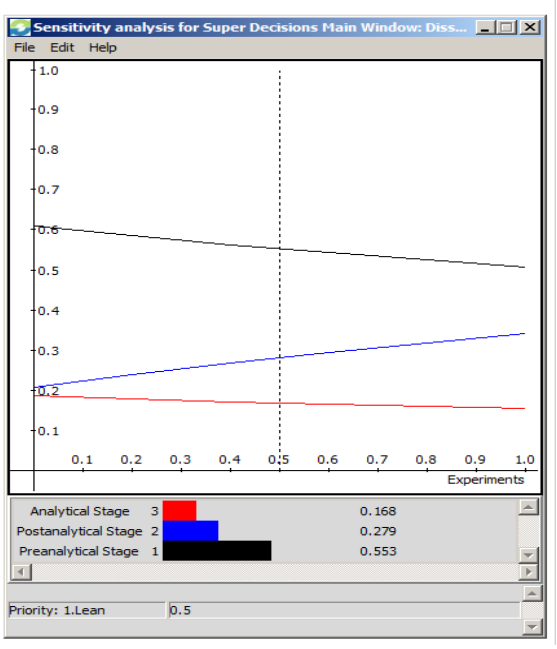

Figure 3.9. The sensitivity graph with lean as the independent variable.

Figure 3.10 represents the unweighted supermatrix for the six sigma sub-network. This unweighted supermatrix contains the local priorities derived from the pairwise comparisons throughout the six sigma sub-network. The attributes, gather key aspects of current process, perform statistical data analysis, propose optimization method, specify project goal, and sustain the future state of the system, have the following priorities with respect to the analytical stage: 0.322856, 0.244679, 0.140531, 0.185432 and 0.106503, respectively. These priorities are shown in the five bottom cells of the first column. This could be interpreted with the following statement, "The gathering of key aspects of the current process is the more dominant attribute when compared to the other attributes in the six sigma sub-network." This dominant attribute is the most critical when utilizing the six sigma technique to obtain improvements in the analytical stage. The same results were obtained in the unweighted matrix for both the preanalytical and postanalytical stages. With respect to the gathering of key aspects of the current process, the priorities of the three alternatives (analytical stage, postanalytical stage, and preanalytical stage), are shown in the three top cells of the fourth column, which are 0.163424, 0.296961, and 0.539615, respectively. This could be interpreted with the following statement, "The preanalytical stage, when incorporating the gathering of key aspects of the current process, will benefit the most when compared to the other alternatives."

The priorities with respect to the six sigma sub-network are shown in Figure 3.11. These priorities, as the result of pairwise comparisons, are referred to as local priorities. When comparing the three stages in the laboratory process, the preanalytical stage has the highest priority with a value of 0.558465.

The sensitivity analysis for the six sigma sub-network indicates how the priorities of the three alternatives will change as the priority of the six sigma independent variable changes.

Figure 3.12 illustrates the sensitivity graph for the six sigma sub-network. The results demonstrate the change in the priority of six sigma does not affect the preanalytical stage having the highest priority, but as the priority of six sigma changes from 0 to 1, the second and third largest priorities change. When the priority of six sigma is less than 0.6, the postanalytical stage has the second highest priority and the analytical stage ranks last; otherwise the analytical stage has the second highest priority and the postanalytical stage ranks last.

Subnet under 2.Six Sigma: Unweighted Super Matrix

Cluster Node Labels		Alternatives			Six Sigma: Attributes				
		Analytical Stage	Postanalytical Stage	Preanalytical Stage	Gather Key Aspects of Current Process	Perform Statistical Data Analysis	Propose Optimization Method	Specify Project Goal	Sustain the Future State of the System
Alternatives	Analytical Stage	0.000000	0.000000	0.000000	0.163424	0.238476	0.238487	0.310814	0.310814
	Postanalytical Stage	0.000000	0.000000	0.000000	0.296961	0.136498	0.136500	0.195800	0.195800
	Preanalytical Stage	0.000000	0.000000	0.000000	0.539615	0.625026	0.625013	0.493386	0.493386
Six Sigma: Attributes	Gather Key Aspects of Current Process	0.322856	0.254268	0.322856	0.000000	0.000000	0.000000	0.000000	0.000000
	Perform Statistical Data Analysis	0.244679	0.254268	0.244679	0.000000	0.000000	0.000000	0.000000	0.000000
	Propose Optimization Method	0.140531	0.134438	0.140531	0.000000	0.000000	0.000000	0.000000	0.000000
	Specify Project Goal	0.185432	0.254268	0.185432	0.000000	0.000000	0.000000	0.000000	0.000000
	Sustain the Future State of the System	0.106503	0.102759	0.106503	0.000000	0.000000	0.000000	0.000000	0.000000

Done

Figure 3.10. The unweighted supermatrix for the six sigma sub-network.

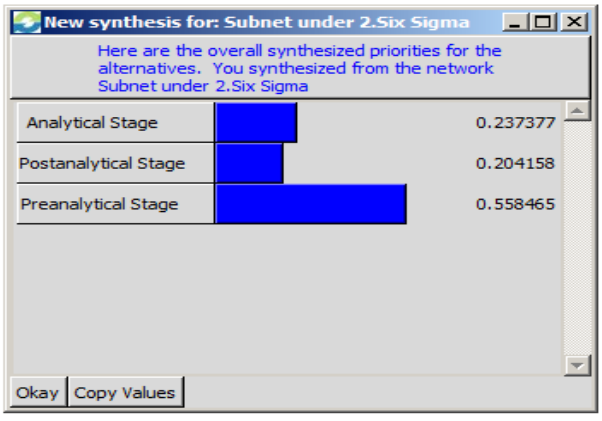

Figure 3.11. The priorities for the alternatives with respect to six sigma sub-network.

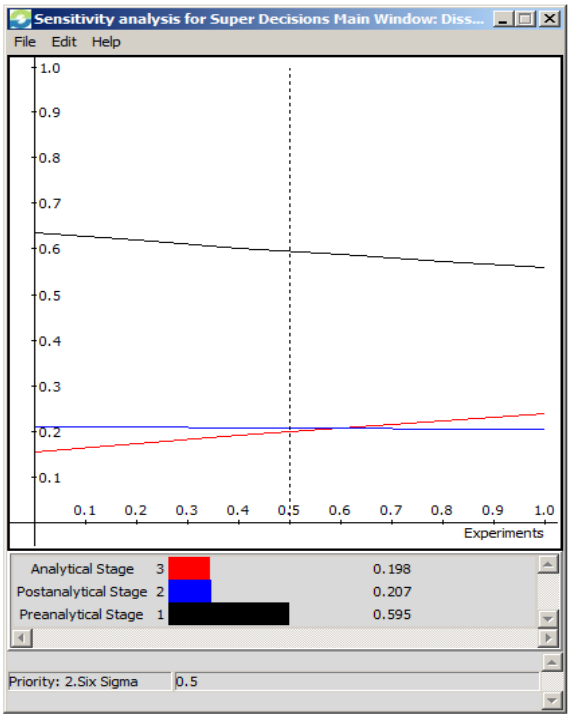

Figure 3.12. The sensitivity graph with six sigma as the independent variable.

Figure 3.13 represents the unweighted supermatrix for the theory of constraints sub-network. This unweighted supermatrix contains the local priorities derived from the pairwise comparisons throughout the theory of constraints sub-network. The attributes, constraint elevation, constraint exploitation, constraint identification, and system alignment, have the following priorities with respect to the analytical stage: 0.104701, 0.229236, 0.482683, and 0.183381, respectively. These priorities are shown in the four bottom cells of the first column. This could be interpreted with the following statement, "Constraint identification is the more dominant attribute when compared to the other attributes in the theory of constraints sub-network." This dominant attribute is the most critical when utilizing the theory of constraints technique to obtain improvements in the analytical stage. The same results were obtained in the unweighted matrix for both the preanalytical and postanalytical stages. With respect to constraint elevation, the priorities of the three alternatives (analytical stage, postanalytical stage, and

preanalytical stage) are shown in the three top cells of the fourth column, 0.238476, 0.136498, and 0.625026, respectively. This could be interpreted with the following statement, "The preanalytical stage, when selecting constraint elevation, will benefit the most when compared to the other alternatives."

Subnet under 3.Theory of Constraints: Unweighted Super Matrix

Cluster Node Labels		Alternatives			Theory of Constraints: Attributes			
		Analytical Stage	Postanalytical Stage	Preanalytical Stage	Constraint Elevation	Constraint Exploitation	Constraint Identification	System Alignment
Alternatives	Analytical Stage	0.000000	0.000000	0.000000	0.238476	0.208127	0.208127	0.163424
	Postanalytical Stage	0.000000	0.000000	0.000000	0.136498	0.131112	0.131112	0.296961
	Preanalytical Stage	0.000000	0.000000	0.000000	0.625026	0.660762	0.660762	0.539615
Theory of Constraints: Attributes	Constraint Elevation	0.104701	0.138071	0.123279	0.000000	0.000000	0.000000	0.000000
	Constraint Exploitation	0.229236	0.276142	0.289202	0.000000	0.000000	0.000000	0.000000
	Constraint Identification	0.482683	0.390525	0.419720	0.000000	0.000000	0.000000	0.000000
	System Alignment	0.183381	0.195262	0.167799	0.000000	0.000000	0.000000	0.000000

Figure 3.13. The unweighted supermatrix for the theory of constraints sub-network.

The priorities with respect to the theory of constraints sub-network are shown in Figure 3.14. These priorities, as the result of doing pairwise comparisons, are referred to as local priorities. The preanalytical stage has the highest priority with a value of 0.635158.

Figure 3.15 illustrates the sensitivity graph for the theory of constraints sub-network. The sensitivity analysis for the theory of constraints sub-network indicates how the priorities of the three alternatives change as the priority of the theory of constraints independent variable changes. The results demonstrate that the change in the priority of theory of constraints does not affect the preanalytical stage having the highest priority, but as the priority of theory of constraints changes from 0 to 1 the second and third largest priorities change. When the priority

of theory of constraints is less than 0.57, the postanalytical stage has the second highest priority and the analytical stage ranks last; otherwise the analytical stage has the second highest priority and the postanalytical stage ranks last. The sensitivity graph allows one to see how sensitive the rank for alternatives is when a change in the priority occurs.

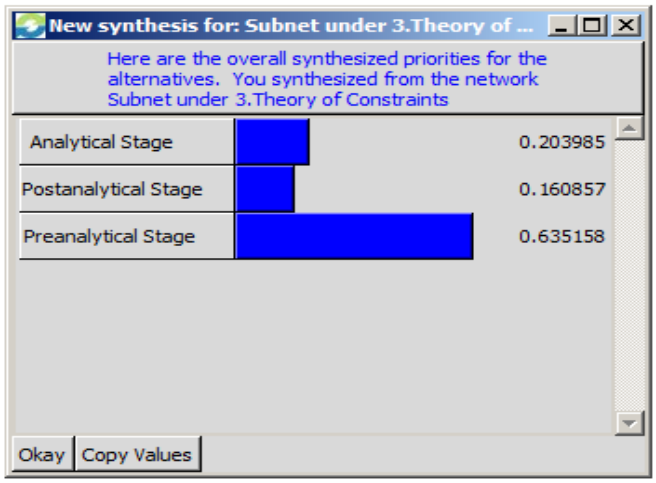

Figure 3.14. The priorities for alternatives with respect to theory of constraints sub-network.

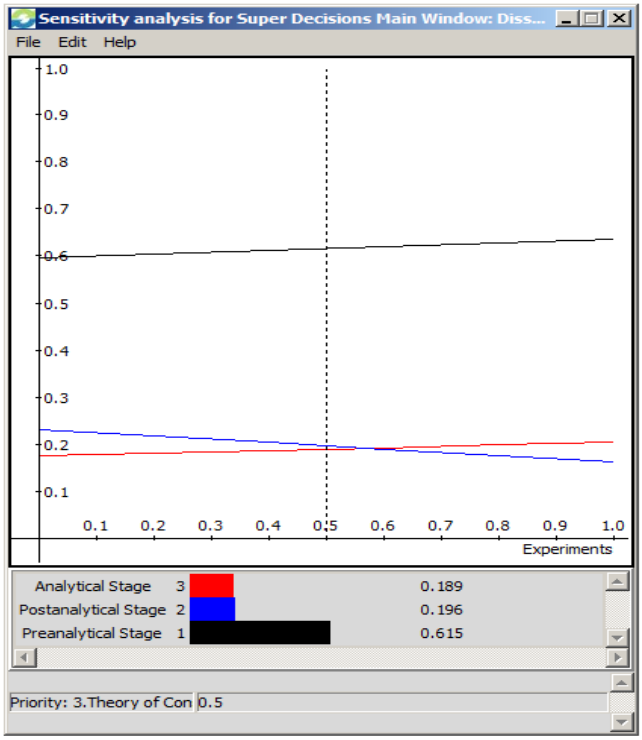

Figure 3.15. The sensitivity graph with theory of constraints as the independent variable.

Figure 3.16 illustrates the unweighted supermatrix for the critical business process sub-network. This unweighted supermatrix contains the local priorities derived from the pairwise comparisons throughout the critical business process sub-network. The attributes, obtaining business effectiveness, final process optimization, and identification of most critical system components, have the following priorities with respect to the analytical stage: 0.296958, 0.163417 and 0.539626, respectively. The priorities are shown in the three bottom cells of the first column. This could be interpreted with the following statement, "The identification of the most critical system components in the analytical stage is the more dominant attribute when compared to the other attributes in the critical business process sub-network." This dominant attribute is the most significant when utilizing the critical business process technique to obtain improvements in the analytical stage. The same results were obtained in the unweighted matrix for both the preanalytical and postanalytical stage. With respect to the identification of the most critical system components, the priorities of the three alternatives (analytical stage, postanalytical stage, and preanalytical stage), are shown in the top three cells of the six column. These values are 0.104728, 0.258273, and 0.636999 respectively. For example, this could be interpreted with the following statement, "The preanalytical stage, when identifying the most critical system components, will benefit the most when compared to the other alternatives."

The priorities of the three alternatives with respect to the critical business process sub-network are shown in Figure 3.17. These priorities, as the result of doing pairwise comparisons, are referred to as local priorities. The preanalytical stage has the highest priority with a value of 0.636999.

The sensitivity analysis for the critical business process sub-network indicates how the priorities of the three alternatives change as the priority of the critical business process

independent variable changes. Figure 3.18 illustrates the sensitivity graph for the critical business process sub-network. The results indicate that the change in the priority of critical business process does not affect the preanalytical stage having the highest priority. On the other hand, when the priority of critical business process is less than 0.2 the analytical stage has the second highest priority and the postanalytical stage ranks last; otherwise the postanalytical stage has the second highest priority and the analytical stage ranks last.

Subnet under 4.Critical Business Process: Unweighted Super Matrix

Cluster Node Labels		Alternatives			Critical Business Process: Attributes		
		Analytical Stage	Postanalytical Stage	Preanalytical Stage	Developing Strategies to Obtain Business Effectiveness	Final Process Optimization	Identification of Most Critical System Components
Alternatives	Analytical Stage	0.000000	0.000000	0.000000	0.104728	0.104728	0.104728
	Postanalytical Stage	0.000000	0.000000	0.000000	0.258273	0.258273	0.258273
	Preanalytical Stage	0.000000	0.000000	0.000000	0.636999	0.636999	0.636999
Critical Business Process: Attributes	Developing Strategies to Obtain Business Effectiveness	0.296958	0.296961	0.332516	0.000000	0.000000	0.000000
	Final Process Optimization	0.163417	0.163424	0.139648	0.000000	0.000000	0.000000
	Identification of Most Critical System Components	0.539626	0.539615	0.527836	0.000000	0.000000	0.000000

Done

Figure 3.16. The unweighted supermatrix for the critical business process sub-network.

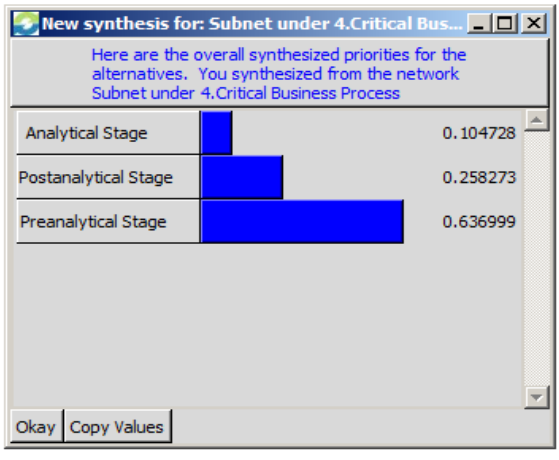

Figure 3.17. The priorities for alternatives in respect to critical business process sub-network.

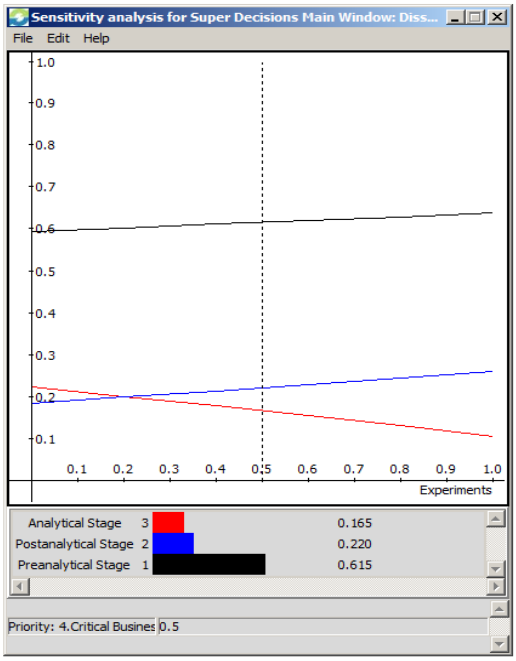

Figure 3.18. The sensitivity graph with critical business process as the independent variable.

The overall priorities for the control network are shown in Figure 3.19. These are the final priorities for the ANP model. The preanalytical stage has the highest priority with a value of 0.607916, the postanalytical stage has the second highest priority with a value of 0.207558, and lastly is the analytical stage with a value of 0.184526. For additional details regarding the ANP analysis reference *Appendix B.*

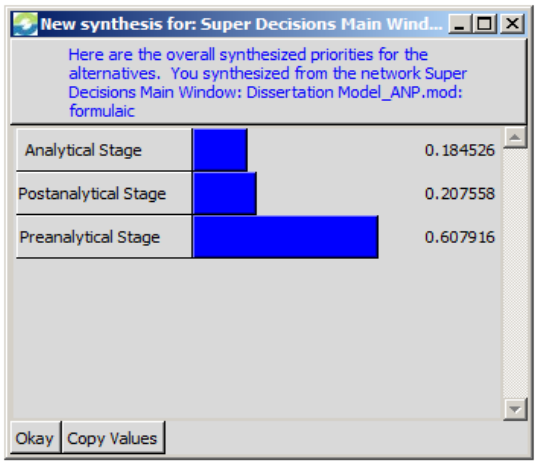

Figure 3.19. The overall priorities for the alternatives.

3.7 Conclusions

The results from both the AHP and ANP models indicate that the preanalytical stage is the most critical stage in the entire testing process. The results from the AHP model rank the analytical stage as the second most critical stage and the postanalytical stage as the least critical. However, the ANP model selects the postanalytical stage as the second most critical and the analytical stage as the least critical. Although from the two models, the overall ranking of the three stages are not exact, the first priority in both models is the preanalytical stage. Therefore, the preanalytical stage should be improved first. In Chapter 4, optimization modeling is used to foster better decision making at the preanalytical stage.

CHAPTER 4

Two-Stage Stochastic Integer Linear Programming Model for Phlebotomist Scheduling and Blood Draw Assignments

In Chapter 4, a two-stage SILP model for phlebotomist scheduling and blood draw assignments is presented. A brief background on stochastic programming is provided, along with a review of literature on stochastic programming in healthcare scheduling. The review of literature indicates that stochastic programming has not been explored in regards to phlebotomist scheduling and blood draw assignments in the laboratory medicine area. Next, the problem is defined, along with the approach taken to alleviate the problems faced in the preanalytical stage. The objective to be accomplished and the assumptions for the problem are also provided. In the section following, the formulation for a two-stage SILP model is presented to address the defined problems. The solution approach, which includes the scenario reduction model and heuristic algorithm, is then discussed in detail. Lastly, a brief conclusion is presented to summarize the performance of the solution approach.

4.1 Background

One of the analytical approaches used in the study of scheduling systems is mathematical programming. In a mathematical programming or optimization problem, one seeks to minimize or maximize a real function of real or integer variables, subject to constraints on the variables. The term mathematical programming refers to the study of the development and implementation of algorithms to solve optimization problems, and the application of these algorithms to real world problems. This is a popular approach used in scheduling studies due to the rapid advancements in optimization. Different optimization solvers can be used to obtain the optimal solution to a variety of mathematical programming models. There are several types of

mathematical programming methods used in scheduling studies, and one of the main methods utilized in this research area is stochastic programming. Stochastic programming investigates the state in which some of the constraints or parameters depend on random variables, and assumes there's a level of uncertainty associated with the system under study.

To address the second and third research questions, a two- stage SILP model has been developed. This model has been formulated to determine the number of phlebotomists to schedule during each shift and the number of blood draw collections that should be assigned to each phlebotomist, in order to balance workload within and between shifts.

4.2 Stochastic Programming in Healthcare Scheduling: Review of Literature

According to the review of literature, stochastic programming is used mainly in appointment scheduling studies. A sequential bounding approach for optimal appointment scheduling was proposed in a study conducted by Denton and Gupta (2003). The researchers determined the optimal appointment times for a series of tasks with uncertain durations using a two-stage stochastic linear programming model. This model was used due to the flexibility associated with modeling different types of cost considerations. The benefit of this model is that it is generalized to any two stage stochastic linear program for which the upper bounds on dual multipliers can be computed on a partition of the space of random variables.

Scheduling patient appointments has also been studied using optimal and empirically-based heuristics (Robinson & Chen, 2003). In this study, the authors focus on how to achieve a balance between physician idle time and patient waiting time. Heuristic rules were used to aid outpatient facilities in determining appropriate appointment times. The results indicated the heuristic developed achieved a solution within 2% of the optimal policy for patient appointment scheduling.

The nurse assignment problem is investigated using a stochastic integer programming model (Punnakitikashem, Rosenberger, & Buckley Behan, 2008). The researchers in this study have an objective of minimizing the excess workload on the nurses scheduled. The results indicate the scheduling templates for several different cases that minimize the excess workload experienced by the nurses. Through the implementation of the scheduling templates from this study, 273 hours of excess workload on nurses per year was saved.

A two-stage stochastic programming model, for scheduling and allocating cross trained workers, has been investigated for multi-department service environments with random demands (Campbell, 2010). The researcher investigates how this model will be useful in hospital nurse scheduling. The objective was to determine the days off to allocate to each nurse and also the number of nurses to schedule for each day in order to meet the realized demand. The scheduling and allocation models presented in this study have the potential to help managers better utilize cross-trained workers.

Nurse rostering falls under the umbrella of scheduling and is a challenge for many healthcare delivery facilities (Burke, De Causmaecker, Berghe, & Van Landeghem, 2004). The researchers in this study discuss how stochastic programming is a viable approach for evaluating nurse scheduling and rostering. The specific skills and the demand uncertainty are all considered in the stochastic programming model. The results indicate this method is beneficial in staff planning and scheduling for many hospital systems.

The optimization of surgery sequencing and scheduling decisions under uncertainty was investigated to determine optimal operating room scheduling policies (Denton, Viapiano, & Vogl, 2007). In this study, the authors used a two-stage stochastic linear programming model to determine the optimal surgery schedule. This model was utilized in order to prevaricate against

the uncertainty associated with surgery durations. The benefit of this model is that it provided significant improvements to daily operating room schedules.

Operating room and parallel surgery scheduling was studied using a two-stage stochastic mixed integer linear programming model to minimize operating cost (Batun, Denton, Huschka, & Schaefer, 2011). The researchers want to determine the optimal schedule, which indicates the number of operating rooms to open each day, how surgeries should be allocated to operating rooms, and the start time for each surgeon. In order to reach a near optimal solution, the authors solve both the stochastic and mean value problem using L-shaped and branch and bound algorithms. After testing different resource scenarios, the authors can conclude the impact of parallel surgery processing and the benefit of operating pooling are significant. Operating pooling could result in significant cost savings for many hospital systems.

A stochastic model was developed to study operating room planning with elective and emergency demand for surgery (Lamiri, Xie, Dolgui, & Grimaud, 2008). In this study, the authors address the different scheduling policies that should be in place for the surgeries that are planned (elective) and the surgeries that are random (emergency). The objective of this study was to reduce the cost associated with performing a surgery and the associated overtime cost. Monte Carlo optimization methods were used to solve the stochastic model. From this study, the authors were able to conclude the planning model proposed is best useful in healthcare delivery systems that use a blocked advance scheduling system, which allocates blocks of operating room time to surgical specialties. Table 4.1 provides a synopsis of the studies reviewed on stochastic programming in healthcare scheduling.

There are many studies that have utilized stochastic programming to improve scheduling in healthcare systems. Studies that are closely related to this research include nurse scheduling.

Table 4.1

Synopsis of Articles Reviewed for Stochastic Programming in Healthcare Scheduling

Study	Objective	Recommendation	Results
(Denton & Gupta, 2003)	Determine optimal appointment times for a sequence of jobs	Optimal scheduling of jobs can increase utilization and reduce costs	Illustrate properties of the optimal solution with respect to distribution type and number of jobs
(Robinson and Chen, 2003)	Identify optimal appointment times	Apply heuristics to get close to optimal solutions	Developed scheduling policy within 2% of optimal policy
(Burke, De Causmaecker et al. 2004)	Evaluate nurse scheduling	Add constraints that indicate pair scheduling for nurses	Better scheduling templates
(Denton, Viapiano et al., 2007)	Determine the optimal surgery scheduling policy under uncertainty	Simple sequencing rule for surgery duration variance can be used to gain reductions in cost, idle, and waiting times	Optimal schedule determined for the hospital under study
(Lamiri, et al., 2008)	Identify optimal surgery schedule for elective and emergency cases	Apply Monte Carlo optimization techniques to reach near optimal solution	Best results seen in blocked advance scheduling systems
(Punnakitikashem, Rosenberger et al. 2008)	Develop a stochastic integer programming model to assign nurses to patients	Utilize scheduling template to minimize excess workload	273 hours of excess workload on nurses per year was saved

Table 4.1 (*cont.*)

Study	Objective	Recommendation	Results
(Campbell, 2010)	Develop a two stage stochastic scheduling model for cross trained worker assignments	Implement nurse scheduling templates provided from the model results	Allows managers to better utilize cross-trained workers
(Batun, et al., 2011)	Develop a two stage stochastic mixed integer programming model to address operating room and parallel surgery scheduling	Implement operating room pooling along with parallel surgery scheduling	Determined operating cost reductions between 21% and 59% could be achieved

4.3 Problem Definition

The major problems faced in the preanalytical stage of hospital laboratories are how to schedule the phlebotomists for each shift while accounting for the uncertainty associated with the number of tests that will be ordered, and how to assign blood draw collections to each phlebotomist in order to balance workload. In order to alleviate the problems faced in hospital laboratories, the phlebotomist shift scheduling and blood draw assignment problem is studied to determine the optimal number of phlebotomists to schedule and the optimal number of blood collections to assign during each shift. Poor scheduling policies can result in work overload for the phlebotomists. Work overload can lead to patient neglect as each patient will not get the time and attention they require. Therefore, the objective is to balance workload amongst phlebotomists between and within shifts. The only resource considered in this problem is the service providers, which are the phlebotomists. In the phlebotomist shift scheduling and blood draw assignment problem studied, the following assumptions have been made:

- There are only K phlebotomists available.

- There are a total of *N* shifts in which phlebotomists could be scheduled.
- Each phlebotomist must work one shift per day and five days per week.
- Each shift is eight hours in length.
- The service time to perform a regular blood draw and a STAT blood draw is the same.
- A regular blood draw can be delayed up to three hours and a STAT blood draw has to be collected in the hour ordered without delay.
- The phlebotomists are divided into three levels: beginner, average, and experienced.
- A phlebotomist could not be scheduled in two consecutive shifts.
- *N* shifts are separated into three groups: Morning, Afternoon, and Night shifts.
- The service time for the phlebotomists correspond to the level they are associated with.
- The same weekly scheduling template is used for each week.
- Only one resource (Phlebotomists) is considered.

4.4 Mathematical Model Formulation

The phlebotomist shift scheduling and blood draw assignment problem has been formulated as a two-stage SILP model. The indices, sets, parameters, random variables, and decision variables for the two-stage SILP model are defined in Table 4.2. The decision variables x_{jkn} are the first-stage decision variables, while $y_{ik}(\omega)$ are the second-stage decision variables.

Table 4.2

Indices, Sets, Parameters, Random Variables and Decision Variables

Indices		
i	Time block index;	$i \in I$
j	Days worked;	$j \in \{1, \dots, J\}$
k	Phlebotomist index;	$k \in \{1, \dots, K\}$
n	Hospital shift;	$n \in N$
Sets		
I_1	Set for time blocks with no task delay	
I_2	Set for time blocks with an up to one time block task delay	
I_3	Set for time blocks with an up to two time block task delay	
I_4	Set for time blocks with an up to three time block task delay	
I	$I_1 \cup I_2 \cup I_3 \cup I_4$	
N_1	Set of morning shifts	
N_2	Set of afternoon shifts	
N_3	Set of night shifts	
N =	$N_1 \cup N_2 \cup N_3$	
Parameters		
a_{ijn} =	$\begin{cases} 1, & \text{if time block } i \text{ is included in shift } n \text{ on day } j \\ 0, & \text{otherwise} \end{cases}$	
b_i	Max number of STAT tests ordered in time block i	
D	Total number of days required to work	
F	Max hours for which a regular blood draw could be delayed in subset I_3	
F'	Max hours for which a regular blood draw could be delayed in subset I_4	
J	Total number of days available	
K	Total number of phlebotomists available	
s_k	Average time for phlebotomist k to perform a task	
T_i	Total time for time block i	
Random Variables		
$X_i(\omega)$	Number of tasks occurring in time block i under realization ω	
Decision Variables		
$y_{ik}(\omega)$	Number of tasks assigned to phlebotomist k in time block i under realization ω	
x_{jkn}	$= \begin{cases} 1, & \text{if phlebtomist } k \text{ works on day } j \text{ during shift } n \\ 0, & \text{otherwise} \end{cases}$	
$z_i(\omega)$	Number of tasks left over at the end of time block i under realization ω	
$t_{\max}(\omega)$	Maximum phlebotomist workload in each shift under realization ω	

The phlebotomist shift scheduling and blood draw assignment problem defined in Section 4.3 is formulated as follows:

$$\min \quad E[t_{\max}(\omega)] \tag{1}$$

$$\text{s.t.} \quad \sum_{n\in N}\sum_{k=1}^{K} x_{jkn} \le K, \qquad \forall j \in \{1,...,J\} \tag{2}$$

$$\sum_{n\in N} x_{jkn} \le 1, \qquad \forall j \in \{1,...,J\}\ \forall k \in \{1,...,K\} \tag{3}$$

$$x_{jkn} + x_{j-1,k,n'} \le 1, \qquad \forall j \in \{1,...,J\},\ \forall k \in \{1,...,K\},\ \forall n \in N_1,\ \forall n' \in N_3 \tag{4}$$

$$\sum_{n=1}^{N}\sum_{j=1}^{J} x_{jkn} = D, \qquad \forall k \in \{1,...,K\} \tag{5}$$

$$s_k y_{ik}(\omega) \le T_i \sum_{j=1}^{J}\sum_{n=1}^{N} a_{ijn} x_{jkn}, \qquad \forall i \in I, \forall k \in \{1,...,K\}, \forall \omega \in \Omega \tag{6}$$

$$z_i(\omega) = z_{i-1}(\omega) + X_i(\omega) - \sum_{k=1}^{K} y_{ik}(\omega), \qquad \forall i \in I, \forall \omega \in \Omega \tag{7}$$

$$\sum_{k=1}^{k} y_{ik}(\omega) \ge b_i, \qquad \forall i \in I, \forall \omega \in \Omega \tag{8}$$

$$z_i(\omega) = 0, \qquad \forall i \in I_1, \forall \omega \in \Omega \tag{9}$$

$$z_i(\omega) \le \sum_{k=1}^{K} y_{i+1,k}(\omega), \qquad \forall i \in I_2,\ \forall \omega \in \Omega \tag{10}$$

$$z_i(\omega) \le \sum_{i'=i+1}^{i+F}\sum_{k=1}^{K} y_{i'k}(\omega), \qquad \forall i \in I_3,\ \forall \omega \in \Omega \tag{11}$$

$$z_i(\omega) \le \sum_{i'=i+1}^{i+F'}\sum_{k=1}^{K} y_{i'k}(\omega), \qquad \forall i \in I_4,\ \forall \omega \in \Omega \tag{12}$$

$$t_{\max}(\omega) \ge \sum_{i\in I} s_k\ y_{ik}(\omega) a_{ijn}, \qquad \forall j \in \{1,.,J\}, \forall k \in \{1,...,K\},\ n \in N\ , \forall \omega \in \Omega \tag{13}$$

$$x_{jkn} = 0,1, \qquad \forall j \in \{1,...,J\}, \forall k \in \{1,...,K\}, \ n \in N \qquad (14)$$

$$y_{ik}(\omega) \geq 0, \text{int}, \qquad \forall i \in I, \ \forall k \in \{1,...,K\}, \forall \omega \in \Omega \qquad (15)$$

$$z_i(\omega) \geq 0, \text{int}, \qquad \forall i \in I, \forall \omega \in \Omega \qquad (16)$$

$$t_{\max}(\omega) \geq 0, \qquad \forall \omega \in \Omega \qquad (17)$$

The objective function (1) aims to minimize the expected maximum workload of the phlebotomists in each shift. Constraints (2) enforce the total number of phlebotomists scheduled for all shifts to be less than or equal to the total number of phlebotomists available. Constraints (3) and (4) guarantees that each phlebotomist works at most one shift per day. Constraints (5) enforce each phlebotomist to work five days a week. Constraints (6) are stage linkage constraints and guarantee that all blood draws assigned can be completed based on the phlebotomist time availability. Constraints (7) determine the number of blood draw collections left over at the end of each time block. Constraints (8) force all STAT blood collections to be completed in the time block requested. Constraints (9-12) place restrictions on the number of tests that can be left over at the end of each time block. Constraints (13) determine the maximum workload amongst the phlebotomists and shifts. Constraints (14-17) ensure binary, integer, and non-negativity variables. In this model, the decision variables $y_{ik}(\omega)$ are non-negative integer variables and x_{jkn} are binary variables. Meanwhile, the number of patients requiring a blood draw during time block i (X_i) is a random variable. Therefore, the model formulated is a two-stage SILP model.

4.5 Solution Approach

The two-stage SILP model is solved using a scenario reduction model and a heuristic algorithm. The scenarios in the two-stage SILP model represent the different combinations of the number of blood draws that could be requested in each time block. For example, if there are a

total of *N* time blocks, one scenario would represent the number of blood collections ordered in each block, for blocks one through *N*. For this study, there are 15 time blocks, where each time block includes one to five hours. The number of blood draw collections in each time block is treated as a random demand. An assumption for this study is the blood collection demands in time blocks are independent of one another.

A new heuristic algorithm is proposed to solve the phlebotomist shift scheduling and blood draw assignment problem. In the two-stage SILP model, the heuristic algorithm has used the results from the scenario reduction model to determine a schedule that balances the workload amongst the phlebotomists in hospital laboratories. The scenario reduction model and heuristic algorithm, along with the results, are discussed in detail in the following sections.

4.5.1 Scenario reduction model. Due to thousands of possible scenarios in the two-stage SILP model, a scenario reduction model has been formulated and solved to reduce the number of scenarios to be considered. The scenario reduction model is a heuristic often utilized to reduce the number of scenarios in two-stage stochastic programming models (Karuppiah, Martín, & Grossmann, 2010). The idea behind the scenario reduction model is to select only the scenarios with the highest probability of occurrence. The authors of this study tested four different cases and determined by implementing this heuristic, a high quality solution would be achieved within 10% of the best solution.

The scenario reduction problem has been formulated as a linear programming (LP) model. In Table 4.3, the indices, sets, parameters, and decision variables are defined for the scenario reduction LP model.

Table 4.3

Indices, Sets, Parameters, and Decision Variables

Indices	
i	Time block index; $i \in \{1, \dots, |I|\}$
m_i	Value index; $m_i \in \{1, \dots, |V_i|\}$
Sets	
I	Set of time blocks
V_i	Set of possible values for the number of blood draws requested in time block i
Parameters	
$v_i^{m_i}$	Value of the m_i^{th} element in V_i
$p_i^{m_i}$	Probability that the number of blood draws requested in time block i equals $v_i^{m_i}$ over all scenarios
Decision Variables	
$p'_{m_1,m_2,\cdots,m_{|I|}}$	Probability of a scenario with the numbers of blood draws in time blocks 1, ..., |I| equal to $v_1^{m_1}, \dots, v_{|I|}^{m_{|I|}}$, respectively, in the reduced scenario set

The scenario reduction LP model is formulated as follows:

$$\min \quad \sum_{m_1=1}^{|V_1|}\sum_{m_2=1}^{|V_2|}\cdots\sum_{m_{|I|}=1}^{|V_{|I|}|}(1-p_1^{m_1}p_2^{m_2}\cdots p_{|I|}^{m_{|I|}})\,p'_{m_1,m_2,\cdots,m_{|I|}} \tag{18}$$

$$\text{s.t.} \quad \sum_{m_2=1}^{|V_2|}\sum_{m_3=1}^{|V_3|}\cdots\sum_{m_{|I|}=1}^{|V_{|I|}|}p'_{m_1,m_2,\cdots,m_{|I|}} = p_1^{m_1}, \qquad \forall m_1 \in \{1, \dots, |V_1|\} \tag{19-1}$$

$$\sum_{m_1=1}^{|V_1|}\sum_{m_3=1}^{|V_3|}\cdots\sum_{m_{|I|}=1}^{|V_{|I|}|}p'_{m_1,m_2,\cdots,m_{|I|}} = p_2^{m_2}, \qquad \forall m_2 \in \{1, \dots, |V_2|\} \tag{19-2}$$

$$\vdots$$

$$\sum_{m_1=1}^{|V_1|}\sum_{m_2=1}^{|V_2|}\cdots\sum_{m_{|I|-1}=1}^{|V_{|I|-1}|}p'_{m_1,m_2,\cdots,m_{|I|}} = p_{|I|}^{m_{|I|}}, \qquad \forall m_{|I|} \in \{1, \dots, |V_{|I|}|\} \tag{19-|I|}$$

$$\sum_{m_1=1}^{|V_1|}\sum_{m_2=1}^{|V_2|}\cdots\sum_{m_{|I|}=1}^{|V_{|I|}|}p'_{m_1,m_2,\cdots,m_{|I|}} = 1 \tag{20}$$

$$p'_{m_1,m_2,\cdots,m_{|I|}} \le 1, \qquad \forall m_1 \in \{1, \dots, |V_1|\}, \dots, \forall m_{|I|} \in \{1, \dots, |V_{|I|}|\} \tag{21}$$

$$p'_{m_1,m_2,\cdots,m_{|I|}} \geq 0, \qquad \forall m_1 \in \{1, \ldots, |V_1|\}, \ldots, \forall m_{|I|} \in \{1, \ldots, |V_{|I|}|\} \qquad (22)$$

The objective function (18) includes the known probabilities of the existing set of scenarios and these are present to force the optimization to reduce the number of scenarios, while selecting the scenarios that have the reasonably larger probabilities. Constraints (19-1) – (19-|I|) enforce the sum of the probabilities of the scenarios selected in which $v_i^{m_i}$ appear to be equal to $p_i^{m_i}$. Constraints (20) force the sum of the probabilities of the scenarios selected to be equal to one. Constraints (21) guarantee the probabilities of all scenarios selected to be less than or equal to one. Constraints (22) guarantee the probabilities of all scenarios selected to be larger than or equal to zero.

The scenario reduction model was solved using the optimization software package, General Algebraic Modeling System (GAMS). GAMS is a high level modeling software for mathematical programming and optimization problems. GAMS is tailored for complex, large scale modeling applications and allows the user to build large maintainable models that can be adapted quickly to new situations. The scenarios selected by the scenario reduction model are considered in the two-stage SILP model.

4.5.2 Heuristic algorithm. The two-stage SILP model, considering the scenarios selected by the scenario reduction model, was first solved using a commercial solver. It took the commercial solver several days to find a few feasible solutions to the two-stage SILP model. Their objective function values were far from the estimated lower bound. To verify the estimated lower bound, the two-stage SILP model was reduced by only considering a single scenario. After the reduced two-stage SILP model was solved under each selected scenario, it is realized that for each selected scenario, the objective function value of the best feasible solution found is close to the estimated lower bound. Based on this discovery, an efficient heuristic algorithm is developed.

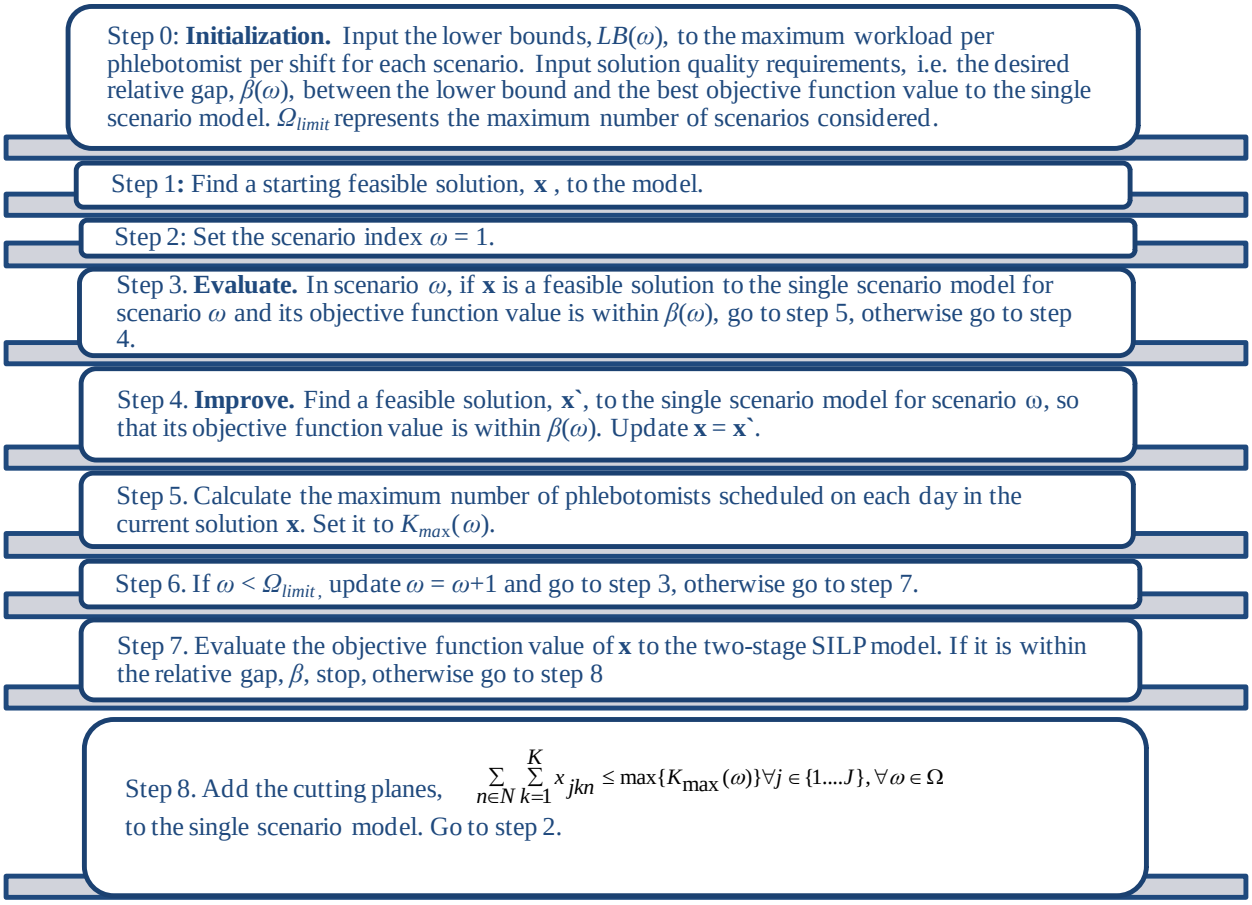

Figure 4.1. Procedure of the proposed heuristic algorithm.

The procedure of the heuristic algorithm is provided in Figure 4.1. The key idea of this heuristic algorithm is to achieve a schedule that works for all selected scenarios, such that the relative gap between the lower bound for each scenario and the best objective function for each scenario is less than 5%. The lower bound for each scenario represents the best possible case with phlebotomist workload completely balanced. This lower bound is calculated using the following equation, where D is the blood draw demand, J is the total number of days, S is the average phlebotomist service time, K is the total number of phlebotomists available, and N is the total number of shifts required to work for each phlebotomist:

$$Lower\ Bound\ for\ Balanced\ Phlebotomist\ Workload = \frac{D * J * S}{K * N}$$

Thus, the lower bound to the optimal objective function of the two-stage SILP model is calculated using the sum of the probabilities of each scenario multiplied by the lower bound for each scenario.

4.5.3 Evaluation of algorithm performance. There are two metrics for evaluating algorithm performance: computation time and solution quality. When the heuristic algorithm in Figure 4.1 was implemented to solve the two-stage SILP model, a computation time of 12 minutes was achieved. In comparison to the computation time achieved by the commercial solver of several days, this is a significant improvement. The next performance metric for the heuristic algorithm includes comparing the solution quality to that of a commercial solver solution. The heuristic algorithm significantly outperformed the commercial solver in this regard as well.

It was important to determine how the heuristic algorithm performed against an existing optimization solver. The performance of the proposed heuristic algorithm was first compared to that of the CPLEX solver in the GAMS software package under the base case. The base case represents the current state of the hospital laboratory. For the base case, there are 34 phlebotomists available to schedule. The shift availability is 400 minutes for each phlebotomist, which represents the amount of time available to perform blood collections. There are 15 time blocks, which do not overlap and cover all 24 hours. The time blocks are presented in Table 4.4. There are ten shifts in which phlebotomists could be scheduled. Table 4.5 presents the working hours of the ten shifts, which are grouped into morning, afternoon, and evening shifts. Lastly, the blood collection demand in each time block is presented in Table 4.6.

Table 4.4

Time Blocks for Hospital Laboratory

Time Block Index	Hours
T1	10pm-11pm
T2	11pm-4am
T3	4am-5am
T4	5am-6am
T5	6am-7am
T6	7am-8am
T7	8am-11am
T8	11am-12pm
T9	12pm-1pm
T10	1pm-2pm
T11	2pm-3pm
T12	3pm-4pm
T13	4pm-7pm
T14	7pm-8pm
T15	8pm-10pm

Table 4.5

Shifts for Hospital Laboratory

Group	Shifts	Hours
Morning Shifts	1	4am-12pm
	2	5am-1pm
	3	6am-2pm
	4	7am-3pm
	5	8am-4pm
Afternoon Shifts	6	11am-7pm
	7	12pm-8pm
	8	2pm-10pm
Evening Shifts	9	10pm-6am
	10	11pm-7am

Table 4.6

Blood Collection Demand for Selected Scenarios

Scenario	Blood Collection Demand in Each Time Block	Probability
	S(T1,T2,T3,T4,T5,T6,T7,T8,T9,T10,T11,T12,T13,T14,T1	
1	S(4,98,4,3,5,7,52,13,10,12,9,9,22,5,8)	.001
2	S(4,98,4,3,5,7,52,13,10,8,9,9,22,5,8)	.518
3	S(4,98,4,5,5,7,52,13,10,12,9,9,22,5,8)	.020
4	S(4,113,4,5,5,7,52,13,10,12,9,9,22,5,8)	.049
5	S(4,113,4,5,5,7,64,13,10,12,9,9,22,5,8)	.006
6	S(4,113,4,5,5,7,64,13,10,12,9,9,30,5,8)	.034
7	S(4,113,4,5,5,7,64,13,15,12,9,9,30,5,13)	.009
8	S(4,113,4,5,5,7,64,13,15,12,9,9,30,5,8)	.012
9	S(4,113,4,5,5,7,64,19,15,12,9,9,30,5,13)	.015
10	S(4,113,4,5,5,7,64,19,15,12,14,9,30,5,13)	.061
11	S(4,113,4,5,5,7,64,19,15,12,14,14,30,5,13)	.054
12	S(4,113,4,5,5,12,64,19,15,12,14,14,30,5,13)	.036
13	S(7,113,4,5,5,12,64,19,15,12,14,14,30,5,13)	.007
14	S(7,113,7,5,5,12,64,19,15,12,14,14,30,5,13)	.094
15	S(7,113,7,5,10,12,64,19,15,12,14,14,30,5,13)	.051
16	S(7,113,7,5,10,12,64,19,15,12,14,14,30,10,13)	.033

In Table 4.7 the performance comparison of the proposed heuristic algorithm and the commercial solver is presented. From the results in Table 4.7, it can be concluded that the heuristic algorithm outperforms the commercial solver regarding the best objective function value found and the computation time.

Table 4.7

Performance Comparison between Proposed Heuristic Algorithm and CPLEX Solver in GAMS

Solution Approach	Estimated Lower Bound	Best Objective Function Value Found	Relative Gap	Computation Time
Commercial	90.47	157.34	73.90%	72 hours
Heuristic	90.47	92.85	2.63%	12 minutes

The performance of the proposed heuristic algorithm was also evaluated under two extended cases. The first extended case includes increasing phlebotomist utilization to 33%, which involves decreasing capacity to 25 phlebotomists, but keeping all remaining inputs the same as the base case. The second extended case includes increasing phlebotomist utilization to 50%, which involves decreasing capacity to 17 phlebotomists, but keeping all remaining inputs the same as the base case. The performance comparison of all three cases is provided in Table 4.8. From the results in Table 4.8, it can be concluded the heuristic algorithm can achieve a high quality solution with a relative gap less than 3.5% within 12 minutes for each of the three cases.

Table 4.8

Performance Comparison of the Proposed Heuristic Algorithm under the Base Case and Two Extended Cases

Phlebotomist Capacity	**Estimated Lower Bound**	**Best Objective Function Value Found**	**Relative Gap**	**Computation Time**
34 (Base Case)	90.47	92.85	2.63%	12 minutes
25 (Ext. 1)	123.05	127.30	3.46%	12 minutes
17 (Ext. 2)	180.95	187.09	3.39%	12 minutes

For the base case, there is a corresponding scheduling template, which is presented in Table 4.9. The scheduling templates for the two extended cases can be found in *Appendix E*. The scheduling templates were determined using the proposed heuristic algorithm. Each template represents the number of phlebotomists that should be scheduled in each shift on each day to achieve balanced workload. Figure 4.2 also illustrates how close the maximum workload per shift in each scenario compares to the estimated lower bound for each scenario. This figure indicates for each scenario, the maximum workload achieved is relatively close to the estimated lower bound. For additional details regarding the performance measure analysis reference

Appendix E. For the base case and the two extended cases, it can be concluded that more phlebotomists are needed during Shifts 9 and 10, which correspond to the evening shifts. This is due to the demand of blood collections being highest during these shifts. The blood collection demand is highest during these times because most physicians place blood test orders during the evening shifts. This will allow them to have the results by the time they start working in the following morning.

Table 4.9

Phlebotomist Scheduling Template for the Base Case

	04:00 - 12:00	**05:00 - 13:00**	**06:00 - 14:00**	**07:00 - 15:00**	**08:00 - 16:00**	**11:00 - 19:00**	**12:00 - 20:00**	**14:00 - 22:00**	**22:00 - 06:00**	**23:00 - 07:00**
	Shift 1	**Shift 2**	**Shift 3**	**Shift 4**	**Shift 5**	**Shift 6**	**Shift 7**	**Shift 8**	**Shift 9**	**Shift 10**
Monday	0	0	1	2	0	1	0	2	3	3
Tuesday	2	0	2	0	0	0	2	1	1	5
Wednesday	1	2	1	0	0	0	1	2	2	4
Thursday	0	1	2	0	0	1	1	1	5	1
Friday	1	2	0	0	1	0	1	1	3	2
Saturday	1	2	1	0	0	1	1	1	4	1
Sunday	3	0	0	0	0	1	1	2	2	3

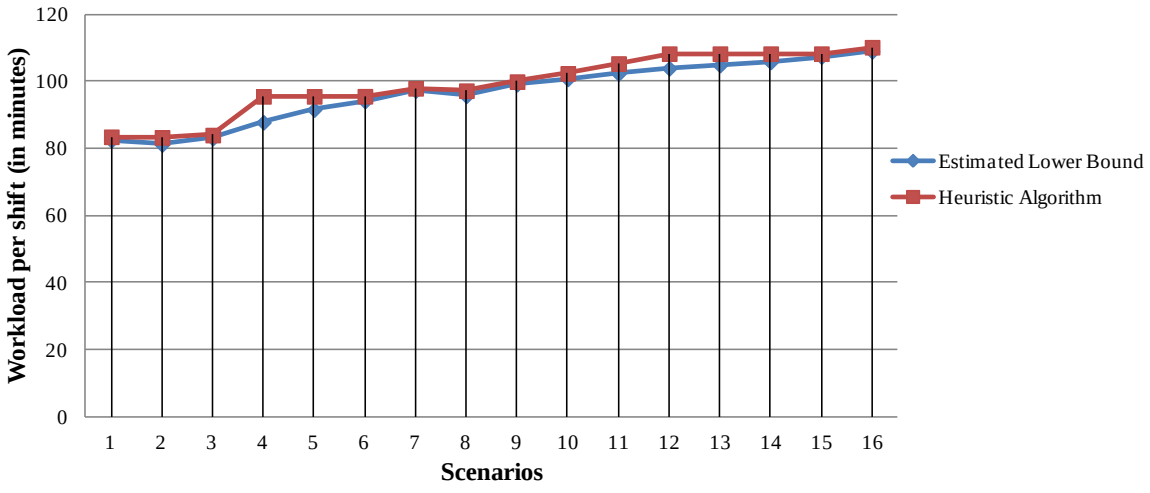

Figure 4.2. Estimated lower bound and heuristic algorithm workload for the base case.

4.6 Conclusions

In order to solve the two-stage SILP model, a scenario reduction model was formulated and solved. The scenario reduction model selected the scenarios with the highest probability of occurrence and the selected scenarios were considered in the two-stage SILP model. This is a high quality solution approach according to Karuppiah et al. (2010). This technique allows one to achieve a solution within 10% of the best solution.

A new heuristic algorithm has been developed to solve the two-stage SILP model with the reduced set of scenarios. The purpose of developing the heuristic algorithm was due to the inability of commercial solvers being able to find a near optimal solution. The heuristic algorithm developed in this study was evaluated in terms of computation time and solution quality. For each of these performance measures, the heuristic algorithm proved that it outperforms existing commercial solvers. It can be concluded that the heuristic algorithm proposed can find a high quality solution.

CHAPTER 5

Experimental Study

5.1 Overview

In this research, an experimental study is conducted. There are three questions addressed in this experimental study. The first question gives insight into how workload varies from hour to hour. The results of this question will provide managerial insights into the hours that typically have the highest blood draw collections. This will aid laboratory managers in making appropriate shift assignments when developing the weekly schedule. The second question addresses how the change in phlebotomist capacity and service time affects the number of phlebotomists to schedule in each shift. This will assist the hospital laboratory in determining proper shift scheduling rules if they desire to increase phlebotomist utilization. The final question addresses how the change in phlebotomist capacity and service time affect the number of phlebotomists scheduled on each day. This will allow laboratory management to determine if there is significant variance in the number of phlebotomists to schedule for each day, i.e. are there certain days that require more phlebotomists than others. The results of each question in the experimental design will serve as support in formulating conclusions for the phlebotomist shift scheduling and blood draw assignment problem. The experimental design to address these questions is provided in the following section. In this chapter, the data collection and analysis required for this study is provided. Next, the experimental design is presented. After that, the experimental results are discussed.

5.2 Data Collection and Analysis

For this dissertation study, data was collected from the laboratory facility of a large urban hospital system over a three month period. The data collected consisted of patient fake id, patient

location, order code, order date, order time, and priority type. The number of patients in the data set totaled 18,169. Data pre-processing was performed on the data, which resulted in a final usable data set consisting of approximately 17,500 patients. The final data set was then grouped into fifteen time blocks, with each block representing the number of patients needing a blood draw in that period for each day. A probability distribution fitting was performed on the data to determine the most appropriate probability distribution. The Poisson distribution had the best fit for the data according to the chi-square test and was therefore used to calculate the probability that a certain number of blood draws would be requested in each time block.

5.3 Experimental Design

To address the three experimental questions, an experimental design is developed and presented in Table 5.1. The independent variables are the blood collection demand, phlebotomist capacity, and phlebotomist service time. The dependent variable for the first experimental question is workload, while the dependent variable for the last two questions is the number of phlebotomists to schedule.

Table 5.1

Experimental Design

Independent Variables	Levels
Blood Draw Demand	16 scenarios selected by the scenario reduction model
Phlebotomist Capacity	(34, 25, 17)
Phlebotomist Service Time/Hour	(50 minutes, 45 minutes, 40 minutes)

5.4 Results and Discussion

5.4.1 Workload distribution over hours. How does the workload differ from hour to hour, i.e. are there typically hours with higher workloads? With this question, the goal is to determine if there are hours that have higher workloads, such that laboratory management can

schedule accordingly. For the time blocks with multiple hours, the average workload per time block has been divided by the number of hours in the time block to accurately represent the hourly workload. The hourly workload is represented in numbers of blood collections assigned. Figures 5.1-5.3 show the range of hourly workloads over the 16 selected scenarios. Each figure indicates the hours that correspond to time blocks two and seven have the highest workload. Time blocks three, four, five, fourteen, and fifteen seem to have the lowest workload. The trend shown in all figures is that there is a higher blood collection demand during the evening time blocks. This trend is attributed to the fact that most physicians would like to have the blood test results available when they start working in the morning. Therefore, it is necessary to request the blood collection for a patient to be performed during the time blocks of the previous evening or in the early morning. Hence, it can be concluded that shifts which include time blocks with lower workloads, should have less phlebotomists scheduled. Shifts that include time blocks with higher workloads should have more phlebotomists scheduled to ensure workload balance. When developing the weekly schedule, the hospital laboratory management should schedule phlebotomists based on the workload required in each time block. For additional details regarding the experimental results analysis reference *Appendix F*.

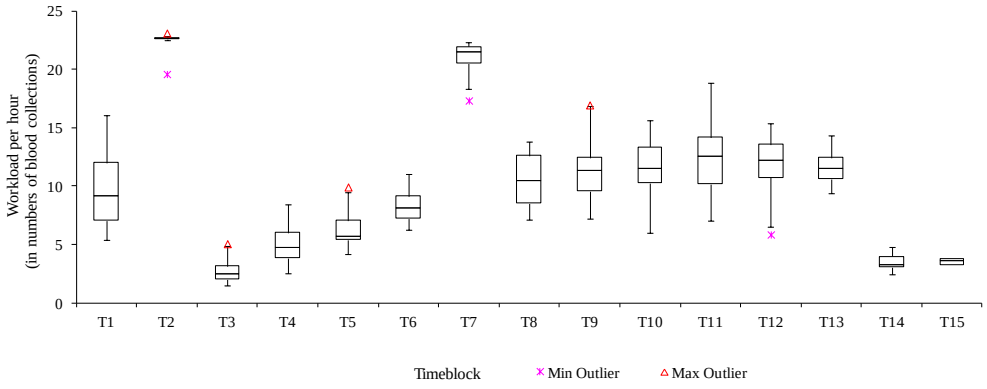

Figure 5.1. Comparison of hourly workload in the base case.

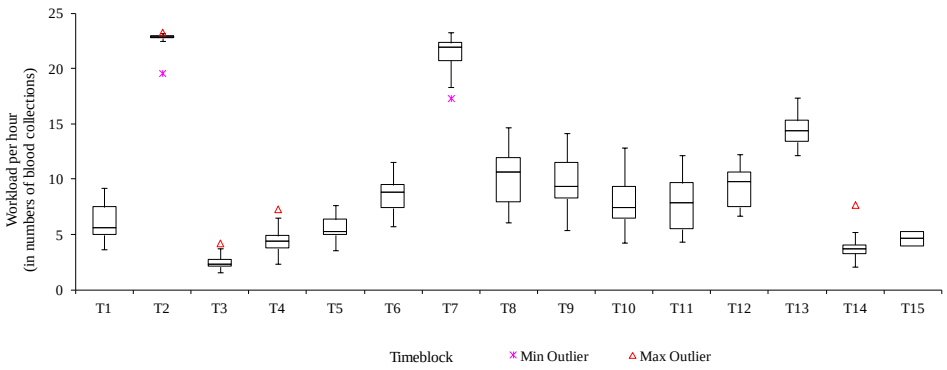

Figure 5.2. Comparison of hourly workload in the case with 25 phlebotomists, who each has 50 minutes per hour available for blood collections.

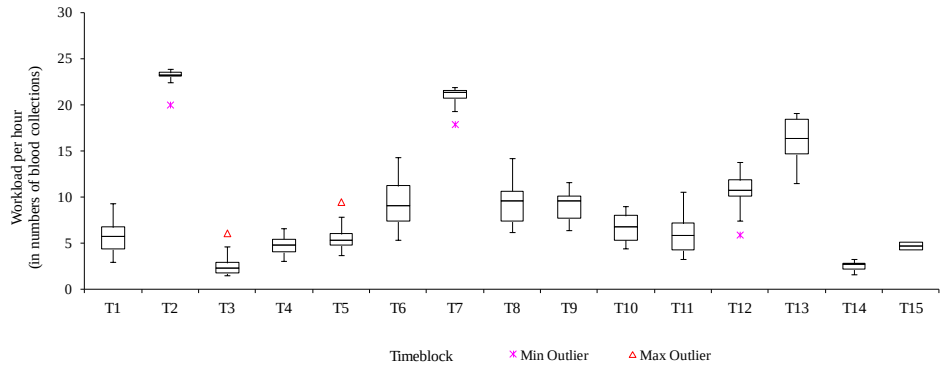

Figure 5.3. Comparison of hourly workload in the case with 17 phlebotomists, who each has 50 minutes per hour available for blood collections.

5.4.2 Impact of phlebotomist capacity on the number of phlebotomists scheduled in each shift. How does the change in phlebotomist capacity affect the number of phlebotomists scheduled for each shift? This question studies how changing phlebotomist capacity, from 34 to 25 to 17 and phlebotomist service time per hour from 50 minutes to 45 minutes to 40 minutes, will affect the number of phlebotomists to schedule during each shift. Currently, the base case considers 34 phlebotomists with a service time of 50 minutes per hour. It is important to study how a change in phlebotomist capacity will affect phlebotomist scheduling, essentially the impact it will have on maximizing resource utilization. Also, a decrease in service time for

scheduled blood draw assignments would allow the phlebotomists to have more time available for STAT tests, which could handle an even higher level of uncertainty. The results are presented as the number of phlebotomists scheduled for each shift and the percentage of phlebotomists scheduled for each shift. The results illustrated in Figures 5.4 and 5.5 include the number and percentage of phlebotomists, respectively, to be scheduled for each shift over the course of a week. The results in Figures 5.4 and 5.5 show that the number of phlebotomists scheduled in each shift is positively correlated with phlebotomist capacity, and is negatively correlated with the numbers of phlebotomists scheduled in its adjacent shifts. The results indicate that for all nine cases, shifts nine and ten remain to have the highest number of phlebotomists scheduled. This holds true whether there is a change in phlebotomist capacity or service time availability. This trend is attributed to the fact that shifts nine and ten correspond to the evening shifts and again physicians will place more blood draw collection requests during the evening to have the tests results by the time they come in the following morning. Therefore, more phlebotomists should be scheduled during the evening shifts.

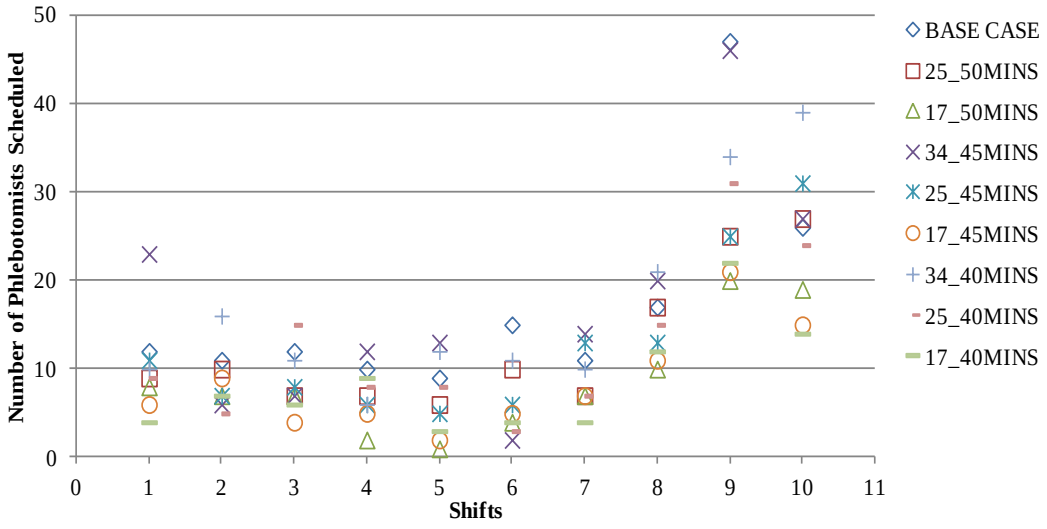

Figure 5.4. Number of phlebotomists scheduled per shift for all cases.

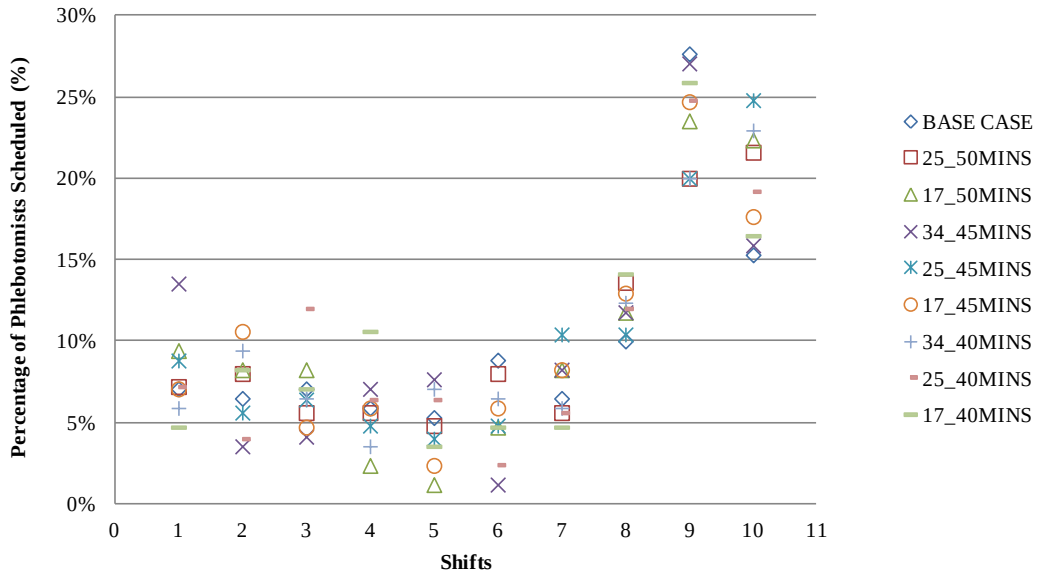

Figure 5.5. Percentage of phlebotomists scheduled per shift for all cases.

5.4.3 Impact of phlebotomist capacity on the number of phlebotomists scheduled on each day. How does the change in phlebotomist capacity affect the number of phlebotomists scheduled for each day? This question attempts to determine if there is any variation in the number of phlebotomists to schedule from day to day. The results are presented as the number of phlebotomists scheduled for each day and the percentage of phlebotomists scheduled for each day. These results illustrated in Figures 5.6 and 5.7 include the number and percentage of phlebotomists, respectively, to be scheduled on each day. These figures indicate that there is very little variance in the number of phlebotomists to schedule from day to day. Although, the number of phlebotomists to schedule will alter based on phlebotomist capacity, overall from day to day the number of phlebotomists scheduled is mainly stable. This trend is attributed to the fact that the blood collection demand does not fluctuate much from day to day. Therefore, the number of phlebotomists to schedule is approximately the same for each day.

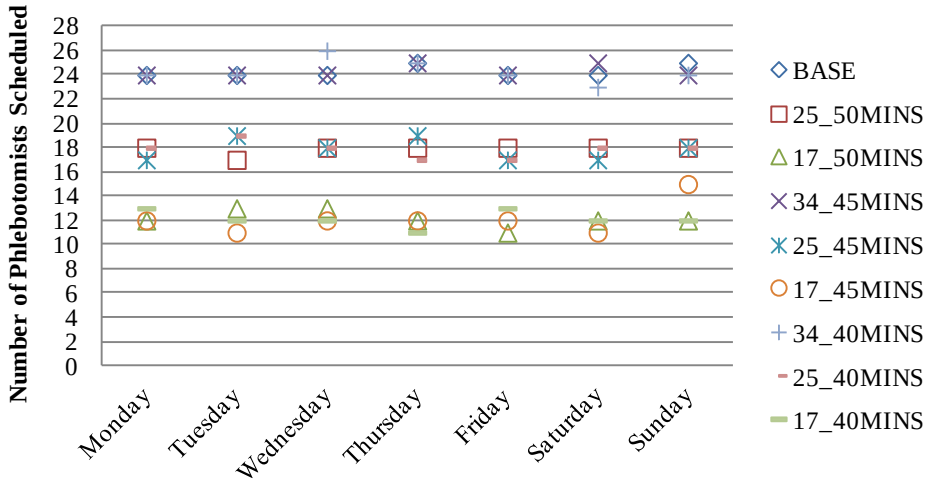

Figure 5.6. Number of phlebotomists scheduled daily for all cases.

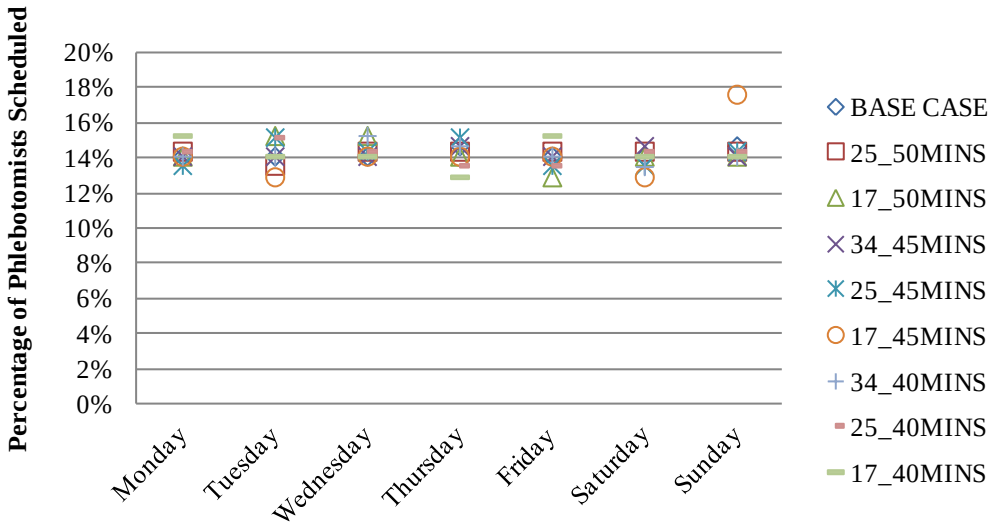

Figure 5.7. Percentage of phlebotomists scheduled daily for all cases.

5.5 Tools for Blood Draw Assignment

In order for laboratory management to balance workload within each hour, blood draw assignments for phlebotomists should be determined using the automated blood draw assignment template. The blood draw assignment template requires the laboratory manager to input the phlebotomists who are scheduled to work during each hour, which is displayed in Figure 5.8. Next, the demand for the current hour, which is based on task type, should be provided. Blood

collection tasks are grouped by no delay, one hour delay, and two hour delay. This information is illustrated in Figure 5.9. Using these inputs, the blood draw assignment model will allocate blood collections to the phlebotomists based on their skill level. Any blood collections that are left undone will roll over to the following hour and will be categorized under a new task level. For example, if there are 20 type three blood collections left over at 1pm, then these 20 tasks will roll over to 2pm and become type 2 blood collections. This model also keeps track of the tasks that have been assigned to each phlebotomist in previous hours. This is to ensure the number of blood collections allocated does not exceed the specified balanced workload for phlebotomists. This model should be run hourly, as the blood collection demand changes from hour to hour. The automated blood draw assignment template is provided in Figure 5.10. This efficient blood draw assignment model could be developed using any spreadsheet software such as Microsoft Excel or Microsoft Access. By implementing the blood draw assignment model, laboratory management should see significant improvements in the hourly workload balance of the phlebotomists scheduled.

Phlebotomist	k1	k2	k3	k4	k5	k6	k7	k8	k9	k10	k11	k12	k13	k14	k15	k16	k17
Service time	10	10	10	10	10	8	8	8	8	8	8	8	5	5	5	5	5
Maximum Collections/Hour	5	5	5	5	5	6	6	6	6	6	6	6	10	10	10	10	10
12am	1	1	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0
1am	1	1	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0
2am	1	1	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0
3am	1	1	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0
4am	1	1	1	0	0	1	1	0	0	0	0	0	1	0	0	1	0
5am	1	1	1	0	0	1	1	0	0	0	0	0	1	0	0	1	0
6am	1	1	0	0	0	1	1	0	0	0	0	0	1	0	0	1	0
7am	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	1	0
8am	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0
9am	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0
10am	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0
11am	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1
12pm	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
1pm	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
2pm	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0	1
3pm	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0	1
4pm	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0	1
5pm	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0	1
6pm	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0	1
7pm	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0	0
8pm	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0
9pm	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0
10pm	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11pm	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0

Figure 5.8: Phlebotomist schedule for one day.

Previuos day			
12am	13	0	53
1am	1	0	6
2am	1	0	4
3am	1	0	3
4am	0	0	5
5am	0	0	3
6am	2	0	2
7am	6	0	2
8am	4	0	14
9am	4	0	9
10am	4	0	7
11am	1	0	12
12pm	2	0	7
1pm	6	0	8
2pm	2	0	7
3pm	3	0	12
4pm	5	0	5
5pm	3	0	9
6pm	0	0	4
7pm	2	0	3
8pm	1	0	2
9pm	0	0	5
10pm	0	0	4
11pm	2	0	3

Figure 5.9. Blood collection demand for one day.

	Demand				Blood Draw Assignment																Tasks undone		
	Type 1	Type 2	Type 3	Total	k1	k2	k3	k4	k5	k6	k7	k8	k9	k10	k11	k12	k13	k14	k15	k16	k17	Type 1	Type 2	Type 3
Previuos day	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
12am	13	0	53	66	5	5	5	0	0	6	0	0	0	0	0	0	10	0	0	0	0	0	0	35
1am	1	35	6	42	5	5	5	0	0	6	0	0	0	0	0	0	8	0	0	0	0	0	7	6
2am	8	6	4	18	3	3	3	0	0	3	0	0	0	0	0	0	3	0	0	0	0	0	0	3
3am	1	3	3	7	1	1	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	2
4am	0	2	5	7	1	1	1	0	0	1	1	0	0	0	0	0	1	0	0	1	0	0	0	0
5am	0	0	3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
6am	2	3	2	7	1	1	0	0	0	1	1	0	0	0	0	0	1	0	0	1	0	0	0	1
7am	6	1	2	9	0	0	0	0	0	0	3	0	0	0	0	0	3	0	0	3	0	0	0	0
8am	4	0	14	18	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	9	0	0	0	3
9am	4	3	9	16	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	8	0	0	0	2
10am	4	2	7	13	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	6	0	0	0	1
11am	1	1	12	14	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	4	4	0	0	2
12pm	2	2	7	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	5	0	0	1
1pm	6	1	8	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	7	0	0	1
2pm	2	1	7	10	0	0	0	0	0	0	0	2	2	0	0	0	0	0	2	0	2	0	0	2
3pm	3	2	12	17	0	0	0	0	0	0	0	4	4	0	0	0	0	0	4	0	4	0	0	1
4pm	5	1	5	11	0	0	0	0	0	0	0	2	2	0	0	0	0	0	2	0	2	0	0	3
5pm	3	3	9	15	0	0	0	0	0	0	0	3	3	0	0	0	0	0	3	0	3	0	0	3
6pm	0	3	4	7	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0	1	0	0	3
7pm	2	3	3	8	0	0	0	0	0	0	0	2	2	0	0	0	0	0	2	0	0	0	0	2
8pm	1	2	2	5	0	0	0	0	0	0	0	2	2	0	0	0	0	0	0	0	0	0	0	1
9pm	0	1	5	6	0	0	0	0	0	0	0	3	3	0	0	0	0	0	0	0	0	0	0	0
10pm	0	0	4	4	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11pm	2	0	3	5	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Figure 5.10. Automated template for blood draw assignment.

CHAPTER 6

Conclusions and Future Work

6.1 Conclusions

Laboratory medicine plays an imperative role in clinicians being able to reach a diagnosis for patients. Therefore, laboratory medicine is a key component in healthcare delivery systems due to the amount of spending that occurs and the medical decisions that are involved. As the healthcare industry continues to grow rapidly, obtaining both efficiency and effectiveness within healthcare delivery systems has become a major priority. Healthcare scheduling remains one of the main obstacles in providing timely access to medical services and improving the efficiency of healthcare delivery.

In order to increase patient satisfaction and patient safety, hospital laboratories must improve their overall effectiveness. There are three main stages in the total testing process conducted in hospital laboratories, and one of the objectives of this study was to determine which stage was the most critical for improvement purposes. The AHP and ANP models developed in this study indicated the most critical stage in the entire testing process of hospital laboratories. The stage selected was the preanalytical stage, which confirms what has been stated in the literature. The preanalytical stage was then improved using mathematical modeling to optimize phlebotomist scheduling. The two-stage SILP model presented in this research study was formulated to determine the number of phlebotomists to be scheduled and the amount of blood draw collections to be assigned for each shift to balance phlebotomist workload within and between shifts.

A commercial solver was first used to solve the two stage SILP model, but proved to be inefficient. Therefore, a heuristic algorithm was developed to solve the two-stage SILP model.

According to the performance measures, the heuristic algorithm proposed is an efficient and effective method to solve the phlebotomist shift scheduling and blood draw assignment problem achieving a relative gap of 3.5% or less in all cases. Using the two-stage SILP model and the heuristic algorithm developed, an experimental study was conducted to investigate the workload distribution over hours and the impact of the phlebotomist capacity on their shift schedule.

The results of the experimental study provide insight into scheduling policies that will be most beneficial to the phlebotomists and the patients. Regarding workload distribution over hours, there are certain hours with a higher workload. Therefore, the number of phlebotomists scheduled should match the workload. The hours with the highest workload correspond to the evening shifts. Changing phlebotomist capacity and service time does present an evident trend in the number of phlebotomists to be scheduled during each shift. More phlebotomists should be scheduled for shifts 9 and 10 to balance phlebotomist workload. Changing phlebotomist capacity and service time availability also presents an evident trend for the number of phlebotomists to be scheduled on each day, but not between days. As the available capacity decreases, the number of phlebotomists to schedule decreases as well. It is imperative for laboratory management to remember to match the number of phlebotomists scheduled with the workload required. The higher the workload, the more phlebotomists they should schedule. This is a major finding that was not practiced in the hospital laboratory motivating this study. Without optimal scheduling policies in place for laboratory medicine, there is a great risk for patients to be negatively affected due to work overload. Work overload causes patient neglect and is introduced when patients do not receive the time and attention they require. Also, with work overload there is a risk of decrease in the phlebotomist performance. Phlebotomist performance is critical in laboratory medicine because in the event of an error this could result in serious consequences for

the patient. If laboratory management does not consider balancing workload when scheduling phlebotomists, they may miss an opportunity to provide safe and quality healthcare services to hospital patients. Through balancing workload, phlebotomists can provide the necessary time and attention required for each patient.

Furthermore, it is imperative to consider increasing phlebotomist utilization. The hospital laboratory motivating this study is only utilizing each phlebotomist 25% of the time they are available. Therefore, to meet their blood draw demand, they do not need the full capacity currently available. If laboratory management is only utilizing each phlebotomist 25% of the time they are available, they could reduce their phlebotomist capacity by 50% and still have enough phlebotomists to meet their blood draw demand. Reducing phlebotomist capacity would significantly reduce the costs associated with resource capacity. If reducing phlebotomist capacity is not a desire for laboratory management, they should at the very least find other areas where the phlebotomists can serve. An option would be to cross train the phlebotomists such that they could serve in other stages of the testing process.

In conclusion, there have been methods used to improve laboratory medicine. Yet, there are currently not any studies that focus on balancing phlebotomist workload using mathematical modeling. This dissertation study has closed that gap due to the development of a two-stage SILP model to address phlebotomist scheduling and blood draw assignments in laboratory medicine. The two-stage SILP model and the heuristic algorithm developed in this study demonstrated that it is possible to improve scheduling in laboratory medicine through balancing phlebotomist workload and increasing phlebotomist utilization. As hospital laboratories in healthcare delivery systems need to improve phlebotomist scheduling policies, the two-stage SILP model presented in this study can help healthcare schedulers and laboratory administrators plan accordingly. The

two-stage SILP model is generalized in order to be applicable to other hospital laboratories. The parameter values can be altered in order to represent the system being evaluated, and an optimal phlebotomist scheduling template can be determined.

6.2 Future Work

The limitation of this study is that only the stage selected from the AHP and ANP models is optimized. This is due to the assumption that improving the stage selected will have an indirect effect on improving the other two stages. Future work will consist of testing the performance of the heuristic algorithm proposed for the two-stage SILP model under more varying cases. Also, using the two-stage SILP model and heuristic algorithm developed in this research study, optimal staff scheduling for medical technicians and pathologists will be explored for the analytical and postanalytical stages of the laboratory process to balance shift workload.

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Appendix A

AHP Analysis

Table A.1

Pairwise Comparisons of the Methodologies

Pairwise Comparison MATRIX	***Lean***	***Six Sigma***	***Theory of Constraints***	***Critical Business***
Lean	1	$\frac{1}{3}$	3	5
Six Sigma	3	1	3	4
Theory of Constraints	$\frac{1}{3}$	$\frac{1}{3}$	1	2
Critical Business Process	$\frac{1}{5}$	$\frac{1}{4}$	$\frac{1}{2}$	1

Table A.2

Normalized Pairwise Comparison Matrix

Pairwise Comparison Matrix Normalized	**Lean**	**Six Sigma**	**Theory of Constraints**	**Critical Business Process**
Lean	0.220588	0.173913043	0.4	0.416666667
Six Sigma	0.661765	0.52173913	0.4	0.333333333
Theory of Constraints	0.073529	0.173913043	0.133333333	0.166666667
Critical Business Process	0.044118	0.130434783	0.066666667	0.083333333

Table A.3

Pairwise Comparison for Stages Using Lean

Pairwise Matrix	**Preanalytical Process**	**Analytical Process**	**Postanalytical Process**
Preanalytical Process	1	3	3
Analytical Process	1/3	1	5
Postanalytical Process	1/3	1/5	1

Table A.4

Normalized Pairwise Comparison Matrix for Stages Using Lean

Pairwise Matrix	Preanalytical Process	Analytical Process	Postanalytical Process
Preanalytical Process	0.6	0.714285714	0.333333333
Analytical Process	0.2	0.238095238	0.555555556
Postanalytical Process	0.2	0.047619048	0.111111111

Table A.5

Pairwise Comparison for Stages Using Six Sigma

Pairwise Matrix	Preanalytical Process	Analytical Process	Postanalytical Process
Preanalytical Process	1	4	2
Analytical Process	1/4	1	3
Postanalytical Process	1/2	1/3	1

Table A.6

Normalized Pairwise Comparison Matrix for Stages Using Six Sigma

Pairwise Matrix	Preanalytical Process	Analytical Process	Postanalytical Process
Preanalytical Process	0.571428571	0.75	0.333333333
Analytical Process	0.142857143	0.1875	0.5
Postanalytical Process	0.285714286	0.0625	0.166666667

Table A.7

Pairwise Comparison for Stages Using Theory of Constraints

Pairwise Matrix	Preanalytical Process	Analytical Process	Postanalytical Process
Preanalytical Process	1	2	3
Analytical Process	1/2	1	2
Postanalytical Process	1/3	1/2	1

Table A.8

Normalized Pairwise Comparison Matrix for Stages Using Theory of Constraints

Pairwise Matrix (Normalized)	Preanalytical Process	Analytical Process	Postanalytical Process
Preanalytical Process	0.545454545	0.571428571	0.5
Analytical Process	2/7	0.285714286	0.333333333
Postanalytical Process	0.181818182	0.142857143	0.166666667

Table A.9

Pairwise Comparison for Stages Using Critical Business Process

Pairwise Matrix	Preanalytical Process	Analytical Process	Postanalytical Process
Preanalytical Process	1	2	2
Analytical Process	1/2	1	4
Postanalytical Process	1/2	1/4	1

Table A.10

Normalized Pairwise Comparison Matrix for Stages Using Critical Business Process

Pairwise Matrix (Normalized)	Preanalytical Process	Analytical Process	Postanalytical Process
Preanalytical Process	0.5	0.615384615	0.285714286
Analytical Process	1/4	0.307692308	0.571428571
Postanalytical Process	0.25	0.076923077	0.142857143

Appendix B

ANP Analysis

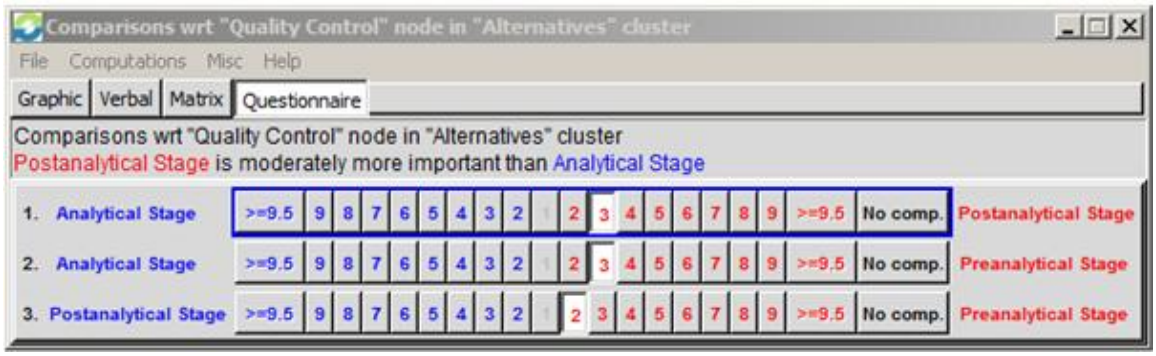

Figure B.1. Comparisons in the questionnaire mode for the alternatives under quality control.

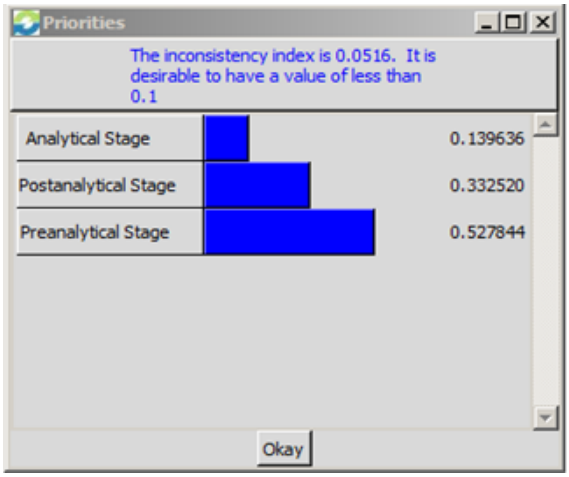

Figure B.2. The priorities for the alternatives with respect to quality control.

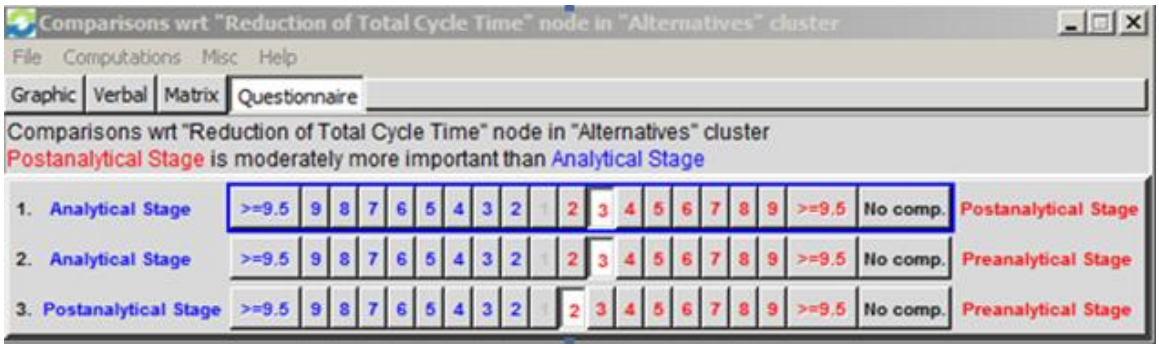

Figure B.3. Comparisons in the questionnaire mode for the alternatives under reduction of total cycle time.

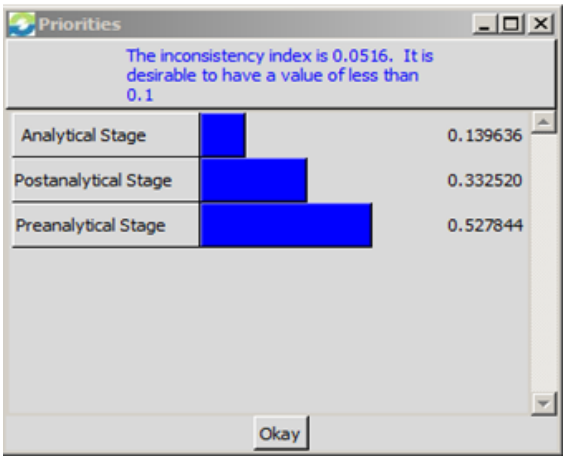

Figure B.4. The priorities for the alternatives with respect to reduction of total cycle time.

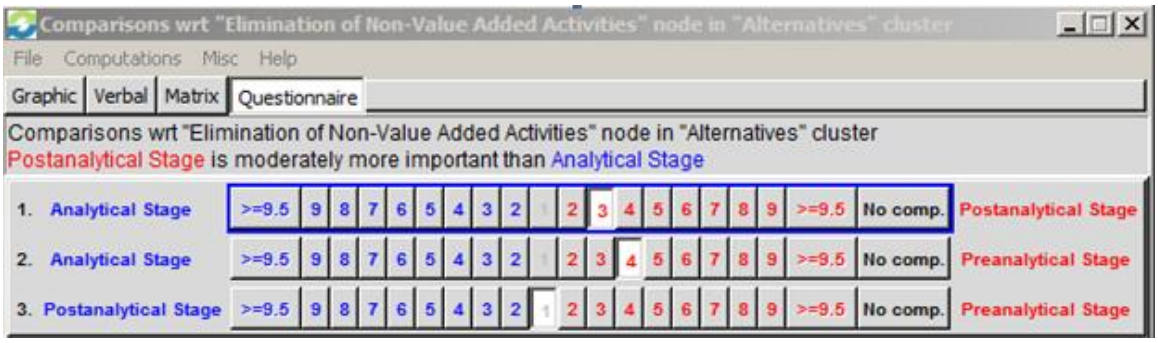

Figure B.5. Comparisons in the questionnaire mode for the alternatives under elimination of non-value added activities.

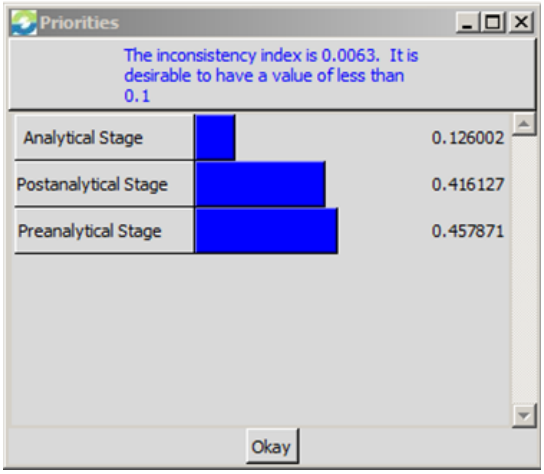

Figure B.6. The priorities for the alternatives with respect to the elimination of non-value added activities.

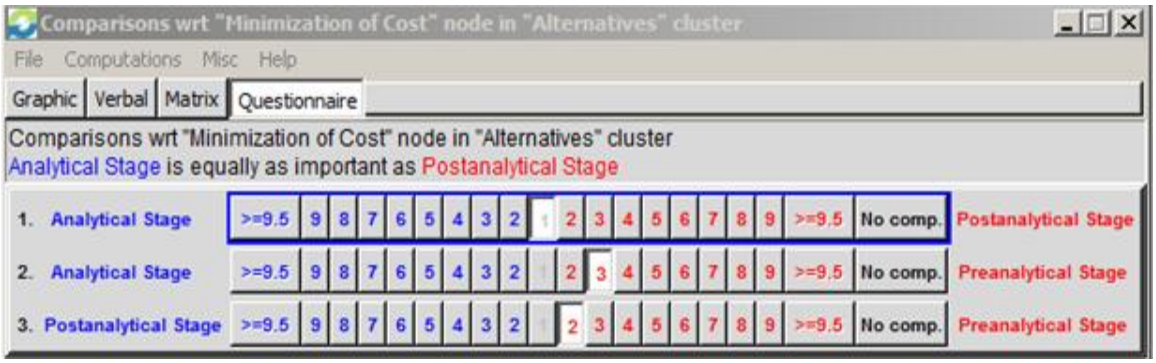

Figure B.7. Comparisons in the questionnaire mode for the alternatives under minimization of cost.

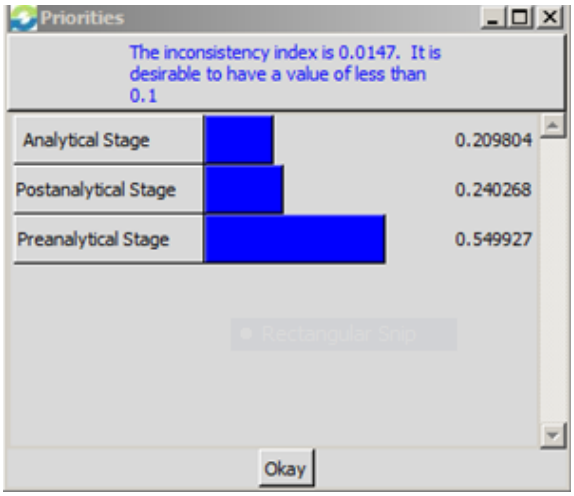

Figure B.8. The priorities for the alternatives with respect to minimization of cost.

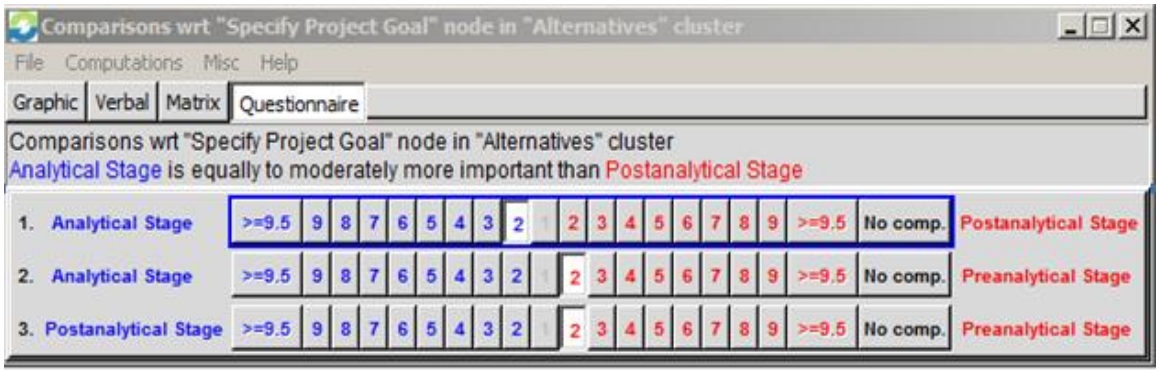

Figure B.9. Comparisons in the questionnaire mode for the alternatives under specify project goal.

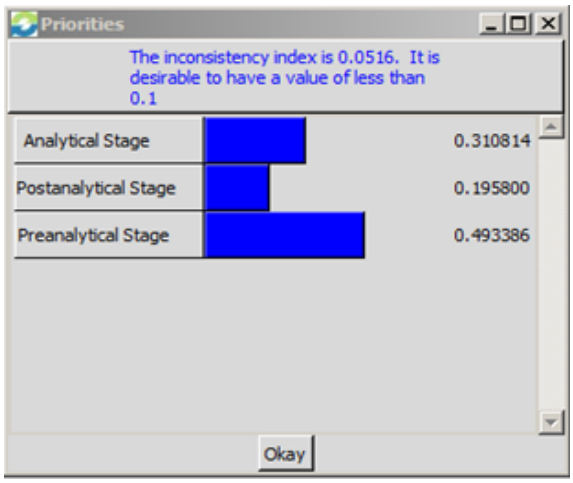

Figure B.10. The priorities for the alternatives with respect to specifying project goal.

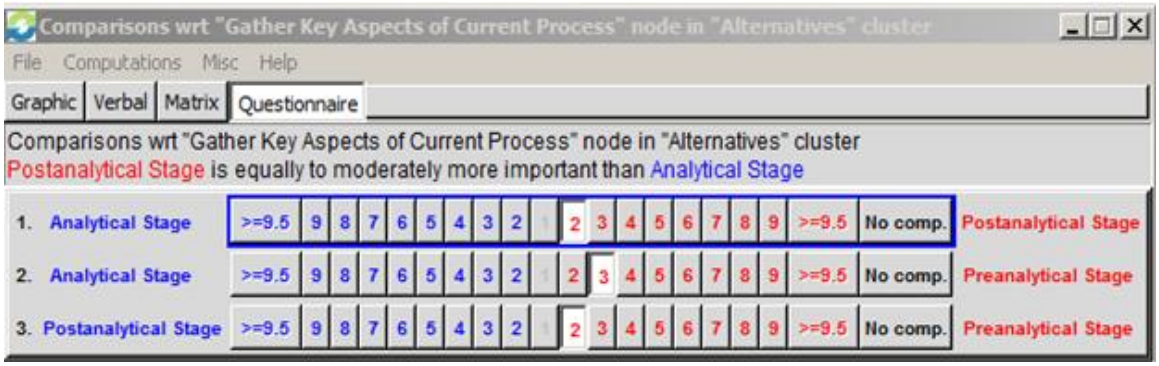

Figure B.11. Comparisons in the questionnaire mode for the alternatives under gather key aspects of current process.

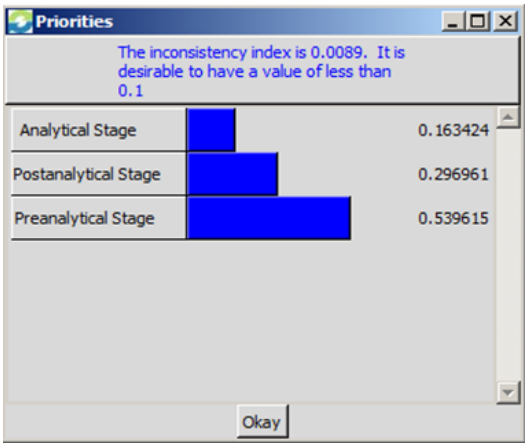

Figure B.12. The priorities for the alternatives with respect to gathering key aspects of current process.

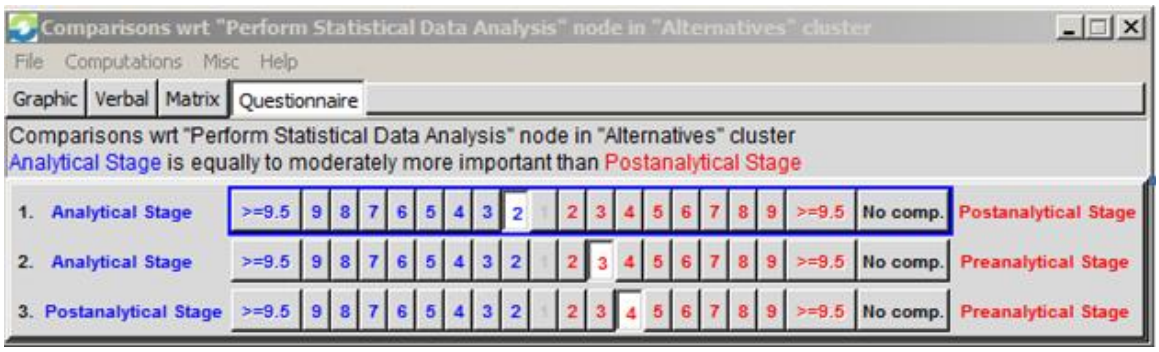

Figure B.13. Comparisons in the questionnaire mode for the alternatives under perform statistical data analysis.

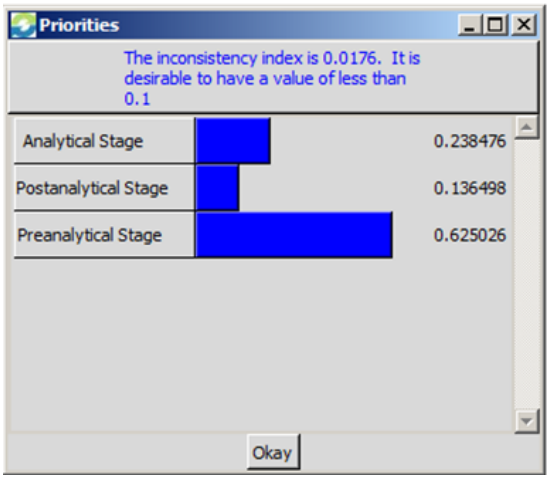

Figure B.14. The priorities for the alternatives with respect to performing statistical data analysis.

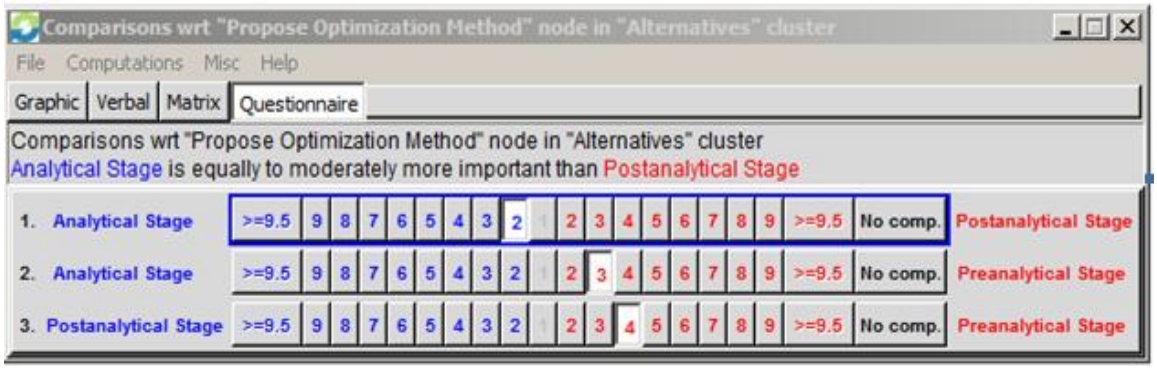

Figure B.15. Comparisons in the questionnaire mode for the alternatives under propose optimization method.

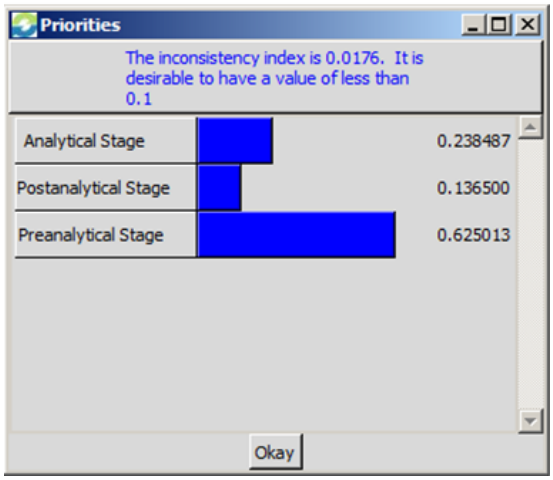

Figure B.16. The priorities for the alternatives with respect to proposing an optimization method.

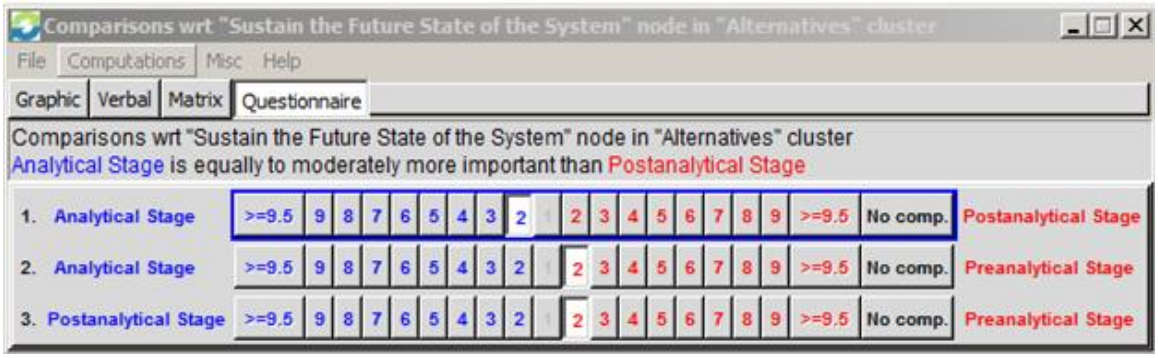

Figure B.17. Comparisons in the questionnaire mode for the alternatives under sustain future state of the system.

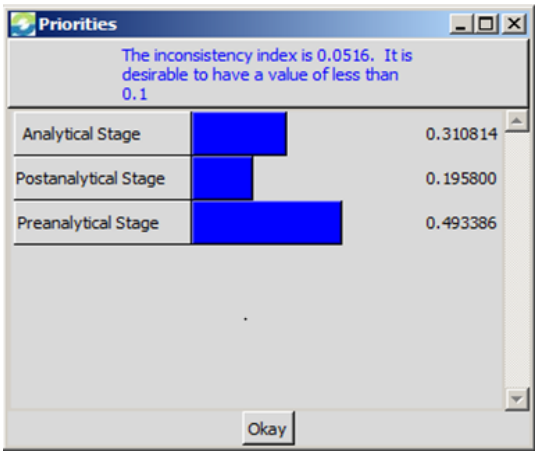

Figure B.18. The priorities for the alternatives with respect to sustaining future state of the system.

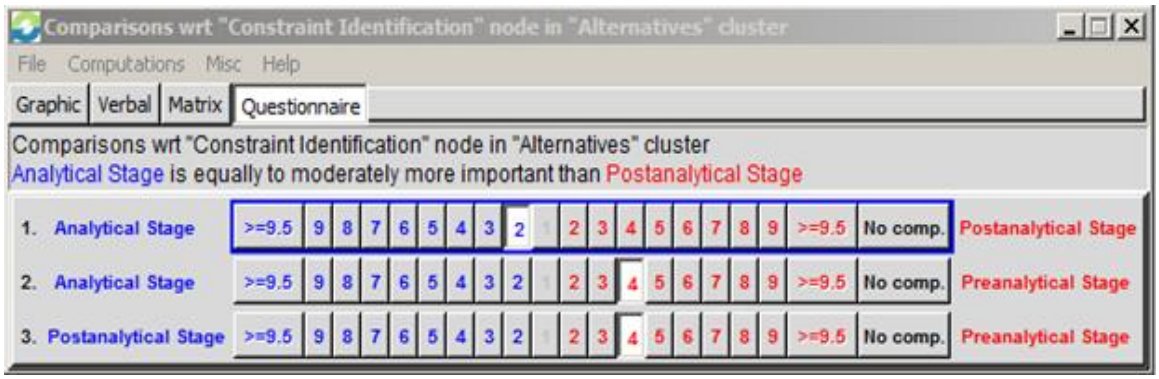

Figure B.19. Comparisons in the questionnaire mode for the alternatives under constraint identification.

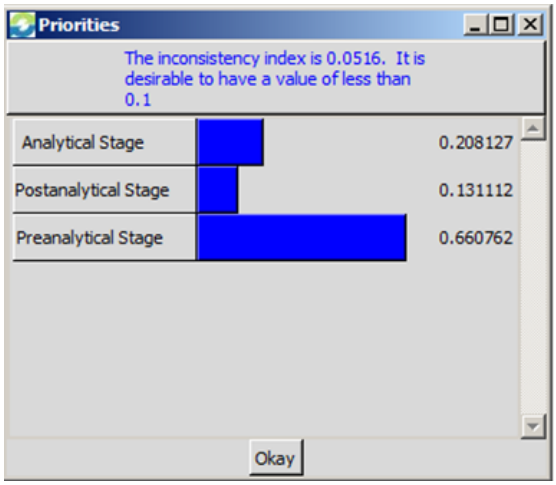

Figure B.20. The priorities for the alternatives with respect to constraint identification.

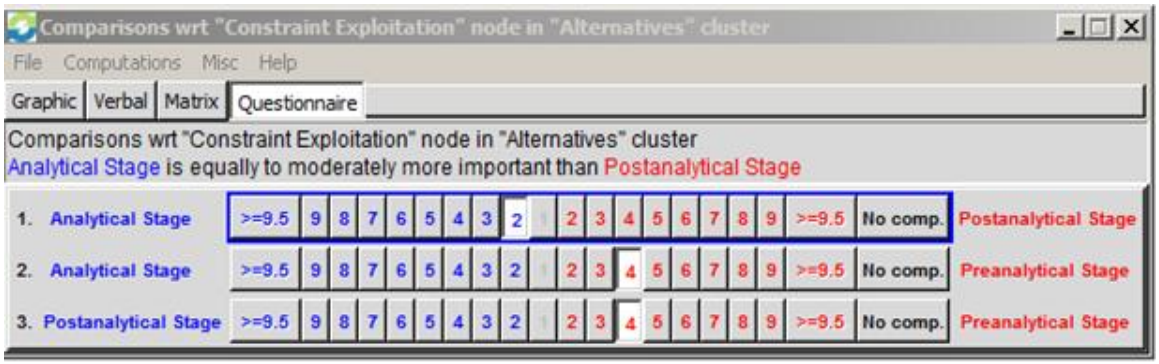

Figure B.21. Comparisons in the questionnaire mode for the alternatives under constraint exploitation.

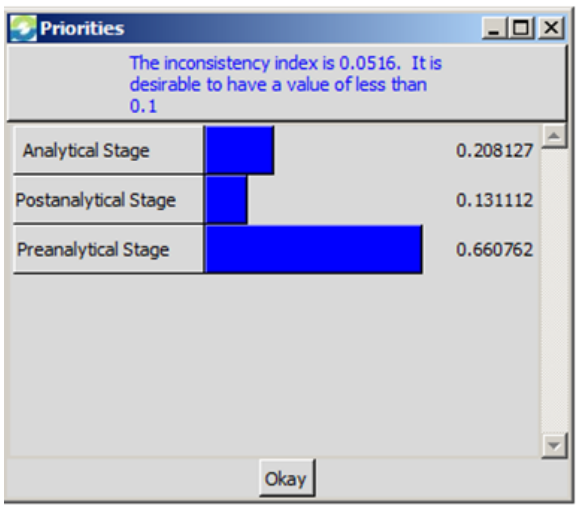

Figure B.22. The priorities for the alternatives with respect to constraint exploitation.

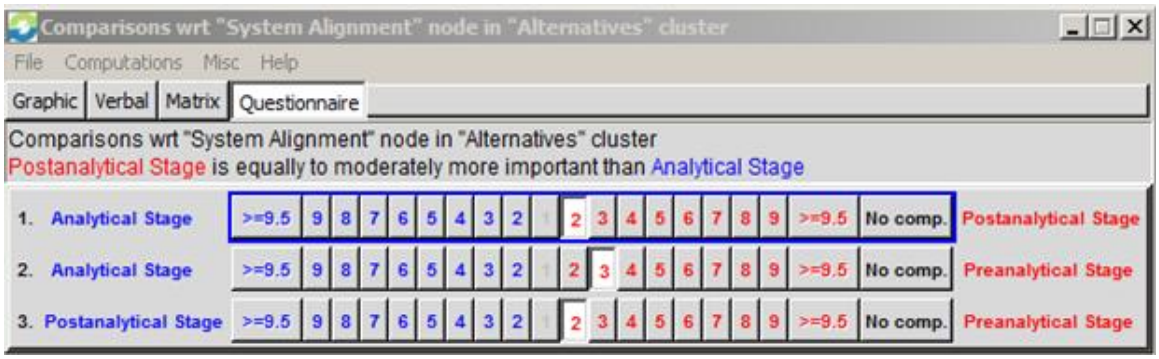

Figure B.23. Comparisons in the questionnaire mode for the alternatives under system alignment.

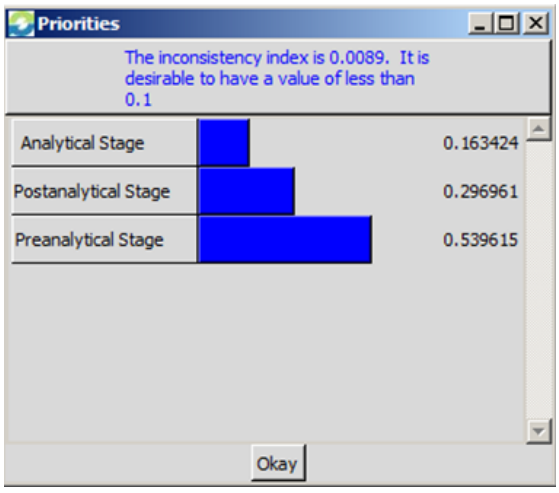

Figure B.24. The priorities for the alternatives with respect to system alignment.

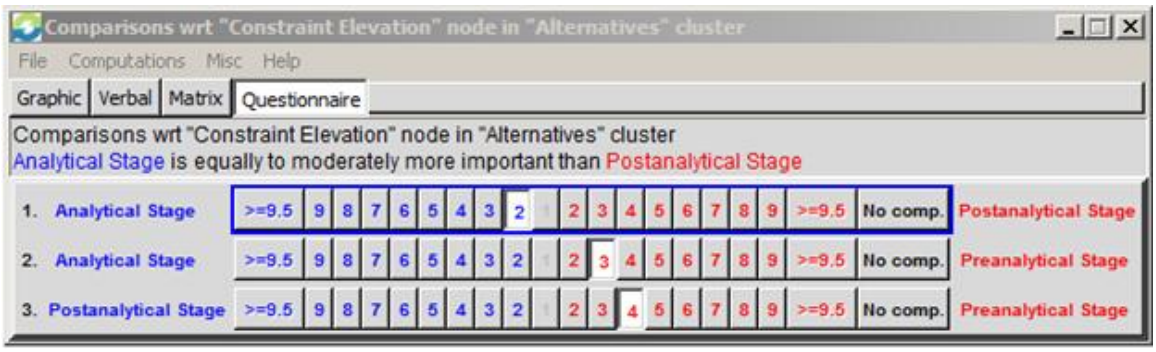

Figure B.25. Comparisons in the questionnaire mode for the alternatives under constraint elevation.

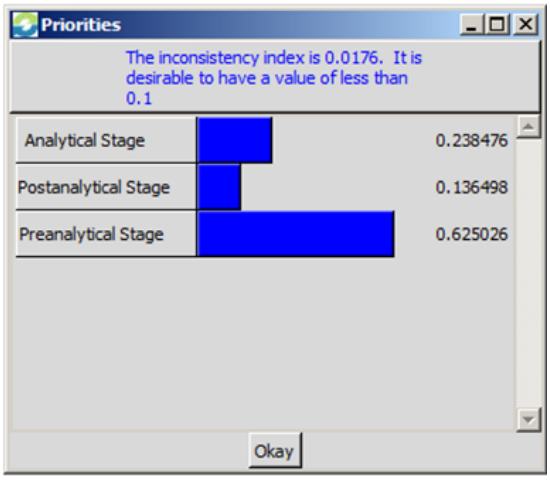

Figure B.26. The priorities for the alternatives with respect to constraint elevation.

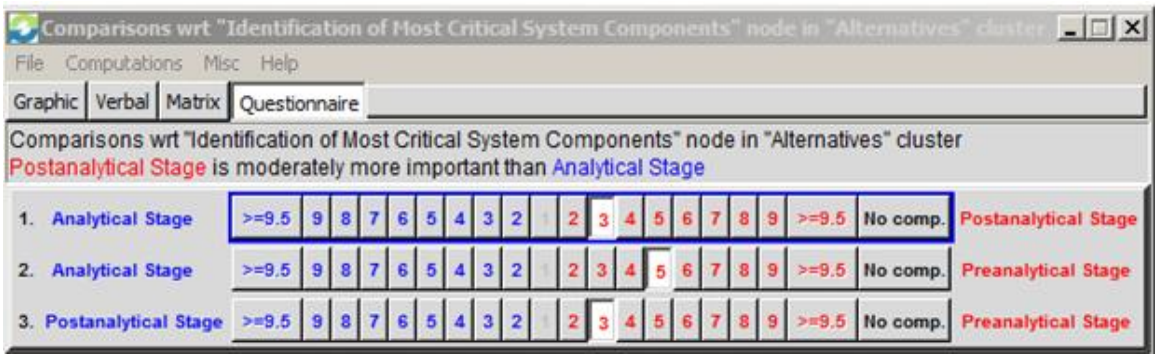

Figure B.27. Comparisons in the questionnaire mode for the alternatives under the identification of most critical system components.

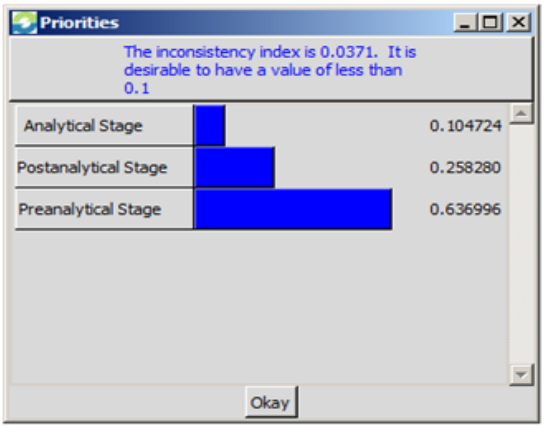

Figure B.28. The priorities for the alternatives with respect to identification of most critical system components.

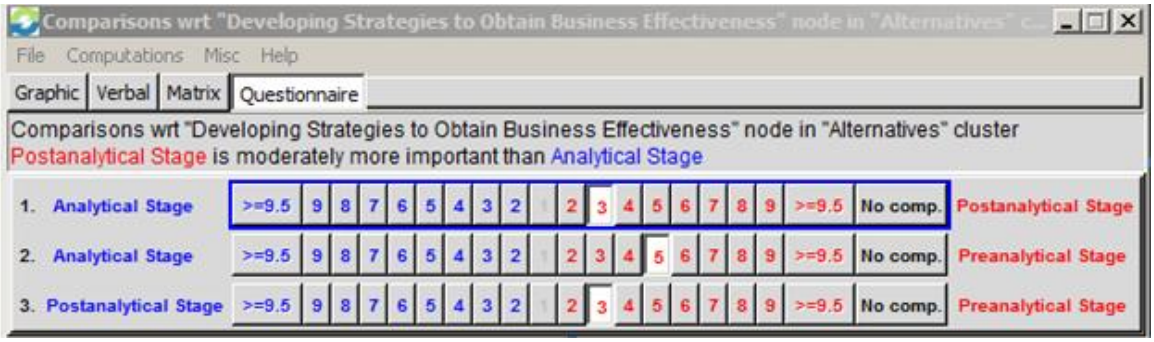

Figure B.29. Comparisons in the questionnaire mode for the alternatives under developing strategies to obtain business effectiveness.

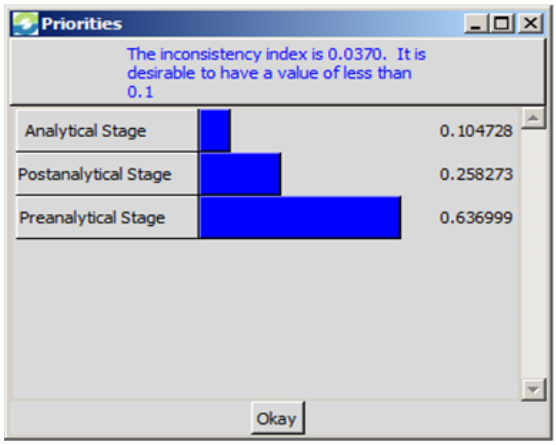

Figure B.30. The priorities for the alternatives with respect to developing strategies to obtain business effectiveness.

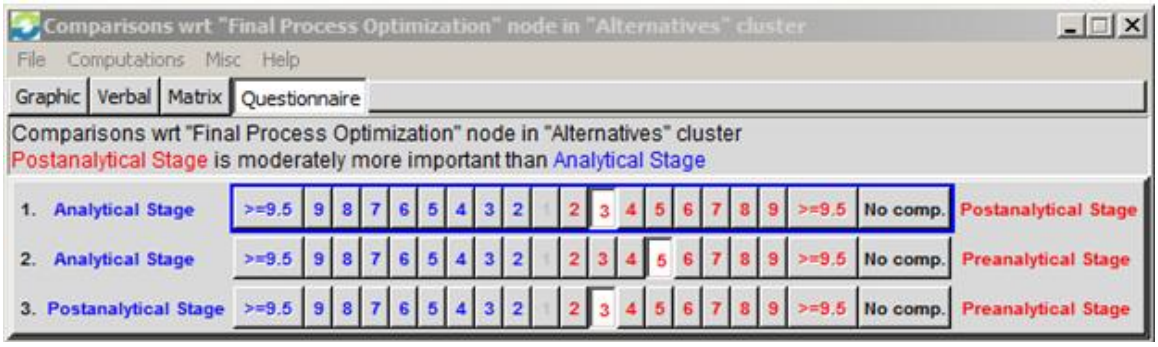

Figure B.31. Comparisons in the questionnaire mode for the alternatives under final process optimization.

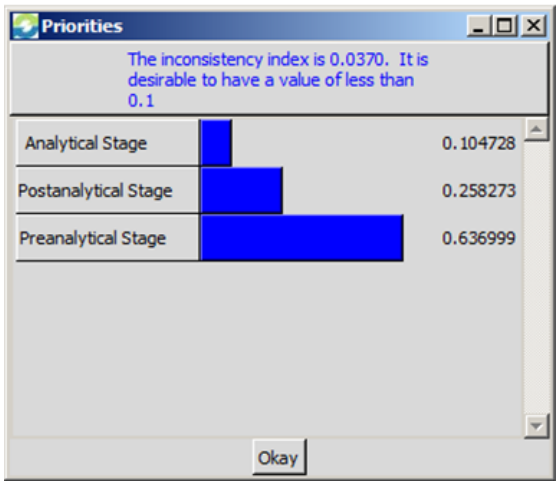

Figure B.32. The priorities for the alternatives with respect to final process optimization.

Appendix C

Scenario Reduction Model Code

```
Sets

        i1      "# of routine tests ordered during hour 1" /4,7/
        i2      "# of routine tests ordered during hour 2" /98,113/
        i3      "# of routine tests ordered during hour 3" /4,7/
        i4      "# of routine tests ordered during hour 4" /3,5/
        i5      "# of routine tests ordered during hour 5" /5,10/
        i6      "# of routine tests ordered during hour 6" /7,12/
        i7      "# of routine tests ordered during hour 7" /52,64/
        i8      "# of routine tests ordered during hour 8" /13,19/
        i9      "# of routine tests ordered during hour 9" /10,15/
        i10     "# of routine tests ordered during hour 10" /8,12/
        i11     "# of routine tests ordered during hour 11" /9,14/
        i12     "# of routine tests ordered during hour 12" /9,14/
        i13     "# of routine tests ordered during hour 13" /22,30/
        i14     "# of routine tests ordered during hour 14" /5,10/
        i15     "# of routine tests ordered during hour 15" /8,13/
        ;


Parameters

        P1(i1) probability that random variable 1 will take on a certain value
/
4       0.814602302
7       0.185397698
/

        P2(i2) probability that random variable 2 will take on a certain value
/98       0.539097673
113       0.460902327
/

        P3(i3) probability that random variable 3 will take on a certain value
/4       0.821709197
7       0.178290803
/

        P4(i4) probability that random variable 4 will take on a certain value
/3       0.519334999
 5       0.480665001
/
```

```
        P5(i5) probability that random variable 5 will take on a certain value
/5       0.916164268
10       0.083835732
/

        P6(i6) probability that random variable 6 will take on a certain value
/7       0.778250441
12       0.221749559
/

        P7(i7) probability that random variable 7 will take on a certain value
/52      0.587839135
 64      0.412160865
/


        P8(i8) probability that random variable 8 will take on a certain value
/13      0.648473521
 19      0.351526479
/


       P9(i9) probability that random variable 9 will take on a certain value
/10      0.627466538
 15      0.372533462
/

        P10(i10) probability that random variable 10 will take on a certain value
/ 8      0.517636022
 12      0.482363978
/

     P11(i11) probability that random variable 11 will take on a certain value
/ 9      0.663323237
 14      0.336676763
/

      P12(i12) probability that random variable 12 will take on a certain value
/9       0.723933495
14       0.276066505
/

      P13(i13) probability that random variable 13 will take on a certain value
/22      0.59389199
 30      0.40610801
```

```
     P14(i14) probability that random variable 14 will take on a certain value
/ 5        0.967404814
 10        0.032595186
/
     P15(i15) probability that random variable 15 will take on a certain value
/  8        0.639345154
  13        0.360654846
/

;

Variables

z minimize the number of  scenarios
p(i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i14,i15) probability of scenario sets

positive variable
p;

free variable
z;

Equations

minimize_scenarios objective function
con1(i1) scenario set 1
con2(i2) scenario set 2
con3(i3) scenario set 3
con4(i4) scenario set 4
con5(i5) scenario set 5
con6(i6) scenario set 6
con7(i7) scenario set 7
con8(i8) scenario set 8
con9(i9) scenario set 9
con10(i10) scenario set 10
con11(i11) scenario set 11
con12(i12) scenario set 12
con13(i13) scenario set 13
con14(i14) scenario set 14
con15(i15) scenario set 15
con16 Total Probability ;


minimize_scenarios..  z =e= sum((i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i14,i15),(1-
     (P1(i1)*P2(i2)*P3(i3)*P4(i4)*P5(i5)*P6(i6)*P7(i7)*P8(i8)*P9(i9)*P10(i10)*P11(i11)*P12(i
     12)*P13(i13)*P14(i14)*P15(i15)))*(p(i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i14,i15))) ;
```

```
con1(i1)..
    sum((i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i14,i15),p(i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i1
    4,i15)) =e= P1(i1);

con2(i2)..
    sum((i1,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i14,i15),p(i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i1
    4,i15)) =e= P2(i2);

con3(i3)..
    sum((i1,i2,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i14,i15),p(i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i1
    4,i15)) =e= P3(i3);

con4(i4)..
    sum((i1,i2,i3,i5,i6,i7,i8,i9,i10,i11,i12,i13,i14,i15),p(i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i1
    4,i15)) =e= P4(i4);

con5(i5)..
    sum((i1,i2,i3,i4,i6,i7,i8,i9,i10,i11,i12,i13,i14,i15),p(i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i1
    4,i15)) =e= P5(i5);

con6(i6)..
    sum((i1,i2,i3,i4,i5,i7,i8,i9,i10,i11,i12,i13,i14,i15),p(i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i1
    4,i15)) =e= P6(i6);

con7(i7)..
    sum((i1,i2,i3,i4,i5,i6,i8,i9,i10,i11,i12,i13,i14,i15),p(i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i1
    4,i15)) =e= P7(i7);

con8(i8)..
    sum((i1,i2,i3,i4,i5,i6,i7,i9,i10,i11,i12,i13,i14,i15),p(i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i1
    4,i15)) =e= P8(i8);

con9(i9)..
    sum((i1,i2,i3,i4,i5,i6,i7,i8,i10,i11,i12,i13,i14,i15),p(i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i1
    4,i15)) =e= P9(i9);

con10(i10)..
    sum((i1,i2,i3,i4,i5,i6,i7,i8,i9,i11,i12,i13,i14,i15),p(i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i14,
    i15)) =e= P10(i10);

con11(i11)..
    sum((i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i12,i13,i14,i15),p(i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i14,
    i15)) =e= P11(i11);
```

```
con12(i12)..
    sum((i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i13,i14,i15),p(i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i14,
    i15)) =e= P12(i12);

con13(i13)..
    sum((i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i14,i15),p(i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i14,
    i15)) =e= P13(i13);

con14(i14)..
    sum((i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i15),p(i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i14,
    i15)) =e= P14(i14);

con15(i15)..
    sum((i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i14),p(i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i14,
    i15)) =e= P15(i15);

con16..
    sum((i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i14,i15),(p(i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13
    ,i14,i15))) =e= 1;


Model Test_Model_3 /all/;

Solve Test_Model_3 using LP minimizing z;

Display p.l, z.l, p.m, z.m;
```

Appendix D

Two-Stage Stochastic Integer Linear Programming Model Code

```
Sets

          i        time block index/
          i1       "10pm-11pm on Day 1"
          i2       "11pm-4am  on Day 1"
          i3       "4am-5am   on Day 1"
          i4       "5am-6am   on Day 1"
          i5       "6am-7am   on Day 1"
          i6       "7am-8am   on Day 1"
          i7       "8am-11am  on Day 1"
          i8       "11am-12pm on Day 1"
          i9       "12pm-1pm  on Day 1"
          i10      "1pm-2pm   on Day 1"
          i11      "2pm-3pm   on Day 1"
          i12      "3pm-4pm   on Day 1"
          i13      "4pm-7pm   on Day 1"
          i14      "7pm-8pm   on Day 1"
          i15      "8pm-10pm  on Day 1"
          i16      "10pm-11pm on Day 2"
          i17      "11pm-4am  on Day 2"
          i18      "4am-5am   on Day 2"
          i19      "5am-6am   on Day 2"
          i20      "6am-7am   on Day 2"
          i21      "7am-8am   on Day 2"
          i22      "8am-11am  on Day 2"
          i23      "11am-12pm on Day 2"
          i24      "12pm-1pm  on Day 2"
          i25      "1pm-2pm   on Day 2"
          i26      "2pm-3pm   on Day 2"
          i27      "3pm-4pm   on Day 2"
          i28      "4pm-7pm   on Day 2"
          i29      "7pm-8pm   on Day 2"
          i30      "8pm-10pm  on Day 2"
          i31      "10pm-11pm on Day 3"
          i32      "11pm-4am  on Day 3"
          i33      "4am-5am   on Day 3"
          i34      "5am-6am   on Day 3"
          i35      "6am-7am   on Day 3"
          i36      "7am-8am   on Day 3"
          i37      "8am-11am  on Day 3"
          i38      "11am-12pm on Day 3"
          i39      "12pm-1pm  on Day 3"
          i40      "1pm-2pm   on Day 3"
          i41      "2pm-3pm   on Day 3"
          i42      "3pm-4pm   on Day 3"
          i43      "4pm-7pm   on Day 3"
          i44      "7pm-8pm   on Day 3"
          i45      "8pm-10pm  on Day 3"
          i46      "10pm-11pm on Day 4"
          i47      "11pm-4am  on Day 4"
          i48      "4am-5am   on Day 4"
          i49      "5am-6am   on Day 4"
```

```
i50     "6am-7am   on Day 4"
i51     "7am-8am   on Day 4"
i52     "8am-11am  on Day 4"
i53     "11am-12pm on Day 4"
i54     "12pm-1pm  on Day 4"
i55     "1pm-2pm   on Day 4"
i56     "2pm-3pm   on Day 4"
i57     "3pm-4pm   on Day 4"
i58     "4pm-7pm   on Day 4"
i59     "7pm-8pm   on Day 4"
i60     "8pm-10pm  on Day 4"
i61     "10pm-11pm on Day 5"
i62     "11pm-4am  on Day 5"
i63     "4am-5am   on Day 5"
i64     "5am-6am   on Day 5"
i65     "6am-7am   on Day 5"
i66     "7am-8am   on Day 5"
i67     "8am-11am  on Day 5"
i68     "11am-12pm on Day 5"-
i69     "12pm-1pm  on Day 5"
i70     "1pm-2pm   on Day 5"
i71     "2pm-3pm   on Day 5"
i72     "3pm-4pm   on Day 5"
i73     "4pm-7pm   on Day 5"
i74     "7pm-8pm   on Day 5"
i75     "8pm-10pm  on Day 5"
i76     "10pm-11pm on Day 6"
i77     "11pm-4am  on Day 6"
i78     "4am-5am   on Day 6"
i79     "5am-6am   on Day 6"
i80     "6am-7am   on Day 6"
i81     "7am-8am   on Day 6"
i82     "8am-11am  on Day 6"
i83     "11am-12pm on Day 6"
i84     "12pm-1pm  on Day 6"
i85     "1pm-2pm   on Day 6"
i86     "2pm-3pm   on Day 6"
i87     "3pm-4pm   on Day 6"
i88     "4pm-7pm   on Day 6"
i89     "7pm-8pm   on Day 6"
i90     "8pm-10pm  on Day 6"
i91     "10pm-11pm on Day 7"
i92     "11pm-4am  on Day 7"
i93     "4am-5am   on Day 7"
i94     "5am-6am   on Day 7"
i95     "6am-7am   on Day 7"
i96     "7am-8am   on Day 7"
i97     "8am-11am  on Day 7"
i98     "11am-12pm on Day 7"
i99     "12pm-1pm  on Day 7"
i100    "1pm-2pm   on Day 7"
i101    "2pm-3pm   on Day 7"
i102    "3pm-4pm   on Day 7"
i103    "4pm-7pm   on Day 7"
i104    "7pm-8pm   on Day 7"
i105    "8pm-10pm  on Day 7"/
```

```
i_1(i)  "set with no delay"
/i2,i7,i13,i17,i22,i28,i32,i37,i43,i47,i52,i58,i62,
i67,i73,i77,i82,i88,i92,i97,i103/

i_2(i)  "set with 1 time block delay"
/i1,i6,i12,i15,i16,i21,i27,i30,i31,i36,i42,i45,i46,i51,i57,
i60,i61,i66,i72,i75,i76,i81,i87,i90,i91,i96,i102,i105/

i_3(i)  "set with 2 time block delay"
/i5,i11,i14,i20,i26,i29,i35,i41,i44,i50,i56,i59,i65,
i71,i74,i80,i86,i89,i95,i101,i104/

i_4(i)  "set with 3 time block delay" /i3,i4,i8,i9,i10,i18,i19,i23,
i24,i25,i33,i34,i38,i39,i40,i48,i49,i53,i54,i55,i63,i64,i68,i69,i70,
i78,i79,i83,i84,i85,i93,i94,i98,i99,i100/


j       days worked/
j1      "Monday"
j2      "Tuesday"
j3      "Wednesday"
j4      "Thursday"
j5      "Friday"
j6      "Saturday"
j7      "Sunday"
/

k       phlebotomist index/
k1      "phlebotomist 1"
k2      "phlebotomist 2"
k3      "phlebotomist 3"
k4      "phlebotomist 4"
k5      "phlebotomist 5"
k6      "phlebotomist 6"
k7      "phlebotomist 7"
k8      "phlebotomist 8"
k9      "phlebotomist 9"
k10     "phlebotomist 10"
k11     "phlebotomist 11"
k12     "phlebotomist 12"
k13     "phlebotomist 13"
k14      "phlebotomist 14"
k15      "phlebotomist 15"
k16      "phlebotomist 16"
k17      "phlebotomist 17"
k18      "phlebotomist 18"
k19      "phlebotomist 19"
k20      "phlebotomist 20"
k21     "phlebotomist 21"
k22     "phlebotomist 22"
k23     "phlebotomist 23"
k24      "phlebotomist 24"
k25      "phlebotomist 25"
k26      "phlebotomist 26"
k27      "phlebotomist 27"
k28      "phlebotomist 28"
k29      "phlebotomist 29"
```

```
k30      "phlebotomist 30"
k31     "phlebotomist 31"
k32     "phlebotomist 32"
k33     "phlebotomist 33"
k34      "phlebotomist 34"/

n       hospital shift/
n1      "04:00-12:00"
n2      "05:00-13:00"
n3      "06:00-14:00"
n4      "07:00-15:00"
n5      "08:00-16:00"
n6      "11:00-19:00"
n7      "12:00-20:00"
n8      "14:00-22:00"
n9      "22:00-06:00"
n10     "23:00-07:00"
/
n_1(n) "first shift" / n1, n2, n3, n4, n5/
n_2(n) "second shift" / n6, n7, n8/
n_3(n) "third shift"   /n9 , n10/

 o       scenarios/
o1      "scenario 1"
o2      "scenario 2"
o3      "scenario 3"
o4      "scenario 4"
o5      "scenario 5"
o6      "scenario 6"
o7      "scenario 7"
o8      "scenario 8"
o9      "scenario 9"
o10     "scenario 10"
o11     "scenario 11"
o12     "scenario 12"
o13     "scenario 13"
o14     "scenario 14"
o15     "scenario 15"
o16     "scenario 16"/
 ;

Parameters

LB(o) lower bound for scenario o

/
o1          82.39411765
o2          81.13137255
o3          83.0254902
o4          87.76078431
o5          91.54901961
o6          94.0745098
o7          97.23137255
o8          95.65294118
o9          99.1254902
o10         100.7039216
o11         102.2823529
```

```
o12          103.8607843
o13          104.8078431
o14          105.754902
o15          107.3333333
o16          108.9117647

         b(i) max number of stat tests ordered in time block i
/
i1           1
i2           18
i3           1
i4           1
i5           2
i6           3
i7           13
i8           3
i9           3
i10          2
i11          2
i12          2
i13          5
i14          1
i15          3
i16          1
i17          18
i18          1
i19          1
i20          2
i21          3
i22          13
i23          3
i24          3
i25          2
i26          2
i27          2
i28          5
i29          1
i30          3
i31          1
i32          18
i33          1
i34          1
i35          2
i36          3
i37          13
i38          3
i39          3
i40          2
i41          2
i42          2
i43          5
i44          1
i45          3
i46          1
i47          18
i48          1
i49          1
```

```
i50       2
i51       3
i52       13
i53       3
i54       3
i55       2
i56       2
i57       2
i58       5
i59       1
i60       3
i61       1
i62       18
i63       1
i64       1
i65       2
i66       3
i67       13
i68       3
i69       3
i70       2
i71       2
i72       2
i73       5
i74       1
i75       3
i76       1
i77       18
i78       1
i79       1
i80       2
i81       3
i82       13
i83       3
i84       3
i85       2
i86       2
i87       2
i88       5
i89       1
i90       3
i91       1
i92       18
i93       1
i94       1
i95       2
i96       3
i97       13
i98       3
i99       3
i100      2
i101      2
i102      2
i103      5
i104      1
i105      3
 /
```

```
T(i) total time of time block i

/

i1          50
i2          250
i3          50
i4          50
i5          50
i6          50
i7          150
i8          50
i9          50
i10         50
i11         50
i12         50
i13         150
i14         50
i15         100
i16         50
i17         250
i18         50
i19         50
i20         50
i21         50
i22         150
i23         50
i24         50
i25         50
i26         50
i27         50
i28         150
i29         50
i30         100
i31         50
i32         250
i33         50
i34         50
i35         50
i36         50
i37         150
i38         50
i39         50
i40         50
i41         50
i42         50
i43         150
i44         50
i45         100
i46         50
i47         250
i48         50
i49         50
i50         50
i51         50
i52         150
```

```
i53       50
i54       50
i55       50
i56       50
i57       50
i58       150
i59       50
i60       100
i61       50
i62       250
i63       50
i64       50
i65       50
i66       50
i67       150
i68       50
i69       50
i70       50
i71       50
i72       50
i73       150
i74       50
i75       100
i76       50
i77       250
i78       50
i79       50
i80       50
i81       50
i82       150
i83       50
i84       50
i85       50
i86       50
i87       50
i88       150
i89       50
i90       100
i91       50
i92       250
i93       50
i94       50
i95       50
i96       50
i97       150
i98       50
i99       50
i100      50
i101      50
i102      50
i103      150
i104      50
i105      100 /
```

```
s(k) average time for phlebotomist k to perform a task
              /k1*k5    10
               k6*k30   8
               k31*k34  5
               /

u(i) blood draw demand for scenario  /
i1          4
i2          98
i3          4
i4          3
i5          5
i6          7
i7          52
i8          13
i9          10
i10          12
i11          9
i12          9
i13          22
i14          5
i15          8
i16          4
i17          98
i18          4
i19          3
i20          5
i21          7
i22          52
i23          13
i24          10
i25          12
i26          9
i27          9
i28          22
i29          5
i30          8
i31          4
i32          98
i33          4
i34          3
i35          5
i36          7
i37          52
i38          13
i39          10
i40          12
i41          9
i42          9
i43          22
i44          5
i45          8
i46          4
i47          98
i48          4
i49          3
i50          5
```

```
i51         7
i52         52
i53         13
i54         10
i55         12
i56         9
i57         9
i58         22
i59         5
i60         8
i61         4
i62         98
i63         4
i64         3
i65         5
i66         7
i67         52
i68         13
i69         10
i70         12
i71         9
i72         9
i73         22
i74         5
i75         8
i76         4
i77         98
i78         4
i79         3
i80         5
i81         7
i82         52
i83         13
i84         10
i85         12
i86         9
i87         9
i88         22
i89         5
i90         8
i91         4
i92         98
i93         4
i94         3
i95         5
i96         7
i97         52
i98         13
i99         10
i100         12
i101         9
i102         9
i103         22
i104         5
i105         8
/
```

```
p(o) probabilities for each scenario o /
         o1  .001
         o2  .518
         o3  .020
         o4  .049
         o5  .006
         o6  .034
         o7  .009
         o8  .012
         o9  .015
         o10 .061
         o11 .054
         o12 .036
         o13 .007
         o14 .094
         o15 .051
         o16 .033/
;

Table
R(i,o) amount of blood draws requested in time block i under scenario o
```

	o1	o2	o3	o4	o5	o6	o7	o8	o9	o10	o11	o12	o13	o14	o15	o16
i1	4	4	4	4	4	4	4	4	4	4	4	4	7	7	7	7
i2	98	98	98	113	113	113	113	113	113	113	113	113	113	113	113	113
i3	4	4	4	4	4	4	4	4	4	4	4	4	4	7	7	7
i4	3	3	5	5	5	5	5	5	5	5	5	5	5	5	5	5
i5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	10	10
i6	7	7	7	7	7	7	7	7	7	7	7	12	12	12	12	12
i7	52	52	52	52	64	64	64	64	64	64	64	64	64	64	64	64
i8	13	13	13	13	13	13	13	13	19	19	19	19	19	19	19	19
i9	10	10	10	10	10	10	15	15	15	15	15	15	15	15	15	15
i10	12	8	12	12	12	12	12	12	12	12	12	12	12	12	12	12
i11	9	9	9	9	9	9	9	9	9	14	14	14	14	14	14	14
i12	9	9	9	9	9	9	9	9	9	9	14	14	14	14	14	14
i13	22	22	22	22	22	30	30	30	30	30	30	30	30	30	30	30
i14	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	10
i15	8	8	8	8	8	8	13	8	13	13	13	13	13	13	13	13
i16	4	4	4	4	4	4	4	4	4	4	4	4	7	7	7	7
i17	98	98	98	113	113	113	113	113	113	113	113	113	113	113	113	113
i18	4	4	4	4	4	4	4	4	4	4	4	4	4	7	7	7
i19	3	3	5	5	5	5	5	5	5	5	5	5	5	5	5	5
i20	5	5	5	5	5	5	5	5	5	5	5	5	5	5	10	10
i21	7	7	7	7	7	7	7	7	7	7	7	12	12	12	12	12
i22	52	52	52	52	64	64	64	64	64	64	64	64	64	64	64	64
i23	13	13	13	13	13	13	13	13	19	19	19	19	19	19	19	19
i24	10	10	10	10	10	10	15	15	15	15	15	15	15	15	15	15
i25	12	8	12	12	12	12	12	12	12	12	12	12	12	12	12	12

i26	9	9	9	9	9	9	9	9	9	14	14	14	14	14	14	14
i27	9	9	9	9	9	9	9	9	9	9	14	14	14	14	14	14
i28	22	22	22	22	22	30	30	30	30	30	30	30	30	30	30	30
i29	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	10
i30	8	8	8	8	8	8	13	8	13	13	13	13	13	13	13	13
i31	4	4	4	4	4	4	4	4	4	4	4	4	7	7	7	7
i32	98	98	98	113	113	113	113	113	113	113	113	113	113	113	113	113
i33	4	4	4	4	4	4	4	4	4	4	4	4	4	7	7	7
i34	3	3	5	5	5	5	5	5	5	5	5	5	5	5	5	5
i35	5	5	5	5	5	5	5	5	5	5	5	5	5	5	10	10
i36	7	7	7	7	7	7	7	7	7	7	7	12	12	12	12	12
i37	52	52	52	52	64	64	64	64	64	64	64	64	64	64	64	64
i38	13	13	13	13	13	13	13	13	19	19	19	19	19	19	19	19
i39	10	10	10	10	10	10	15	15	15	15	15	15	15	15	15	15
i40	12	8	12	12	12	12	12	12	12	12	12	12	12	12	12	12
i41	9	9	9	9	9	9	9	9	9	14	14	14	14	14	14	14
i42	9	9	9	9	9	9	9	9	9	9	14	14	14	14	14	14
i43	22	22	22	22	22	30	30	30	30	30	30	30	30	30	30	30
i44	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	10
i45	8	8	8	8	8	8	13	8	13	13	13	13	13	13	13	13
i46	4	4	4	4	4	4	4	4	4	4	4	4	7	7	7	7
i47	98	98	98	113	113	113	113	113	113	113	113	113	113	113	113	113
i48	4	4	4	4	4	4	4	4	4	4	4	4	4	7	7	7
i49	3	3	5	5	5	5	5	5	5	5	5	5	5	5	5	5
i50	5	5	5	5	5	5	5	5	5	5	5	5	5	5	10	10
i51	7	7	7	7	7	7	7	7	7	7	7	12	12	12	12	12
i52	52	52	52	52	64	64	64	64	64	64	64	64	64	64	64	64
i53	13	13	13	13	13	13	13	13	19	19	19	19	19	19	19	19
i54	10	10	10	10	10	10	15	15	15	15	15	15	15	15	15	15
i55	12	8	12	12	12	12	12	12	12	12	12	12	12	12	12	12
i56	9	9	9	9	9	9	9	9	9	14	14	14	14	14	14	14
i57	9	9	9	9	9	9	9	9	9	9	14	14	14	14	14	14
i58	22	22	22	22	22	30	30	30	30	30	30	30	30	30	30	30
i59	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	10
i60	8	8	8	8	8	8	13	8	13	13	13	13	13	13	13	13
i61	4	4	4	4	4	4	4	4	4	4	4	4	7	7	7	7
i62	98	98	98	113	113	113	113	113	113	113	113	113	113	113	113	113
i63	4	4	4	4	4	4	4	4	4	4	4	4	4	7	7	7
i64	3	3	5	5	5	5	5	5	5	5	5	5	5	5	5	5
i65	5	5	5	5	5	5	5	5	5	5	5	5	5	5	10	10
i66	7	7	7	7	7	7	7	7	7	7	7	12	12	12	12	12
i67	52	52	52	52	64	64	64	64	64	64	64	64	64	64	64	64
i68	13	13	13	13	13	13	13	13	19	19	19	19	19	19	19	19

```
i69     10  10  10  10  10  10  15  15  15  15  15  15  15  15  15  15
i70     12   8  12  12  12  12  12  12  12  12  12  12  12  12  12  12
i71      9   9   9   9   9   9   9   9   9  14  14  14  14  14  14  14
i72      9   9   9   9   9   9   9   9   9   9  14  14  14  14  14  14
i73     22  22  22  22  22  30  30  30  30  30  30  30  30  30  30  30
i74      5   5   5   5   5   5   5   5   5   5   5   5   5   5   5  10
i75      8   8   8   8   8   8  13   8  13  13  13  13  13  13  13  13
i76      4   4   4   4   4   4   4   4   4   4   4   4   7   7   7   7
i77     98  98  98 113 113 113 113 113 113 113 113 113 113 113 113 113
i78      4   4   4   4   4   4   4   4   4   4   4   4   4   7   7   7
i79      3   3   5   5   5   5   5   5   5   5   5   5   5   5   5   5
i80      5   5   5   5   5   5   5   5   5   5   5   5   5   5  10  10
i81      7   7   7   7   7   7   7   7   7   7   7  12  12  12  12  12
i82     52  52  52  52  64  64  64  64  64  64  64  64  64  64  64  64
i83     13  13  13  13  13  13  13  13  19  19  19  19  19  19  19  19
i84     10  10  10  10  10  10  15  15  15  15  15  15  15  15  15  15
i85     12   8  12  12  12  12  12  12  12  12  12  12  12  12  12  12
i86      9   9   9   9   9   9   9   9   9  14  14  14  14  14  14  14
i87      9   9   9   9   9   9   9   9   9   9  14  14  14  14  14  14
i88     22  22  22  22  22  30  30  30  30  30  30  30  30  30  30  30
i89      5   5   5   5   5   5   5   5   5   5   5   5   5   5   5  10
i90      8   8   8   8   8   8  13   8  13  13  13  13  13  13  13  13
i91      4   4   4   4   4   4   4   4   4   4   4   4   7   7   7   7
i92     98  98  98 113 113 113 113 113 113 113 113 113 113 113 113 113
i93      4   4   4   4   4   4   4   4   4   4   4   4   4   7   7   7
i94      3   3   5   5   5   5   5   5   5   5   5   5   5   5   5   5
i95      5   5   5   5   5   5   5   5   5   5   5   5   5   5  10  10
i96      7   7   7   7   7   7   7   7   7   7   7  12  12  12  12  12
i97     52  52  52  52  64  64  64  64  64  64  64  64  64  64  64  64
i98     13  13  13  13  13  13  13  13  19  19  19  19  19  19  19  19
i99     10  10  10  10  10  10  15  15  15  15  15  15  15  15  15  15
i100    12   8  12  12  12  12  12  12  12  12  12  12  12  12  12  12
i101     9   9   9   9   9   9   9   9   9  14  14  14  14  14  14  14
i102     9   9   9   9   9   9   9   9   9   9  14  14  14  14  14  14
i103    22  22  22  22  22  30  30  30  30  30  30  30  30  30  30  30
i104     5   5   5   5   5   5   5   5   5   5   5   5   5   5   5  10
i105     8   8   8   8   8   8  13   8  13  13  13  13  13  13  13  13

Scalar


        KT /34/
        D /5/
        MaxScenarios /16/
;
```

```
Parameter
a(i,j,n) 1 if timeblock i is included in shift n on day j 0 otherwise

 /i3*i8.j1.n1    1
  i4*i9.j1.n2    1
  i5*i10.j1.n3    1
  i6*i11.j1.n4    1
  i7*i12.j1.n5    1
  i8*i13.j1.n6    1
  i9*i14.j1.n7    1
  i11*i15.j1.n8    1
  i16*i19.j1.n9    1
  i17*i20.j1.n10    1
  i18*i23.j2.n1    1
  i19*i24.j2.n2    1
  i20*i25.j2.n3    1
  i21*i26.j2.n4    1
  i22*i27.j2.n5    1
  i23*i28.j2.n6    1
  i24*i29.j2.n7    1
  i26*i30.j2.n8    1
  i31*i34.j2.n9    1
  i32*i35.j2.n10    1
  i33*i38.j3.n1    1
  i34*i39.j3.n2    1
  i35*i40.j3.n3    1
  i36*i41.j3.n4    1
  i37*i42.j3.n5    1
  i38*i43.j3.n6    1
  i39*i44.j3.n7    1
  i41*i45.j3.n8    1
  i46*i49.j3.n9    1
  i47*i50.j3.n10    1
  i48*i53.j4.n1    1
  i49*i54.j4.n2    1
  i50*i55.j4.n3    1
  i51*i56.j4.n4    1
  i52*i57.j4.n5    1
  i53*i58.j4.n6    1
  i54*i59.j4.n7    1
  i56*i60.j4.n8    1
  i61*i64.j4.n9    1
  i62*i65.j4.n10    1
  i63*i68.j5.n1    1
  i64*i69.j5.n2    1
  i65*i70.j5.n3    1
  i66*i71.j5.n4    1
  i67*i72.j5.n5    1
  i68*i73.j5.n6    1
  i69*i74.j5.n7    1
  i71*i75.j5.n8    1
  i76*i79.j5.n9    1
  i77*i80.j5.n10    1
  i78*i83.j6.n1    1
  i79*i84.j6.n2    1
```

```
  i80*i85.j6.n3    1
  i81*i86.j6.n4    1
  i82*i87.j6.n5    1
  i83*i88.j6.n6    1
  i84*i89.j6.n7    1
  i86*i90.j6.n8    1
  i91*i94.j6.n9    1
  i92*i95.j6.n10   1
  i93*i98.j7.n1    1
  i94*i99.j7.n2    1
  i95*i100.j7.n3   1
  i96*i101.j7.n4   1
  i97*i102.j7.n5   1
  i98*i103.j7.n6   1
  i99*i104.j7.n7   1
  i101*i105.j7.n8  1
  i1*i4.j7.n9    1
  i2*i5.j7.n10   1    /;

Parameter R_MIN(j,n) minimum number of phlebotomists in each shift on each
day
/ j1*j7.n1*n10  0
/;

Parameter WL_MAX(o) maximum workload in scenario o
/ o1*o16  400
/;

Parameter KT_MAX(o) maximum workload in scenario o
/ o1*o16  34
/;

Variables
     q difference between max. and min. workload
     x(j,k,n) whether phlebotomist k works on day j during shift n
     y(i,k)the number of tasks assigned to phlebotomist k in time block i
under the realization o
     z(i) the number of tasks left over at the end of time block i under the
realization o
     workload(j,k,n,o) workload of phlebotomist k in shift n on day j in
scenario o
     workload_single(j,k,n) workload of phlebotomist k in shift n on day j in
a scenario
     tmax maximum expected workload in each shift
     tmin minimum expected workload in each shift
     flag control variable
     ;

positive variables y, z, tmax, tmin;

binary variable x;

free variable  q, flag;


Equations
```

```
         balanceworkload  objective function
         con0 minimum number of phlebotomists in each shift on each day
         con1 phlebotomist capacity constraint
         con2 shift limit per day for each phlebotomist constraint
         con3 consecutive shift restriction constraint
         con4 total shift requirement for phlebotomists constraint
         con5 stage link constraint
         con6 task inventory balance constraint
         con7 stat test constraint
         con8 inventory constraint
         con9 inventory constraint II
         con10 inventory constraint III
         con11 inventory constraint IV
         con12 maximum workload constraint
         con13 workload of each phlebotomist in each shift on each day
;


balanceworkload..  q =e= tmax;

con0(j,n).. sum(k,x(j,k,n)) =g= R_MIN(j,n);

con1(j).. sum(n,sum(k,x(j,k,n))) =l= KT;

con2(j,k).. sum(n,x(j,k,n)) =l= 1;

con3(j,k,n_1,n_3).. x(j,k,n_1)+ x(j-1,k,n_3) =l= 1;

con4(k).. sum((j,n),x(j,k,n)) =e= D;

con5(i,k).. (s(k)*y(i,k)) =l= T(i)*sum((j,n),(a(i,j,n))*x(j,k,n));

con6(i).. z(i) =e= z(i-1) + u(i)- sum(k,y(i,k));

con7(i).. sum(k,y(i,k)) =g= b(i);

con8(i_1).. z(i_1) =e= 0;

con9(i)$i_2(i).. z(i) =l= sum(k,y(i+1,k));

con10(i)$i_3(i).. z(i)=l= sum(k,y(i+1,k)+y(i+2,k));

con11(i)$i_4(i).. z(i)=l= sum(k,y(i+1,k)+y(i+2,k)+y(i+3,k));

con12(j,k,n).. tmax =g= workload_single(j,k,n);

con13(j,k,n).. workload_single(j,k,n) =e= sum(i,s(k)*y(i,k)*a(i,j,n));

OPTION RESLIM = 200;
Option Bratio = 1;

Model TSSPS_Model1 /all/;

Solve TSSPS_Model1 using MIP minimizing q;

WL_MAX("o1") = tmax.l;
```

```
TSSPS_Model1.optfile=1;

flag.l = 0;
while ((flag.l le 0.5),
         flag.l = 1;

         loop(o,
                  u(i) = R(i,o);

                  x.lo(j,k,n) = x.l(j,k,n);
                  x.up(j,k,n) = x.l(j,k,n);
                  Solve TSSPS_Model1 using MIP minimizing q;

                  if ((((TSSPS_Model1.modelstat ne 1) and
(TSSPS_Model1.modelstat ne 2) and (TSSPS_Model1.modelstat ne 8)) or (tmax.l
ge (LB(o)+5))),
                     flag.l = 0;
                     while ((((TSSPS_Model1.modelstat ne 1) and
(TSSPS_Model1.modelstat ne 2) and (TSSPS_Model1.modelstat ne 8)) or (tmax.l
ge (LB(o)+5))),
                           x.lo(j,k,n) = 0;
                           x.up(j,k,n) = 1;
                           OPTION RESLIM = 4000;
                           Solve TSSPS_Model1 using MIP minimizing q;
                           );
                  );

                  WL_MAX(o) = tmax.l;

                  KT_MAX(o) = 0;
                  loop(j,
                     if ((KT_MAX(o) lt sum((k,n),x.l(j,k,n))),
                           KT_MAX(o) = sum((k,n),x.l(j,k,n))  );
                  );

                  workload.l(j,k,n,o) = workload_single.l(j,k,n);
                  loop(j, loop(n,
                     if ((R_MIN(j,n) le
(sum(k,workload.l(j,k,n,o)*x.l(j,k,n))/WL_MAX(o))),
                           R_MIN(j,n) =
floor(sum(k,workload.l(j,k,n,o)*x.l(j,k,n))/WL_MAX(o)));
                  ); );

              );

         KT = 0;
         loop(o,
                  if((KT lt ceil(KT_MAX(o))), KT = ceil(KT_MAX(o)) );
         );

         loop(o,
                  u(i) = R(i,o);

                  x.lo(j,k,n) = x.l(j,k,n);
                  x.up(j,k,n) = x.l(j,k,n);
                  Solve TSSPS_Model1 using MIP minimizing q;
```

```
                WL_MAX(o) = tmax.l;
                if (((TSSPS_Model1.modelstat ne 1) and
(TSSPS_Model1.modelstat ne 2) and (TSSPS_Model1.modelstat ne 8)), WL_MAX(o) =
400);
        );

        if ((sum(o,p(o)*WL_MAX(o)) lt 1.05*sum(o, p(o)*LB(o))), flag.l = 1);
);

Display x.L, y.L, z.L, q.L, tmax.L;
```

Appendix E

Performance Measure Analysis

Table E.1

Phlebotomist Scheduling Template for Ext. Case 1

	04:00 - 12:00	05:00 - 13:00	06:00 - 14:00	07:00 - 15:00	08:00 - 16:00	11:00 - 19:00	12:00 - 20:00	14:00 - 22:00	22:00 - 06:00	23:00 - 07:00
	Shift 1	**Shift 2**	**Shift 3**	**Shift 4**	**Shift 5**	**Shift 6**	**Shift 7**	**Shift 8**	**Shift 9**	**Shift 10**
Monday	2	1	1	2	0	1	1	3	2	5
Tuesday	1	2	1	0	1	2	0	3	4	3
Wednesday	1	1	1	1	2	1	2	1	5	3
Thursday	0	1	1	2	2	1	1	2	5	3
Friday	1	3	1	0	0	1	0	5	2	5
Saturday	2	1	2	1	0	1	3	1	4	3
Sunday	2	1	0	1	1	3	0	2	3	5

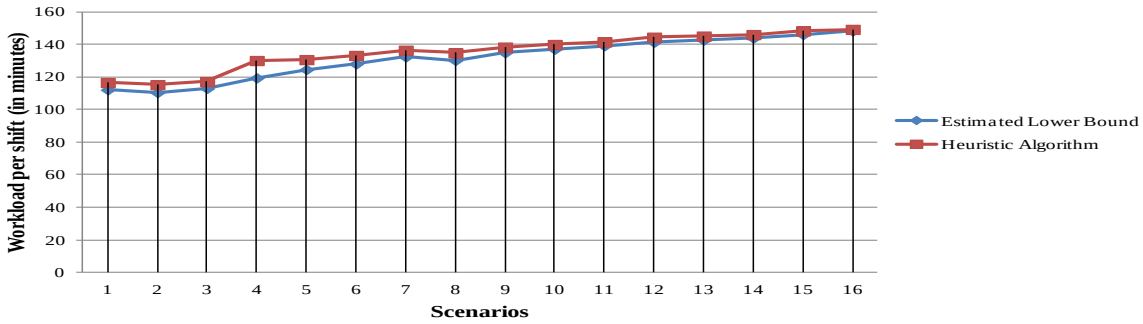

Figure E.1. Estimated lower bound and heuristic algorithm workload for ext. case 1.

Table E.2

Phlebotomist Scheduling Template for Ext. Case 2

	04:00 - 12:00	05:00 - 13:00	06:00 - 14:00	07:00 - 15:00	08:00 - 16:00	11:00 - 19:00	12:00 - 20:00	14:00 - 22:00	22:00 - 06:00	23:00 - 07:00
	Shift 1	**Shift 2**	**Shift 3**	**Shift 4**	**Shift 5**	**Shift 6**	**Shift 7**	**Shift 8**	**Shift 9**	**Shift 10**
Monday	0	0	1	2	0	1	0	2	3	3
Tuesday	2	0	2	0	0	0	2	1	1	5
Wednesday	1	2	1	0	0	0	1	2	2	4
Thursday	0	1	2	0	0	1	1	1	5	1
Friday	1	2	0	0	1	0	1	1	3	2
Saturday	1	2	1	0	0	1	1	1	4	1
Sunday	3	0	0	0	0	1	1	2	2	3

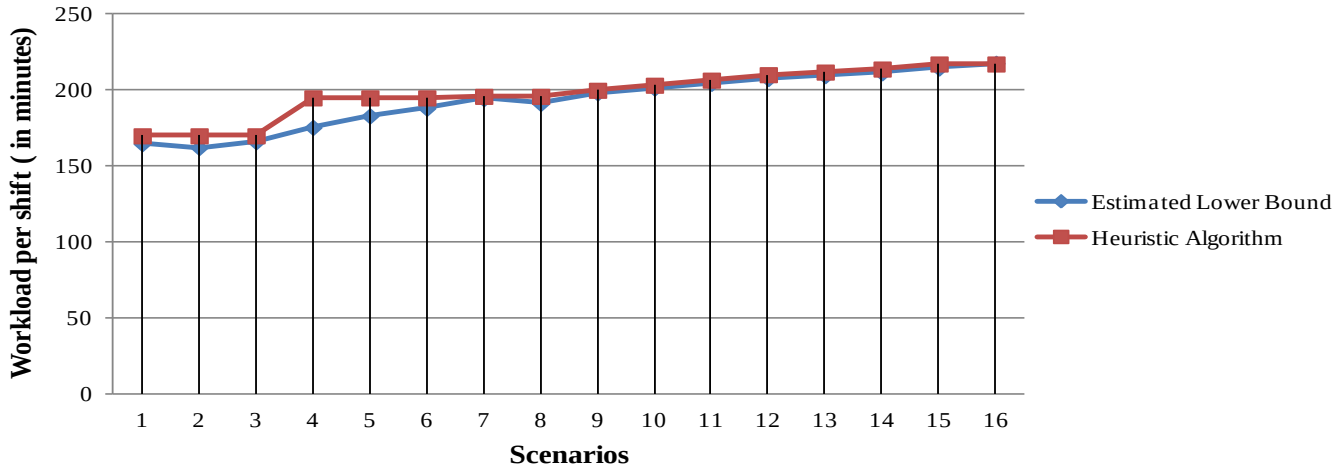

Figure E.2. Estimated lower bound and heuristic algorithm workload for ext. case 2.

Appendix F

Experimental Results Analysis

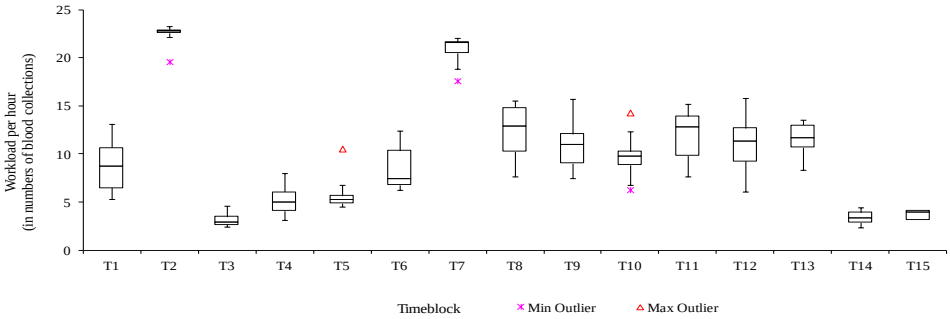

Figure F.1. Comparison of hourly workload in the case with 34 phlebotomists, who each has 45 minutes per hour available for blood collections.

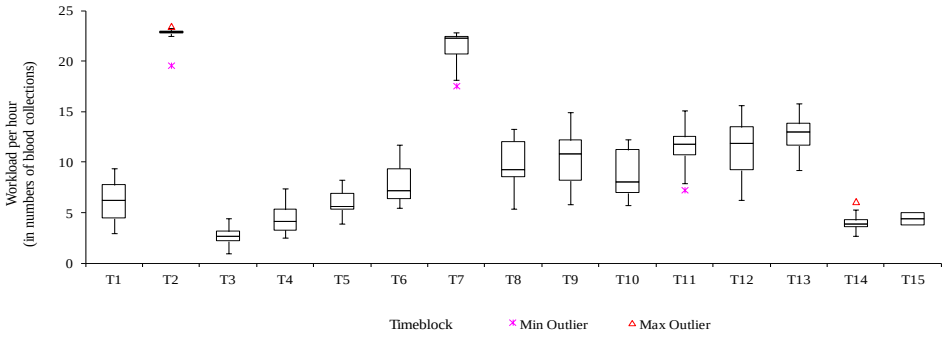

Figure F.2. Comparison of hourly workload in the case with 25 phlebotomists, who each has 45 minutes per hour available for blood collections.

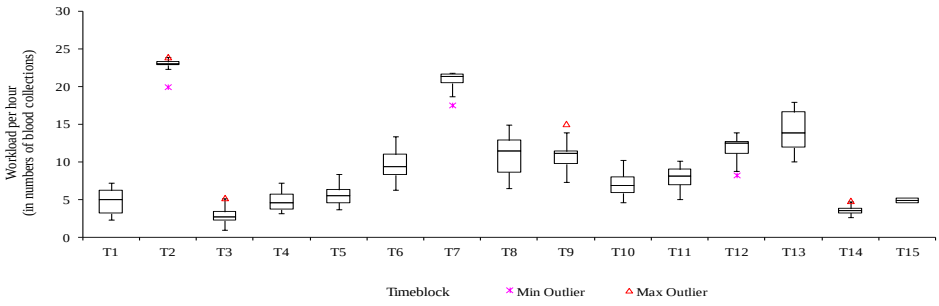

Figure F.3. Comparison of hourly workload in the case with 17 phlebotomists, who each has 45 minutes per hour available for blood collections.

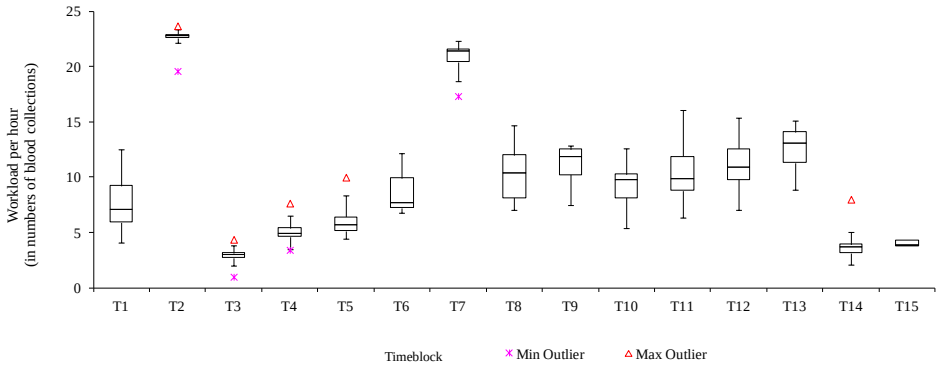

Figure F.4. Comparison of hourly workload in the case with 34 phlebotomists, who each has 40 minutes per hour available for blood collections.

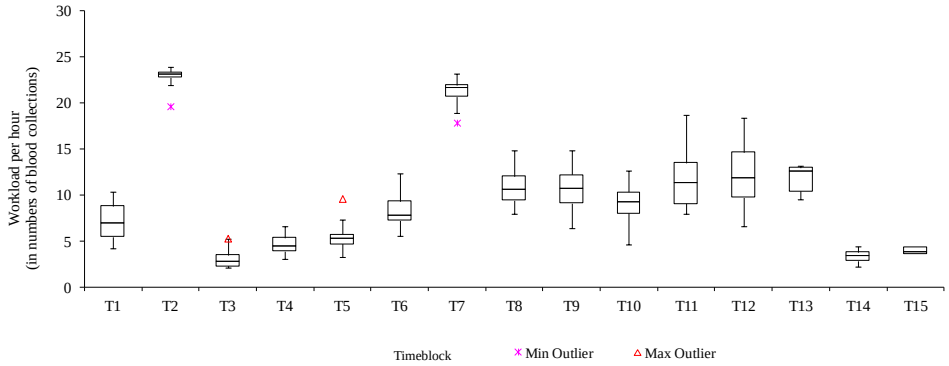

Figure F.5. Comparison of hourly workload in the case with 25 phlebotomists, who each has 40 minutes per hour available for blood collections.

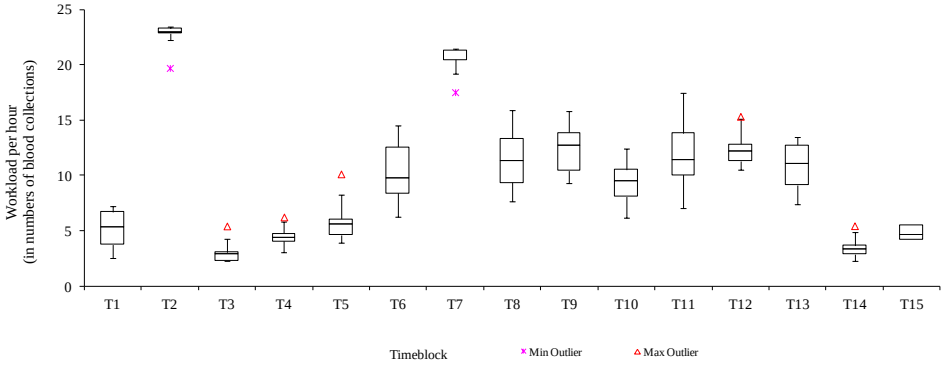

Figure F.6. Comparison of hourly workload in the case with 17 phlebotomists, who each has 40 minutes per hour available for blood collections.